Sum Rate Maximization for NOMA-Based VLC With Optical Intelligent Reflecting Surface

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***Abstract*—Intelligent reflecting surface (IRS) is a novel technology that provides new research perspectives for wireless communications due to its capability of redesigning the wireless electromagnetic environment. In this letter, we investigate the OIRS-aided VLC system employing the power-domain non-orthogonal multiple access (NOMA), where the achievable sum rate is maximized via optimizing the optical IRS (OIRS) reflection matrix. By describing the OIRS attributes in terms of an association matrix, we transform the OIRS optimization problem into a binary programming problem and iteratively optimize the OIRS passive beamforming by the proposed low-complexity algorithm. Simulation results show that the OIRS improves the achievable sum rate of the NOMA-based VLC system and the proposed algorithm is superior to other baseline schemes.**

***Index Terms*—Optical intelligent reflecting surface (OIRS), visible light communication (VLC), non-orthogonal multiple access (NOMA), sum rate maximization.**

I. Introduction

UNDER the background of the explosive growth of communication data traffic and increasingly crowded frequency band, visible light communication (VLC) is regarded as a promising technology for future 6G communication owing to its license-free merit within broad bandwidth and the ubiquity of light-emitting diodes (LEDs) [1]. As a result, VLC is considered to have great potential for green communications, secure communications, and so on [2], [3].

Intelligent reflecting surface (IRS), which is a planar array comprising lots of low-cost passive reflecting components, has drawn a lot of interest in radio frequency (RF) communications recently. With the capability of controlling the reflection characteristics of the adjustable unit, IRS can adaptively reconfigure the wireless electromagnetic environment. Researchers have investigated the optimization of the IRS configuration to improve the system performance, including sum rate, outage probability, etc [4], [5]. Moreover, since visible light can be easily blocked, the ability of the OIRS to exploit the OIRS-reflected paths is very important for the VLC system to overcome its disadvantages. However, the impact of the OIRS on the VLC system is markedly different from the impact of the IRS on the RF communication system because of the features of visible light, such as different propagation characteristics, non-negative and real-valued signals [6].

Despite the emerging *non-orthogonal multiple access* (NOMA) technologies, which are key of massive machine type communication (mMTC) and can be exploited in multiple domains, this letter focuses on the mainstream power-domain NOMA. Specially, it allows multiple users to use the same spectrum resource simultaneously, with superposition code (SC) at the transmitter and allocating different transmit power according to user channel conditions. At the receiver, users decode the signal via successive interference cancellation (SIC) [7]. Studies have shown that NOMA can significantly improve the capacity of VLC systems [8], [9].

In this letter, we study the sum rate maximization problem of the OIRS-aided VLC system employing the power-domain NOMA technique, where both line-of-sight (LoS) paths and OIRS-reflected paths are taken into account. Remarkably, under the point source assumption, the interference among different specular OIRS-reflected paths can be ignored [4] and the connection of the OIRS unit to the user can be considered as a one-to-one correspondence, i.e., an OIRS unit can only reflect the signal from one LED to one user. Therefore, the OIRS optimization problem can be transformed into designing a discrete matrix, which represents the connection between OIRS units and users. By relaxing the constraints of the OIRS reflection matrix, we propose an iterative optimization algorithm and a greedy strategy to obtain a sub-optimal solution to the problem, and the achievable sum rate is chosen as the objective indicator. Simulation results show that the proposed algorithm improves the sum rate of the system with low computational complexity and outperforms other baseline schemes.

Notations: a, $\mathbf{a}$, $\mathbf{A}$, and $\mathbf{a}^T$ represent the scaler values, vectors, matrices, and transpose of vectors, respectively. $\mathbb{R}_+$ donates the positive real number set and $\mathcal{A}$ denotes the defined set. Moreover, the gradient operator is represented by ∂.

