Abstract—This paper investigates the problem of maximizing the signal-to-noise ratio (SNR) in reconfigurable intelligent surface (RIS)-assisted MISO communication systems. The problem will be reformulated as a complex quadratic form problem with unit circle constraints. We proved that the SNR maximizing problem has a closed-form global optimal solution when it is a rank-one problem, whereas the former researchers regarded it as an optimization problem. Moreover, We propose a relaxation algorithm (RA) that relaxes the constraints to that of Rayleigh’s quotient problem and then projects the solution back, where the SNR obtained by RA achieves much the same SNR as the upper bound but with significantly low time consumption. Then we asymptotically analyze its performance when the transmitter grows large together with the number of units of RIS $N$ grow large together, with $N/n_t \rightarrow c$. Finally, our numerical simulations show that RA achieves over 98% of the performance of the upper bound and takes below 1% time consumption of manifold optimization (MO) and 0.1% of semidefinite relaxation (SDR).

Index Terms—Reconfigurable intelligent surface, optimization, relaxation algorithm, Rayleigh’s quotient, random matrix theory (RMT).

I. INTRODUCTION

Forward-looking technologies for the sixth generation (6G) communications have become a research hotspot in the wireless communication community. The most effective means to achieve ultra-high data rates is using new spectrum technologies to increase the wireless bandwidth and system capacity. The upward shift of the spectrum causes the weaker electromagnetic waves’ diffraction and the faster-received power decay. Those will lead to a reduction in signal coverage and poor scatter signals. Among all technological works pertaining to 6G, RIS is one of the most eye-catching ideas and a promising technology [1] [2].

The RIS, also called programmable metasurface, is a two-dimensional structure with many passive elements consisting of positive intrinsic-negative (PIN) diodes and microstrip lines. With real-time intelligent phase shifters, RISs enable dynamic control over the wireless propagation channel for passive beamforming [3]. Especially if there is no line of sight (LoS) path between the base station (BS) and the user, the RIS could provide a reflected solid LoS beam compared to other scatter beams. We can manipulate this reflected LoS path channel by intentionally adjusting the shifters in RIS to improve the received power [4].

However, it is a challenge to generate narrow beams in the specified direction efficiently. The difficulty lies in that the reflection coefficients of each array element of the RIS are the same, resulting in a complex non-convex quadratic problem with unit circle constraints as $R$ where $R$ is a semi-definite matrix:

$$\max_w w^\dagger R w \quad \text{s.t. } w_i \in \mathbb{C}, \quad |w_i| = 1, \forall i = 1, \ldots, N.$$ (1)

Related works have proposed many good ideas on passive beamforming to overcome the above challenge. In [5], beamforming at the base station and the passive reflection coefficients at the RIS has been optimized using semidefinite relaxation (SDR). In [6], an alternating maximization algorithm has been proposed, with one adopting gradient descent for the RIS design while the other is a sequential fractional programming-based approach. One discrete beamforming algorithm has been proposed in [7], which approximates the global optimum with twelve quantization levels. Moreover, a data-driven deep reinforcement learning technique was proposed [8], and the manifold optimization (MO) methods have been introduced into the RIS passive beamforming problems in [9] [10]. The solution obtained by MO can be regarded as the global optimum because the problem turns out to be a convex problem in terms of Riemannian geometry [11].

However, it is still challenging to calculate the corresponding optimal beam in a very short coherence time, especially for large-scale RISs. In some communication scenarios where high mobility needs to be satisfied, we need to let the beam track the user in real-time to meet the service requirements due to the high directionality and low robustness of the RIS outcoming beam.

In this paper, we propose a simple but efficient algorithm with the idea of relaxation. Here are our contributions:

- we prove that problem (1) has the closed-form global optimal solution when $R$ is rank-one in Theorem 1.

$${\text{(1)}}$$
we propose that the receiving signal power remains constant as the phases of all units in the RIS change by the same phase difference in Remark 1.

• we provide a relaxation algorithm (RA) whose computational time consumption is below 1% of that of the MO; meanwhile, the performance is close to that of MO whatever the rank(R) is.

