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UAV-Aided Two-Way Relaying for Wireless Communications of Intelligent Robot Swarms

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ABSTRACT In this paper, we consider unmanned aerial vehicle (UAV)-enabled two-way relaying communications between two robot swarms in the absence of communication infrastructures in remote areas or post-disaster rescues. To be more specific, UAV is employed as the relay to expand the communication range between two disconnected ground robot swarms, due to its high maneuverability and flexible deployment. Meanwhile, the two-way relaying mode adopted can improve the transmission performance in terms of delay and throughput in comparison to the conventional one-way relaying, owing to the ability of allowing devices to exchange information simultaneously. In addition, the UAV's trajectory and power allocation are jointly optimized to maximize the sum-rate of the uplink and downlink, where the joint optimization problem is decoupled into two sub-problems to address the non-convexity. Limited to the non-convex formation of the objective function for the trajectory optimization sub-problem, we firstly handle the non-convexity based on successive convex approximation method, and then alternating optimization framework is carried out to obtain the joint suboptimal solution. Numerical results exhibit significant throughput gains of the proposed scheme as compared to other benchmark schemes.

INDEX TERMS Robot swarms, UAV communications, two-way relaying, non-convex optimization.

I. INTRODUCTION

As a result of the advances in computation, communication and sensor technology, it is now popular to build kinds of robot swarms to fulfill certain complicated tasks such as surveillance and rescue [1]–[6]. Over the past two decades, the communication means among members of the robot swarm were well investigated such as pheromone [7]–[9], Infra-Red [10] and Bluetooth [11]. Also, cluster architecture in robot swarm enables better resource allocation and helps to enhance the stability and lifetime of network, while the methods for cluster-head selection have been variously studied in many literatures [12]–[14]. Nevertheless, high data transmission among remote robot swarms in real-time is also required for some specific communication environments. In general, investigating how cluster-heads of robot swarms communicate is a significant topic. For instance, in high-frequency erupting volcano monitoring, the environment monitor information and operational commands between the information collecting robot swarm and the information processing one are necessary to be exchanged. Therefore, it is important to take connectivity of the network into account since the direct links between remote robot swarms are unstable due to the long distance or blockage. Deploying a UAV as mobile relay to achieve the network connectivity is an efficient way owing to the robust line-of-sight (LoS) communication link and its high flexibility [15]–[17].

In recent years, researchers have devoted substantial efforts on UAV-enabled wireless systems for extending the coverage and improving the throughput toward future wireless systems [18]–[20]. More specifically, in [21], altitude optimization was proved to be profoundly important to provide the maximum coverage in the static UAV-assisted wireless systems. In general, the closer the distance between UAV and the ground user is, the better the channel gains are. According to the water-filling algorithm, the system perfor-

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mance can be improved by reasonably allocating the power with induced channel variation. In order to make full use of the UAV's mobility, jointly optimizing the trajectory and resource allocation for UAV communication networks has been rigorously studied [22]–[29]. Specifically, the average secure rate is maximized in [22], [23], the system sum throughput is optimized in UAV-enabled mobile relaying systems [24]–[27] and UAV-aided mobile base station systems [28], [29], respectively. However, most existing works concerned on one-way relay scenario where the data can only be ferried unidirectionally. Against this background, adapting UAV as a mobile bidirectional relay to exchange information between two distant robot swarms is a promising solution.

Compared to traditional one-way wireless relay scheme, two-way relay (TWR) scheme can be regarded as a specific form of network coding that takes less time slots to achieve the interaction between two nodes by relaxing the demand of 'orthogonal/non-interfering' transmissions between the relay and terminals [30]. To be more specific, TWR goes through two time slots in which two terminals simultaneously send data to the relay in the first time slot and then a combined signal is broadcasted by the relay in the second time slot. Due to the advantages of TWR networks, many efforts have been made which mostly concentrate on throughput maximization, achievable rate region, and minimization of the system outage probability [31]–[33]. Owing to the high maneuverability and flexible deployment of UAVs, an increasing attention on UAV-enabled wireless two-way relaying system has been received in recent literatures. In [34], a UAV-aided two-way relaying system was investigated, while the UAV positioning and transmission power were jointly optimized to maximize the sum-rate of both the uplink and downlink. However, it especially focused on the relationship between the constraint power of the base station and the UAV's placement, failing to take full advantage of the mobility of UAVs. In [35], the minimum average rate maximization problem was investigated by jointly optimizing the UAV's trajectory, transmit power and bandwidth.