II. System Model

As shown in Fig. 1, the multi-user downlink of a NOMA-based VLC system with the aid of OIRS is considered, where K users are served by a single LED and an OIRS comprising of N units is fixed on the wall of the room. Without loss of generality, the locations of users and OIRS units are assumed to be

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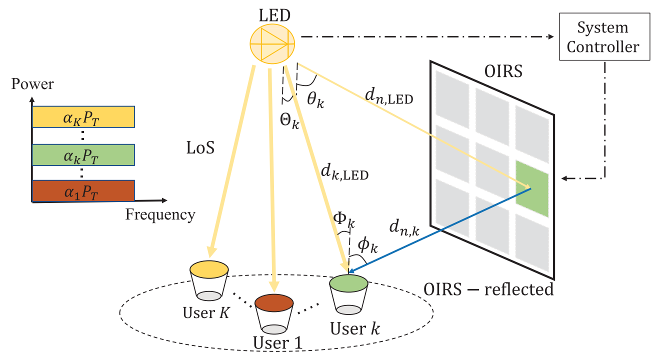

Fig. 1. The system model of the NOMA-based VLC system with OIRS.

known by the system controller, and it can also obtain the full VLC channel state information (CSI) through various channel estimation methods [10], [11]. For the OIRS-aided VLC system, the transmitted signal reaches the receiver via both the LoS path and the OIRS-reflected paths, and the characteristics will be studied in the following.

1) *LoS Channel:* Generally, the direct LoS channel gain follows the Lambertian model in the VLC system [12], so that the mathematics of the gain from the LED to the photodetector (PD) of the k-th user can be written as

$$h_k = \frac{A(m+1)}{2\pi d_{k,\mathrm{LED}}^2} \cos^m(\Theta_k) p_f \cos(\Phi_k) p_c, \tag{1}$$

where A denotes the physical area of the PD, m is Lambertian index, $d_{k,\mathrm{LED}}$ is the distance between the LED and the k-th user. The angles of irradiance and incidence for the LoS path from the LED to the k-th user's PD are represented by Θ_k and Φ_k, respectively. Moreover, p_f and p_c denote the gain of the optical filter and the optical concentrator, respectively. For the convenience of expression, the LoS channel gain between the LED and users is represented by the vector $\mathbf{h} = [h_1, h_2, \ldots, h_K]^T \in \mathbb{R}_+^{K\times 1}$.

2) *OIRS-Reflected Channel:* Typically, the reflections in the OIRS-aided VLC system consist of specular reflection and diffuse reflection. However, the impact of diffuse reflection can be ignored due to its low level compared to the LoS channel gain [1]. For the specular reflection, there are a number of methods for obtaining channel gain through channel estimation [13]. However, an approximate expression of the OIRS-reflected channel gain under the point assumption can be adopted, in which the specular OIRS reflection could be conducted as a signal emitting from an image source and a coefficient factor δ is adopted to represent the energy loss caused by the reflection [6]. Moreover, literature [6] proves that the formula follows an "additive" model, so that the OIRS-reflected gain between the LED and the k-th user through the n-th OIRS unit can be obtained as

$$g_{n,k} = \delta \frac{A(m+1)}{2\pi(d_{n,\mathrm{LED}} + d_{n,k})^2} \cos^m(\theta_k) p_f \cos(\phi_k) p_c, \tag{2}$$

where $d_{n,\mathrm{LED}}$ and $d_{n,k}$ are the distances between the LED and the n-th OIRS unit, the n-th OIRS unit and the k-th user's PD. Then, the angles of irradiance and incidence for the OIRS-reflected path are expressed as θ_k and ϕ_k, respectively. Moreover, a matrix $\mathbf{G} = [\mathbf{g}_1, \mathbf{g}_2, \ldots, \mathbf{g}_K] \in \mathbb{R}_+^{N\times K}$ is defined as the OIRS-reflected channel gain for simplicity, where $\mathbf{g}_k = [g_{1,k}, g_{2,k}, \ldots, g_{N,k}]^T \in \mathbb{R}_+^{N\times 1}$.