II. SYSTEM MODEL AND PROBLEM EVALUATION

This section will establish the RIS-assisted reflected Rician channel model, which consists of the line-of-sight (LoS) path and the non-line-of-sight path between an M-antennas base station (BS) and one single-antenna user over a frequency flat fading channel as shown in Fig. 1. Then we formulate the problem aiming to maximize the total transmit power as the expression of the problem (1).

A. System Model

We assume that the system lacks a direct transmission path between the BS and the user here because it is blocked by big barriers, especially when the central frequency of the carrier wave is high. The Rician cascaded model relating the input signal vector $x \in \mathbb{C}^{n_t}$ and output signal $y \in \mathbb{C}$ takes the form

$$y = h_2^T \Theta H_1 x + n,$$

where $[\cdot]^T$ denoting the transpose, $H_1 \in \mathbb{C}^{N \times n_t}$ and $h_2 \in \mathbb{C}^{1 \times n_t}$ respectively denote the channel matrix from BS to RIS and from RIS, and $\Theta = \text{diag}(\alpha_1 e^{j\theta_1}, \ldots, \alpha_N e^{j\theta_N}) \in \mathbb{C}^{N \times N}$ is a diagonal matrix representing the phase shift matrix of the RIS and $N$ is the number of units in the RIS. The noise scalar $n \in \mathbb{C}$ is a complex Gaussian scalar with zero mean and covariance $\sigma^2$.

For high-frequency communications, like millimeter waves or submillimeter waves, the channels are possibly dominated by the LoS paths. To match the practical implementation, we employ the Rician fading to model the channel $H_1$, which can be written as

$$H_1 = \sqrt{\frac{K_1}{K_1+1}} M_1 + \sqrt{\frac{1}{K_1+1}} H_1^{(w)} ,$$

where $H_1^{(w)}$ is an i.i.d. matrix with zero mean, unit variance complex Gaussian entries, the rank-one matrix $M_1$ is deterministic and arbitrary, normalized such that the channel gain $\text{tr}(M_1 M_1^T) = n_t$ and $K_1$ is Rician factor between the two components. Different from the traditional communication systems, where the channel gain is usually related to both the number of transmitter’s (Tx’s) and receiver’s (Rx’s) antennas, the channel gain of $M$ only depends on $n_t$ because of the lack of radio frequency (RF) chains in the RIS. Because the more elements RIS has, the more energy it reflects, then the channel gain of $h_2$ depends on the number of the RIS’s unit $N$ and Rx’s antenna ($n_r = 1$). So we also have

$$h_2 = \sqrt{\frac{K_2}{K_2+1}} m_2 + \sqrt{\frac{1}{K_2+1}} h_2^{(w)},$$

where $h_2^{(w)}$ is an i.i.d. vector with zero mean, unit variance complex Gaussian entries, and $m_2$ is a deterministic and arbitrary vector meanwhile $\text{tr}(m_2 m_2^T) = N$ and the amplitude of each entry of $m_2$ equals to 1. Accordingly, the signal-noise-ratio (SNR) is given by

$$\text{SNR} = \frac{\|h_2^T \Theta H_1\|^2}{\sigma^2}.$$
We perform an eigenvalue decomposition of the complex hermitian matrix $R$. Assume that the rank of $R$ is $n_r$, and that
\[
R = \sum_{i=1}^{M} \lambda_i v_i v_i^*,
\]  
where $\lambda_i$ denotes $i^{th}$ eigenvalue in descending order (i.e., $\lambda_1 \geq \lambda_2 \geq \lambda_M$), $M$ denotes the rank($R$) and $v_i$ denotes the corresponding eigenvector. And we let $v_i = [a_{i,1} e^{j \tau_{1,i}}, \ldots, a_{i,N} e^{j \tau_{N,i}}]^T$ which satisfy $\sqrt{a_{i,1}^2 + a_{i,2}^2 + \cdots + a_{i,N}^2} = 1$.

1) $M = 1$: Here we proposed a significant theorem so that all the rank-one unit circle constrained complex quadratic problems have no need to be optimized by traditional approaches. All iterative algorithms for solving this kind of rank-one problem are meaningless.