In this paper, we focus on deploying UAV as a two-way relay to provide wireless connectivity between two disconnected robot swarms, which can reduce at least two time slots for system delay over one information interaction. The transmission power allocation in the forward stage and the flying trajectory are jointly optimized for the sake of maximizing the throughput. Except for the maximum speed constraint, the transmission power constraint is also considered. Nevertheless, due to the complicated objective function and power constraint in terms of coupled UAV's trajectory and power allocation factors, the formulated problem is non-convex and thus difficult to be solved. To address this problem, we develop an efficient iterative algorithm with inexact block coordinate descent (IBCD). Specifically, the entire optimization variables are partitioned into two sub-problems, and these blocks of variables are alternately optimized in each iteration. The primary contributions of this paper can be summarized as follows:

1) We present the basic model for UAV-enabled mobile two-way relaying system, where a mobile relay with a given maximum speed as well as initial and final locations is employed to assist the communication between two disconnected ground robot swarms, as shown in Figure 1.
2) We study a problem formulation for the joint optimization of UAV's trajectory and transmit power to maximize the system sum-rate in a finite time horizon, while the constraints take into account the practical mobility and transmit power. Notably, this problem is a combinatorial non-convex optimization with complicated constraints and mutual coupled variables.
3) We develop an efficient suboptimal algorithm for the sum-rate maximization problem by decomposing the non-convex problem into two sub-problems. For the non-convex UAV's trajectory optimization sub-problem, we approximate it into convex problem with first-order Taylor expansions. Furthermore, an iterative algorithm is proposed to solve the sub-problems iteratively.
4) Simulation results reveal that the performance of the proposed designs achieves a significant improvement in sum-rate for the considered UAV-enabled mobile two-way relaying system compared to two baseline schemes.

The remainder of this paper is arranged as follows. In the next section, the system model of the UAV-enabled wireless two-way relaying system is introduced. Problem formulation and proposed algorithm are illustrated in Section III. The numerical results to demonstrate the performance of the proposed scheme are provided in Section IV. Conclusions of this paper are drawn in Section V.

II. ASSUMPTIONS AND SYSTEM MODEL

Consider a UAV-assisted wireless two-way relaying communication system, while two isolated robot swarms separated by L meters are not able to communicate with each other directly due to the long distance or severe blockage. A UAV is employed as a mobile two-way relay to establish the communication between them. For simplicity, decode-and-forward (DF) scheme is adopted at the UAV side. In this paper, we concentrate on the communication between remote robot swarms. Assume that both robot swarms employ centralized control and each of them has a head robot to communicate with the external environment, where the cluster heads are called Alice and Bob.

Without loss of generality, we assume Alice and Bob have fixed locations on the ground, while the UAV flies at a fixed altitude H that is the minimum height for avoiding the collision. Assume a two-way relaying system in which all the nodes are equipped with a single antenna in the context of frequency division duplex (FDD) mode. In addition, the frequency division multiplexing (FDM) is considered so that

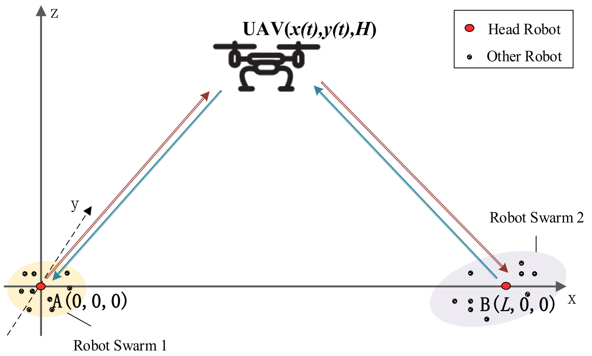


FIGURE 1. Geometrical model of UAV-enabled two-way relaying system.

the communication links of different nodes are orthogonal to each other without cross-link interference.