3) *Combined Channel:* In the OIRS-aided VLC system, the users are sparsely distributed in the space and the specular reflection direction tightly depends on the geometric positions of the OIRS units [4]. As a result, an OIRS unit can only serve a single user and there is no interference between different specular OIRS-reflected paths under the point source assumption. Inspired by this property, a discrete matrix $\mathbf{S} = [\mathbf{s}_1, \mathbf{s}_2, \ldots, \mathbf{s}_K] \in \mathbb{R}_+^{N\times K}$ is introduced to denote the alignment of OIRS units to users. Each element $s_{n,k}$ is a 0/1 variable, and $s_{n,k} = 1$ means that the n-th OIRS unit is allocated to the k-th user, while $s_{n,k} = 0$ implies not allocated. Moreover, since the propagation delays of the direct link and reflected link are small enough to be ignored, the combined channel gain of the k-th user is given by

$$q_k = h_k + \mathbf{g}_k^T \mathbf{s}_k. \tag{3}$$

III. Proposed Algorithm for OIRS Passive Beamforming

In this section, we discuss the OIRS-aided NOMA VLC and formulate the objective function and its constraints. Then, a relaxing iterative optimization algorithm and a greedy strategy are utilized to solve the non-convex problem. After that, the discussion of the computational complexity is carried out at the end of this section.

A. OIRS-Aided NOMA VLC

Without loss of generality, the LED serves all users in the same bandwidth simultaneously, which is shown in Fig. 1. Following the NOMA principle, the transmitter needs to allocate different transmission power according to the channel conditions of different users, and thus determines the demodulation order at the receiver. However, the allocation of OIRS units may lead to a change in the decoding order of all users. If the above situation occurs, we will change the index of users based on the combined channel quality and reallocate the OIRS units to ensure that $q_1 \geq q_2 \geq \cdots \geq q_K$. With the combined channel quality ranking, the allocated transmit power should satisfy $\alpha_1 \leq \alpha_2 \leq \cdots \leq \alpha_K$ and $\sum_{i=1}^{K} \alpha_i = 1$.

For simplicity, it is assumed that the transmit power allocated to each user is set to a fixed value. Hence, the received signal at the k-th user can be written as

$$y_k = q_k \sum_{i=1}^{K} \sqrt{\alpha_i P_T} x_i + z_k, \tag{4}$$

where P_T denotes the total transmit power, α_i and x_i are the power allocation coefficient and transmitted symbol of the i-th user, respectively. Moreover, $z_k \sim \mathcal{N}(0, \sigma^2)$ denotes the zero-mean Gaussian noise at the k-th user with variance of σ.

B. Problem Formulation

In the VLC system, the classic Shannon capacity formula is not suitable because the characteristic of visible light is different from RF signals, thus a tight lower bound of the achievable rate is usually adopted for the dimmable VLC system [14]. The achievable rate of the k-th user can be expressed as

$$R_k = \frac{1}{2} W \log_2\Big(1 + \frac{e}{2\pi}\gamma_k\Big), \tag{5}$$

where $W \in \mathbb{R}_+$ represents the bandwidth of NOMA transmission, and γ_k denotes the individual signal-to-interference-plus-noise ratio (SINR) of the k-th user. As the SIC is employed at the receiver, the higher power signals are demodulated first while the lower power signals are treated as noise. Given the allocated transmit power, the decoding order is from the last user to the first user in this letter.