**Theorem 1:** Problem (8) has the closed-form global optimal solution when $R$ is rank-one, where the optimal solution is
\[
\theta_i = \tau_{1,i} + C, \forall i = 1, \ldots, N,
\]
with $C$ is a constant for all $\theta_i$ and $\tau_{1,i}$ is the phase of the $i^{th}$ entry of eigenvector $v_1$.

**Proof:** Consider the self-adjoint property of the hermitian matrix, and Euler’s equation, Eq.(8) can be derived as follow:
\[
w^* R w = \lambda_1 w_1^* v_1 v_1^* w
= \lambda_1 \sum_{i=1}^{N} \sum_{k=1}^{N} a_{i,k} e^{j (\tau_{1,i} - \theta_i)} a_{k,i} e^{-j (\tau_{1,k} - \theta_k)}.
\]

By the Hermitian property of Eq.(11), we obtain $w^* R w$ equals to its real part $\Re\{w^* R w\}$ so that it can attain its maximum value by letting the phase of each part of it be zero, i.e.,
\[
\tau_{1,i} - \theta_i = \tau_{1,j} - \theta_j, \forall i,j = 1, \ldots, N.
\]

**Remark 1:** The value of the objects function of Problem (8) remains unchanged when $\theta_i, \forall i = 1, \ldots, N$ increase the same skewing $\Delta \theta$ (i.e., $\theta_i + \Delta \theta, \forall i = 1, \ldots, N$) whatever the rank of $R$ is.

The conclusion above results from the following equation:
\[
w^* R w = \sum_{k=1}^{N} |r_{kk}|^2 + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} 2 |r_{ij}| \cos(\theta_i - \theta_j - \phi_{ij}),
\]

where $r_{ij}$ and $\phi_{ij}, \forall i,j$ are the amplitude and the phase of the entry at $i^{th}$ row and $j^{th}$ column of $R$. Eq.(13) illustrates the fact that what is meaningful in passive beamforming is the phase differences.

As shown in Fig.2 by Remark 1, we can intuitively simplify the optimization process of beamforming when there is only one planar incoming electromagnetic (EM) wave. Constructive or destructive interference depends on the relative phase differences between each beam at the receiver. What matters is the phase difference between each unit (i.e., $\theta_i - \theta_j, \forall i, j$) as shown in Fig.2(a) and (13). Actually there are only $N - 1$ non-correlated phase differences among $\frac{N(N-1)}{2}$. So we neglect the redundancy ones and only consider the intrinsic ones, just like decouling shown as Fig.2(b).

2) $M \geq 1$: We can decompose the rank-$M$ problem (8) to the linear combination of $M$ rank-one problem (8):
\[
w^* R w = \sum_{i=1}^{M} \lambda_i w^* v_i v_i^* w.
\]

For convenience, we denote the phases vector of the eigenvector $v_i$ as $\tau_i$ and $\tau_{i,j}$ represents the $j^{th}$ elements of $\tau_i$. Ideally, we hope to get the maximum value of Eq.(14) by Theorem 1. Unfortunately, there does not exist a set of constants $C_i$ such that for all $i,j = 1, \ldots, N$ the $\tau_i + C_i = \tau_j + C_j$ because of the orthogonality of eigenvectors set $\{v_i\}_i$.

So that our proposed algorithm obtains the approximated global optimum by simply applying the closed-form optimal solution (10) into the first component $\lambda_1 w^* v_1 v_1^* w$ of Eq.(14), the margin of error between the result solved by RA and the global optimum is caused by the projection of $w$ on other eigenvectors $v_i, i \neq 1$, which we are going to give the mathematical explanation after we state our relaxation algorithm.

**B. Algorithm description**

The idea of our relaxation algorithm is only dealing with the leading component $\lambda_1 w^* v_1 v_1^* w$ of $w^* R w$ while ignoring the others $\sum_{i=2}^{M} \lambda_i w^* v_i v_i^* w$.