For ease of explanation, a Cartesian coordinate system as shown in Figure 1 is established to describe the geometrical model of such a two-way relaying system. Denote by $\mathbf{A} = (0, 0, 0)^T$ a three dimensions (3D) location of Alice and by $\mathbf{B} = (L, 0, 0)^T$ the 3D location of Bob. Since the UAV flies at a fixed altitude H, at time instant t, its 3D location is $(x(t), y(t), H)^T$ with $0 \leq t \leq T$, where $x(t)$ and $y(t)$ denote the relay's time-varying x- and y-coordinates, respectively, and T is the flight period. We further assume that the initial and final positions of the mobile relay are pre-determined, denoted as $(x_0, y_0, H)^T$ and $(x_F, y_F, H)^T$, respectively. Consequently, there exists a minimum distance the UAV needs to fly during the flight period T, denoted by $d_{\min}$. For a given maximum flying speed $V_{\max}$, $V_{\max}$ should satisfy $V_{\max} \geq d_{\min}/T$

For simplicity, consider that the flight period T is divided into N equal time slots, i.e., $T = N\delta_t$, where δ_t denotes the elemental slot length and N is assumed to be large enough to ensure the position of the UAV is roughly constant within each time slot [25]. Therefore, the trajectory of the UAV over time period T can be approximated as $(x[n], y[n], H)^T$ where $(x[n], y[n])^T$ represents the UAV's x-y coordinate at slot n, and unless otherwise stated, $n \in \{1, \ldots, N\}$. Considering $\mathbf{q}[n] = (x[n], y[n])^T, \forall n$, we further assume that $\mathbf{q}[1] = (x_0, y_0)^T$, $\mathbf{q}[N] = (x_F, y_F)^T$, constrained by the UAV's maximum flying speed so that the UAV's mobility would satisfy

$$\|\mathbf{q}[n+1] - \mathbf{q}[n]\|^2 \leq D^2, \quad n = 1, \ldots, N-1, \tag{1}$$

where $D = V_{\max}\delta_t$ represents the maximum flying distance of UAV for each time slot.

Assume that UAV-ground channel is dominated by the LoS link, since the recent measurement results in [36] have demonstrated that LoS channel model offers a good approximation for UAV-ground communications in practice even if the UAV flies at a moderate altitude. Let us hence consider the free space propagation model, which is mainly determined by the distance between the UAV and the ground user. Under the above assumption, the channel coefficient of A-UAV link $h_{ar}[n]$ and B-UAV link $h_{br}[n]$ at slot n can be respectively expressed as [24]–[26]

$$h_{ar}[n] = \beta_1 d_{ar}^{-2}[n] = \frac{\beta_1}{H^2 + \|\mathbf{q}[n]\|^2}, \quad \forall n, \tag{2}$$

$$h_{br}[n] = \beta_2 d_{br}^{-2}[n] = \frac{\beta_2}{H^2 + \|\mathbf{q}[n] - \mathbf{s_B}\|^2}, \quad \forall n, \tag{3}$$

where β_1, β_2 represent the reference channel coefficient at distance $d_0 = 1$ meter of link A-UAV and B-UAV, while $d_{ar}[n] = \sqrt{H^2 + \|\mathbf{q}[n]\|^2}$ denotes the link distance between A and UAV at time slot n, similarly $d_{br}[n] = \sqrt{H^2 + \|\mathbf{q}[n] - \mathbf{s_B}\|^2}$ denotes the distance between B and UAV, where $\mathbf{s_B} = (L, 0)^T$ is the x-y coordinate of node B. Since the channel gain monotonically decreases with an increasing altitude H, there is a tradeoff between the UAV's altitude and channel gains, which is further studied in [17]. Although the FDD mode is employed, the frequency for uplink can be assumed to very close to the downlink so that the channel coefficient $h_{ar}[n]$ is approximate to $h_{ra}[n]$ with the reason that the values of β_1 and β_2 depend on the carrier frequency and antenna gain, i.e., $\beta_1 = \beta_2 = \beta_0$, $h_{ar}[n] = h_{ra}[n]$, and $h_{br}[n] = h_{rb}[n]$.