For simplicity, the SIC process is assumed to be perfect at the receiver, so that the signals with higher power can be subtracted when the desired signal is extracted. Specially, the signal of the 1-st user is demodulated finally, so that its signal is not interfered with by other users' signals. As a result, the SINR of the k-th user can be given by

$$\begin{cases} \gamma_k = \frac{q_k^2\alpha_k}{\frac{1}{\rho}+q_k^2\sum_{i=1}^{k-1}\alpha_i}, & 2 \le k \le K, \\ \gamma_1 = \rho q_1^2 \alpha_1, & k = 1, \end{cases} \tag{6}$$

where $\rho = P_T/\sigma^2$ donates the transmit signal-to-noise ratio (SNR). To make the discussion simpler, sets $\mathcal{K}$ and $\mathcal{N}$ are defined to represent the index of users and OIRS units, respectively. Given the expression of the achievable rate and the SINR of users, the optimization problem is formulated as

$$\mathbf{P}: \max_{\mathbf{S}} \ R_{sum} = \max_{\mathbf{S}} \sum_{k=1}^{K} R_k \tag{7}$$

$$\text{s.t.} \ \ R_k \ge R_{min}, \quad \forall k \in \mathcal{K}, \tag{8}$$

$$\sum_{k=1}^{K} s_{n,k} = 1, \quad \forall n \in \mathcal{N}, \tag{9}$$

$$s_{n,k} \in \{0,1\}, \quad \forall n \in \mathcal{N}, \ k \in \mathcal{K}. \tag{10}$$

The objective in (7) is to maximize the achievable sum rate of all users, and the constraint in (8) is to guarantee the quality of service (QoS) requirement. Then, constraints in (9) and (10) result from the definition of matrix $\mathbf{S}$.

As $s_{n,k}$ is taken as a discrete value in (10), the integer programming problem $\mathbf{P}$ is non-deterministic polynomial-time (NP) hard according to [15]. Since relaxing the constraints on integer variables to continuous variables can facilitate the use of optimization methods [4], [5], the constraint in (10) is relaxed as

$$0 \le s_{n,k} \le 1, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}. \tag{11}$$

Thus, the original problem is rewritten into the following form

$$\mathbf{P1}: \max_{\mathbf{S}:\ (8),\ (9),\ (11)} \sum_{k=1}^{K} R_k. \tag{12}$$

C. The Iterative Optimization Algorithm and Greedy Strategy

In this letter, the integer programming problem $\mathbf{P}$ was solved by iteratively optimizing the problem $\mathbf{P1}$ with the relaxing constraint and then obtaining the final OIRS reflection matrix $\mathbf{S}$ via a greedy strategy. The detailed solution process is shown in Algorithm 1.

Algorithm 1 Iterative Optimization Algorithm to Solve **P**

Init: $t \leftarrow 0, \epsilon \leftarrow 0.1$, randomly generated $\mathbf{S}^{(0)}$, $\mathbf{S}^{relax} \leftarrow \mathbf{0}$, $\mathbf{S} \leftarrow \mathbf{0}$, $k \leftarrow K$;
repeat
  $t \leftarrow t+1$;
  solve **P1** by gradient descent method and obtain $\mathbf{S}^{(t)}$;
until $\|\mathbf{S}^{(t-1)} - \mathbf{S}^{(t)}\|_2 \le \epsilon$;
$\mathbf{S}^{relax} \leftarrow \mathbf{S}^{(t)}$;
repeat
  $i \leftarrow 1$;
  repeat
    find the index n of the i-th max element in $\mathbf{s}_k^{relax}$;
    if the OIRS unit n is not assigned to other users **then**
      $s_{n,k} \leftarrow 1$;
    end if
    $i \leftarrow i+1$;
  until $R_k \ge R_{min}$
  $k \leftarrow k-1$;
until $k \le 1$
$s_{n,1} \leftarrow 1$, for all unallocated OIRS unit n.