**Algorithm 1 Relaxation Algorithm (RA)**

**Input:** complex vector of variables $w \in \mathbb{C}^{N \times 1}$, complex quadratic form coefficient matrix $R \in \mathbb{C}^{N \times N}$

**Output:** optimal vector $w^*$

1: perform spectral decomposition of matrix $R$ as (9) and obtain the leading eigenvectors $v_1$
2: make $\theta^*$ equals to the phase vector $\tau_1$ of $v_1$
3: obtain the optimal solution vector by $w^* = e^{j \theta^*}$

Step 2 of Algorithm 1, which only considers the leading component corresponding to the largest eigenvalue, transforms the process of searching for optimal solution in the
N-dimensional torus $\mathbb{T}^N$ from the tedious well-designed algorithm to a simple spectrum decomposition of complex hermitian matrix $R \in \mathbb{C}^{N \times N}$. Apparently, the RA can directly obtain the maximum value of problem (8) while $n_t = 1$ as mentioned by Theorem 1.

Let us explain the RA from the perspective of semi-positive definite relaxation [13]. For the Rayleigh’s quotient (RQ), which is constrained by $w^\top w = N$ ($C$ is an arbitrary constant), the objects function $w^\top R w$ attains its maximum value $N \lambda_1$ (leading eigenvalue) when $w = w_{RQ}^* = \sqrt{N} v_1$ (leading eigenvector). That is because $w_{RQ}^*$ is not projected onto any other eigenvector. Noticeably, the set of complex vectors in n-dimensional torus $\mathbb{T}^N$ is a subset of complex vectors in the RQ problem’s constraint space $\mathbb{S}^N$, which means

$$\{w \in \mathbb{C}^N | |w_i| = 1, \forall i = 1, \ldots, N \} \subset \{w \in \mathbb{C}^N | w^\top w = N \}.$$ (15)

The geometry explanation of the relaxation process in the RA can be described as follow:

1) relaxing the feasible set of problem (8) from $\mathbb{T}^N$ to $\mathbb{S}^N$ meanwhile the problem converts into an RQ problem;
2) obtaining the solution of RQ problem $w_{RQ}^*$;
3) projecting the optimal solution $w_{RQ}^*$ from $\mathbb{S}^N$ to $\mathbb{T}^N$ by making amplitude of each entry of $w_{RQ}^*$ equal to 1, then obtaining the solution of the RA, i.e., $w^*$.

C. Spectral Analysis

This subsection will discuss the performance of our proposed algorithm RA, which depends on the spectrum of $R$.

As we know, the solution $w_{MO}^*$ obtained by the MO can be regarded as the global optimum because the problem (1) turns out to be a convex problem in terms of Riemannian geometry [11]. However, it obtains the solution by searching in the scale of the first component and others, which can be measured in terms of the prominence of $\lambda_1$.

1) The angle: The angle $\beta$ of $w^*$ and $w_{RQ}^*$ can be defined as $\cos \beta = \frac{w^\top v_1}{\|w^*\| \|v_1\|} = \sum_{i=1}^N a_i / N$. We find by experiments that the mean of the distribution of $\beta$ will converge to a lower bound as $N$ increases. As shown in Fig. 4 we depict some curves to show how $n_t$, $K_1$, and $K_2$ influence $\beta$. Due to the space limitation, we refer the readers to [14] for detailed proof and discussion on this.

Remark 2 The lower bound of $\beta$ defined in (17) increases as $K_2$ increases. The convergence rate of $\beta$ slows down as $K_1$ or $n_t$ increases.

2) The prominence of $\lambda_1$: Since both $H_1$ and $\text{diag}(h_2^T)$ are information-plus-noise model [15] [16] [17], $R$ is a spike model which has the isolated eigenvalue.