Obviously, the relaxation of constraint (10) is not sufficient to make the problem $\mathbf{P1}$ convex, because the variable $\mathbf{s}_k$ remains quadratic within a logarithmic function in the expression of achievable rate. Therefore, we propose an iterative optimization algorithm in which $\mathbf{s}_k^{(t)}$ represents the OIRS reflection vector for the k-th user in the t-th iteration of optimization. Then, $\mathbf{s}_k^{(t-1)}$ is used to turn $\mathbf{P1}$ into a convex problem in the t-th iteration. Consequently, the expression of users' SINR during the t-th iteration of optimization can be obtained as

$$\begin{cases} \tilde{\gamma}_k^{(t)} = \frac{\left[{h_k}^2 + 2h_k \times \mathbf{g}_k^T\mathbf{s}_k^{(t)} + \mathbf{g}_k^T\mathbf{s}_k^{(t-1)} \times \mathbf{g}_k^T\mathbf{s}_k^{(t)}\right]\alpha_k}{\frac{1}{\rho} + \left[h_k + \mathbf{g}_k^T\mathbf{s}_k^{(t-1)}\right]^2 \sum_{i=1}^{k-1}\alpha_i}, \ 2 \le k \le K, \\ \tilde{\gamma}_1^{(t)} = \rho\Big[{h_1}^2 + 2h_1 \times \mathbf{g}_1^T\mathbf{s}_1^{(t)} + \mathbf{g}_1^T\mathbf{s}_1^{(t-1)} \times \mathbf{g}_1^T\mathbf{s}_1^{(t)}\Big]\alpha_1, \ k = 1. \end{cases} \tag{13}$$

In order to analyze the convexity of the problem $\mathbf{P1}$ in the t-th iteration, the Hessian matrix needs to be calculated. For ease of representation, $C_k^{(t)}$ is defined to represent $\frac{e}{2\pi}/(1 + \frac{e}{2\pi}\tilde{\gamma}_k^{(t)})$ in the following. The second derivative of the k-th user's achievable rate in the t-th iteration is $\tilde{R}_k^{(n_1,n_2,k_1,k_2,t)} = \partial^2 R_k^{(t)}/(\partial s_{n_1,k_1}^{(t)} \partial s_{n_2,k_2}^{(t)})$, and it is obvious that this expression is not zero if and only if $k_1 = k_2 = k$. Therefore, the second derivative of R_1 in the t-th iteration can be written as

$$\begin{aligned} &\tilde{R}_1^{(n_1,n_2,1,1,t)} \\ &= \frac{\partial}{\partial s_{n_2,1}^{(t)}}\left(\frac{W}{2\ln 2}\rho(2h_1 + \mathbf{g}_1^T\mathbf{s}_1^{(t-1)})\alpha_1 C_1^{(t)} g_{n_1,1}\right) \\ &= -\frac{W}{2\ln 2}\left(\rho(2h_1 + \mathbf{g}_1^T\mathbf{s}_1^{(t-1)})\alpha_1 C_1^{(t)}\right)^2 g_{n_1,1}g_{n_2,1}. \end{aligned} \tag{14}$$

When $2 \le k \le K$, the expression of $\tilde{R}_k^{(n_1,n_2,k,k,t)}$ is

$$\begin{aligned} &\tilde{R}_k^{(n_1,n_2,k,k,t)} \\ &= \frac{\partial}{\partial s_{n_2,k}^{(t)}}\left(\frac{W}{2\ln 2}\frac{(2h_k + \mathbf{g}_k^T\mathbf{s}_k^{(t-1)})\alpha_k}{\frac{1}{\rho} + \left(h_k + \mathbf{g}_k^T\mathbf{s}_k^{(t-1)}\right)^2\sum_{i=1}^{k-1}\alpha_i} C_k^{(t)} g_{n_1,k}\right) \end{aligned}$$

$$= -\frac{W}{2\ln 2}\left(\frac{(2h_k + \mathbf{g}_k^T\mathbf{s}_k^{(t-1)})\alpha_k}{\frac{1}{\rho} + \left(h_k + \mathbf{g}_k^T\mathbf{s}_k^{(t-1)}\right)^2 \sum_{i=1}^{k-1}\alpha_i} C_k^{(t)}\right)^2 g_{n_1,k}g_{n_2,k}. \quad (15)$$

Consequently, the Hessian matrix of the 1-st user is given by

$$\mathbf{H}_1^{(t)} \simeq -\frac{W}{2\ln 2}\left(\rho(2h_1 + \mathbf{g}_1^T\mathbf{s}_1^{(t-1)})\alpha_1 C_1^{(t)}\right)^2 \mathbf{g}_1\mathbf{g}_1^T. \quad (16)$$

When $2 \le k \le K$, the Hessian matrix of the k-th user is

$$\mathbf{H}_k^{(t)} \simeq -\frac{W}{2\ln 2}\left(\frac{(2h_k + \mathbf{g}_k^T\mathbf{s}_k^{(t-1)})\alpha_k}{\frac{1}{\rho} + \left(h_k + \mathbf{g}_k^T\mathbf{s}_k^{(t-1)}\right)^2 \sum_{i=1}^{k-1}\alpha_i} C_k^{(t)}\right)^2 \mathbf{g}_k\mathbf{g}_k^T. \quad (17)$$

It can be found that each Hessian matrix $\mathbf{H}_k^{(t)}$ in each iteration is a rank one matrix, and for any positive real number vector $\mathbf{a} \in \mathbb{R}_+$, the inequality $\mathbf{a}^T\mathbf{H}_k^{(t)}\mathbf{a} \le 0$ is always satisfied. As a result, the overall Hessian matrix $\mathbf{H}^{(t)} = [\tilde{R}_{sum}^{(n_1,n_2,k_1,k_2,t)}]_{NK\times NK}$ can be expressed diagonally as

$$\mathbf{H}^{(t)} = diag(\mathbf{H}_1^{(t)}, \mathbf{H}_2^{(t)}, \ldots, \mathbf{H}_K^{(t)}), \quad (18)$$

where $diag(\cdot)$ represents a block diagonal matrix. Since each sub-matrix $\mathbf{H}_k^{(t)}$ is a negative semidefinite matrix, it is easy to obtain that $\mathbf{H}^{(t)}$ is also a negative semidefinite matrix. As a result, the problem **P1** in each iteration is proved to be convex through the Hessian matrix, so **P1** can be solved by a convex optimization method like gradient descent. Then, the relaxed form of the OIRS reflection matrix $\mathbf{S}^{relax}$ can be obtained.

Furthermore, the final matrix **S** can be recovered from $\mathbf{S}^{relax}$ according to a greedy strategy. The formula (6) shows that with the increase of the transmit SNR ρ, the SINR of the k-th user γ_k $(2 \le k \le K)$ converges to $\alpha_k / \sum_{i=1}^{k-1}\alpha_i$, indicating that assigning OIRS units to users with poor channel quality will have little impact on users' rate. Therefore, the greedy strategy allocates OIRS units to the users with better channel quality while ensuring that all users meet the minimum rate, which is described in steps 8-19 of Algorithm 1.

D. Computational Complexity Analysis

A discussion regarding the computational complexity is provided in this subsection. Based on the system model, it can be obtained that the complexity of the brute force search algorithm is $\mathcal{O}(K^N)$, which will take a great deal of time when the amount of OIRS units is large.

The computational complexity of Algorithm 1 is given as follows. The number of iterations in steps 2-6 to converge is $\mathcal{O}(1/\epsilon)$. In each iteration, the computational complexity of the gradient descent method for solving problem **P1** is $\mathcal{O}(NK/\eta)$, where η denotes the permissible error in gradient descent method. For the recovery process of the matrix **S**, step 11 takes operations $\mathcal{O}(N)$, the inner loop in steps 10-16 will run less than N times, and the outer loop in steps 8-18 will run $(K-1)$ times. Moreover, the complexity of last step 19 is $\mathcal{O}(N)$. To sum up, the recovery of **S** leads to a computational complexity $\mathcal{O}(N^2(K-1))$.