Theorem 2: As $n_t, N, K_2 \to \infty$ such that $N/n_t \to c \in (0, \infty)$, denoting $\hat{\lambda}_1$ the leading eigenvalues of $R/N$ and the sole eigenvalue of $M_1 M_1^\top / N$ has been defined as the number...
of transmitting antennas $n_t/N$, then
\[
\lambda_1 \xrightarrow{a.s.} \begin{cases} 
\frac{1}{c} + \frac{1}{K_1} & , K_1 > \sqrt{c} \\
\frac{1}{c} + \frac{1}{K_1} & , K_1 \leq \sqrt{c}
\end{cases}
\] (18)

Theorem 2 identifies an abrupt change in the behavior of the prominence of the leading eigenvalues $\lambda_1$ of $R/N$ (as shown in Fig. 3): if $K_1 \leq \sqrt{c}$, where the LoS path has not dominated the channel from Tx to the RIS, the empirical spectral distribution of $R$ remains unchanged meanwhile its asymptotic limit can be depicted by the Marčenko-Pastur distribution $\mu$ [18]. However, as soon as $K_1 > \sqrt{c}$, $\lambda_1$ converges to a limit $\frac{1}{c} + \frac{1}{K_1}$ beyond the right-edge of $\mu$, and the leading eigenvalue becomes more prominent as $K_1$ increasing. In addition, as mentioned in Theorem 1, the performance of RA is exactly the global optimum when $K_1 \to \infty$ (i.e., $R$ becomes a rank-one matrix).

Remark 3: The max SNR obtained by the RA will approach the upper bound of it (obtained by the MO) as the LoS path dominates the channel (i.e., $K_1 \to \infty$)

IV. VALIDATION OF THE RELAXATION ALGORITHM VIA NUMERICAL SIMULATION

In this section, numerical results are provided to validate the proposed RA’s effectiveness. We will show the extremely low time consumption and high reliability for high-rank $R$ through simulation. The simulation is performed in a Matlab environment in Windows 11 operating system with CPU i7-12700K, and the code has been open-sourced to the GitHub website[^2].

Note that the time consumed of SDR is linearly correlated with the number of Gaussian random vectors we generated [5] (we generated 25 gaussian random vectors every loop in Fig. 6 experiment setting and only one in Fig. 7 settings). Moreover, the SNR obtained by MO can be regarded as the upper bound.

[^2]: https://github.com/DwyaneDong/relaxation-algorithm-on-RIS-MISO.git

The SNR we will evaluate is defined in [5]. The Fig. 6 shows the SNRs of three methods for different ranks of $R$ whose dimensions grow from 50 to 500, averaged over $10^5$ channel realization. From this figure, the proposed RA method obtains exactly the same SNR as the MO method while rank is one, which proves Theorem 1 that the solution given by (12) is the global optimum for the rank-one situation. And RA methods can reach respectively 100%, 99.1%, 98.4% and 98.2% of the SNRs obtained by the MO methods in rank 1, 4, 8, and 16 when $N$ is 500. These results prove Theorem 1 in experiments where we find the closed-form global optimal solution of the rank-one situation. Even though we increased the number of generated Gaussian vectors to over $10^2$ in simulation [5], the SDR method has difficulty in achieving SNR as good as the first two methods, and the higher the rank, the larger the difference in SNR. The reason why SDR failed has been discussed in [5].

The most interesting part about RA is the extremely low time consumption which comes from its simplicity. We perform this comparison using the open source toolboxes Manopt [19] and CVX [20]. As shown in Fig. 7 the time consumption of RA is below 1% of that of MO and below 0.1% of that of SDR. Unlike all the other algorithms, the time consumption of RA does not depend on the rank of $R$. This exciting property makes it possible to perform passive beamforming for RIS-assisted communication in a high-mobility channel environment where the coherence time is very short.

As shown in Fig. 8 the performance of RA will approach the global optimum (obtained by the MO) as $K_1$ increasing. The RA-MO SNR ratio is respectively 97.30%, 97.50%, 98.33% and 99.87% as the $K_1$ equals to 0, 1, 10 and 50. And the ratio is hardly changed by the number of units in RIS when $n_t$ and $K_1$ stay the same.

The Fig. 9 shows that the performance slowly decreases compared to the global optimum (obtained by the MO). At the same time, the number $n_t - 1$ of non-leading and non-zero eigenvalues of $R$ increases, the sum of spectral components except the leading one will increase because the norm of the projection of $w^*$ onto any other eigenvector converges to a
RA) that consumes an extremely short time to get a great performance. The RA truly takes the passive beamforming for RIS-assisted communication systems from tedious to simple.

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