IV. Numerical Results

In this section, the simulation results of the NOMA-based indoor VLC with the OIRS are presented, considering that the number of users is set to $K = 2$. The room size is set as 8 m × 8 m × 3 m, the LED is fixed at (4 m, 4 m, 3 m), and the PDs of users are at (4 m, 3 m, 0.5 m) and (5 m, 3 m, 0.5 m), namely the 1-st user and the 2-nd user. The OIRS units are evenly spaced on the wall near the users, in a rectangle with two corners at (1 m, 0 m, 1.5 m) and (7 m, 0 m, 2.5 m). Since there is no additional direct current bias to ensure the optical signal is positive in the proposed signal model, it is assumed that the power used for information transmission is equal to the power used for illumination, and the transmit power P_T is set to 10 W. The area of every OIRS unit is 10×10 cm^2, and the coefficient factor δ is 0.95. Moreover, the gain of the optical filter, the Lambertian index, PD responsivity, and FoV are 1, 1, 0.25 A/W, and 80°, respectively. Then, the modulation bandwidth W is set to 20 MHz, and the minimum rate requirement of QoS R_{min} is 10 Mbps. The power distribution factors α_1 and α_2 are set as 0.25 and 0.75, respectively.

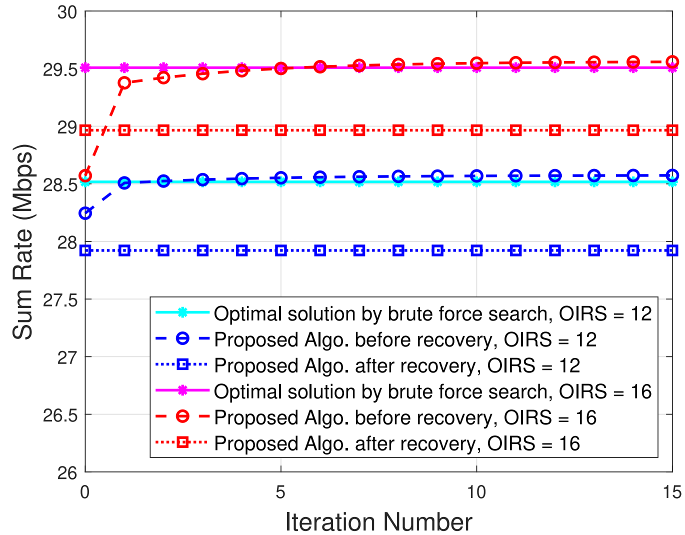

Fig. 2. Performance of the proposed algorithm and brute force search algorithm with the transmit SNR = 47 dB.

Fig. 2 shows the sum rate variation during the iteration to justify the accuracy of the proposed algorithm. Since the complexity of the brute force search algorithm is $\mathcal{O}(K^N)$, the amount of OIRS units should be small enough to obtain the optimal solution. As the number of iterations increases, the sum rate of our algorithm with $\mathbf{S}^{relax}$ gradually converges and exceeds the optimal solution which is obtained by the brute force search algorithm under the integer constraint in (10). However, after recovering to the integer constraint (10), the sum rate of our algorithm is lower than the optimal solution, which means that the proposed algorithm can only obtain a sub-optimal solution with low complexity.

In Fig. 3, the performance of the proposed algorithm is compared with two baselines: (1) assigning the OIRS based on the distance greedily; (2) no OIRS is adopted. To make the result more obvious, the amount of OIRS units is set to 150 and the transmit SNR ρ is changed in simulations. At low transmit SNR region, the users' achievable rate can not meet the requirement of R_{min} without OIRS, but the sum rate increased significantly and both users' rates exceed 10 Mbps with the aid of the OIRS. At high transmit SNR region, the proposed algorithm can approximately provide a sum rate gain of 15 Mbps and 29 Mbps compared to the distance greedy baseline and OIRS-free baseline, respectively. Moreover, as the transmit SNR increases, R_2 tends to be constant while R_1 keeps

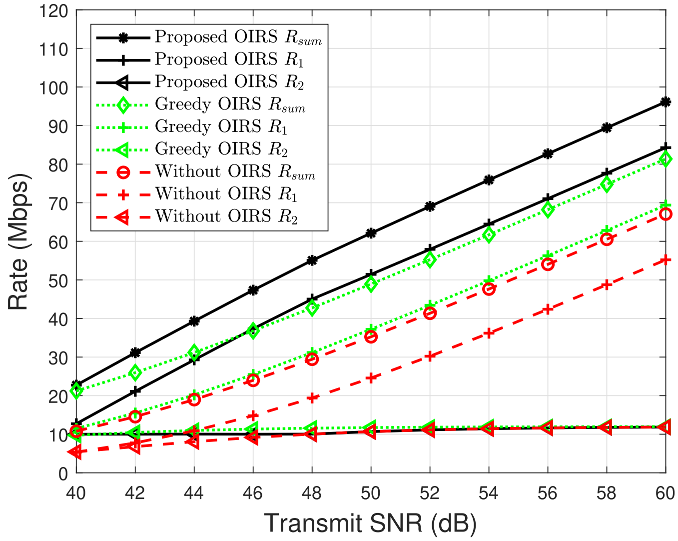

Fig. 3. Performance of our proposed algorithm and other baselines at different transmit SNRs with OIRS units number $N = 150$.

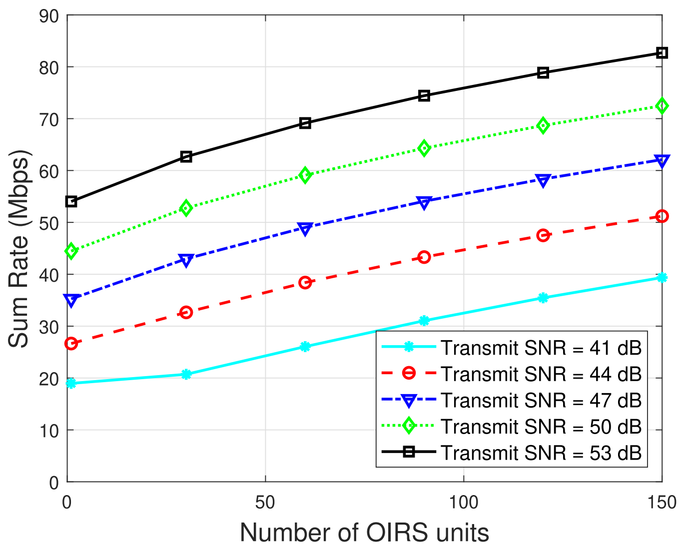

Fig. 4. The achievable sum rate versus the amount of OIRS units with different transmit SNRs.

growing, which justifies the effectiveness of our allocation of the OIRS to the 1-st user. To sum up, our proposed algorithm performs better than two baselines at any transmit SNR region.

Fig. 4 explores the relationship between the achievable sum rate and the amount of OIRS units with different transmit SNRs. It can be observed that the sum rate increases proportionally as the amount of OIRS units grows, which indicates that increasing the OIRS units number can enhance the capability of NOMA-based VLC systems. Moreover, for every 3 dB increase in the transmit SNR, the sum rate increases by about 8 Mbps and 11 Mbps in the absence and presence of the OIRS, respectively, which suggests that the aid of the OIRS can amplify the gain in the system capacity from improving the transmit SNR.

V. Conclusion

In this letter, the OIRS passive beamforming of the NOMA-based VLC system is optimized to maximize the achievable sum rate under the conditions of individual QoS requirements. The proposed algorithm obtains a sub-optimal solution to the problem by iteratively optimizing the OIRS reflection matrix with low complexity. The numerical results show that the proposed algorithm can help users meet the requirements of QoS, and increase the achievable sum rate significantly compared to other baselines. Furthermore, the increase in the number of OIRS units can enhance the capability of NOMA-based VLC systems, demonstrating the potential of the OIRS for future wireless communications research.

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