Considering real-time communication where the data is transmitted to B as soon as UAV receives the signals from A. At the nth time slot, the received signal at UAV for the first stage can be expressed as

$$y_r[n] = \sqrt{p_a h_{ar}[n]}x_a[n] + \sqrt{p_b h_{br}[n]}x_b[n] + n_r[n], \tag{4}$$

where p_a, p_b are the transmission power of terminal A and B, respectively, which do not vary with the time slot n, $x_a[n]$, $x_b[n]$ are the transmitted data at A and B with circularly symmetric complex Gaussian distribution $CN(0, 1)$, $n_r[n]$ is the additive white Gaussian noise (AWGN) observed at UAV with $n_r[n] \sim CN(0, N_0)$. It is worth noting that $x_a[n]$, $x_b[n]$ and $n_r[n]$ are statistically independent. As the DF scheme is considered at relay, a denoised and re-modulated version of the received signal is broadcasted to two ground terminals in the second stage. Therefore, the sent signal at UAV can be represented by

$$x_r[n] = \sqrt{G_1[n]p_b h_{br}[n]}x_b[n] + \sqrt{G_2[n]p_a h_{ar}[n]}x_a[n], \tag{5}$$

where $G_1[n]$, $G_2[n]$ are the power dividing factors of UAV for transmitting data to node A and B, which ensures $G_1[n]p_b h_{br}[n] + G_2[n]p_a h_{ar}[n] = p_r[n]$. Let $p_{r1}[n] = G_1[n]p_b h_{br}[n]$, $p_{r2}[n] = G_2[n]p_a h_{ar}[n]$, which represent the transmit power of UAV-A and UAV-B in the forward stage, respectively. Consequently, the received signal at node A can be expressed as

$$y_a[n] = \sqrt{h_{ra}[n]}x_r[n] + n_a[n], \tag{6}$$

where $n_a[n] \sim CN(0, N_1)$ is the AWGN observed at A. In order to better detect the desired signal, each terminal will first eliminate the self-interference from its received signal [37]. Then the received signal at two terminals can be respectively modified as

$$y_a'[n] = \sqrt{G_1[n]p_b h_{ar}[n]h_{br}[n]}x_b[n] + n_a[n], \tag{7}$$
$$y_b'[n] = \sqrt{G_2[n]p_a h_{ar}[n]h_{br}[n]}x_a[n] + n_b[n], \tag{8}$$

where $n_b[n] \sim CN(0, N_2)$ is the AWGN observed at B, while $N_1 = N_2 = N_0$ is assumed. According to (7) and (8), the signal-to-noise-ratio(SNR) at A and B can be respectively formulated by

$$\gamma_a[n] = \frac{G_1[n]p_b h_{ar}[n]h_{br}[n]}{N_0}, \tag{9}$$
$$\gamma_b[n] = \frac{G_2[n]p_a h_{ar}[n]h_{br}[n]}{N_0}. \tag{10}$$

As a consequence, the corresponding achievable information rate for A-to-B link at the nth time slot can be expressed by

$$R_a[n] = \frac{W}{2}\log_2(1+\gamma_a[n]). \tag{11}$$

Similarly, the rate for B-to-A link can be written as $R_b[n] = \frac{W}{2}\log_2(1+\gamma_b[n])$. As a result, the information rate of the overall system at time slot n is given as

$$R[n] = R_a[n] + R_b[n], \tag{12}$$

where W is the frequency bandwidth for each terminal, and the rate is divided by two parts due to the two-phase DF transmission.

III. PROBLEM FORMULATION AND SOLUTION

A. PROBLEM FORMULATION

In this paper, we aim to maximize the end-to-end system sum-rate by optimizing both the UAV's trajectory $\{\mathbf{q}[n]\}$ and its power allocation factors $\{G_1[n], G_2[n]\}$. By defining $\mathbf{Q} \triangleq \mathbf{q}[n], \forall n$, and $\mathbf{G} \triangleq (G_1[n], G_2[n])^T, \forall n$, the problem can be mathematically formulated as follows

$$(\text{P1}): \max_{\mathbf{G},\mathbf{Q}} \sum_{n=1}^{N} R[n] \tag{13}$$
$$\text{s.t.}\ \frac{1}{N}\sum_{n=1}^{N}(G_1[n]p_b h_{br}[n] + G_2[n]p_a h_{ar}[n]) \le \bar{p}_r, \tag{14}$$
$$0 \le G_1[n]p_b h_{br}[n] + G_2[n]p_a h_{ar}[n] \le p_r^{\max}, \quad \forall n, \tag{15}$$
$$G_1[n] \ge 0, \quad G_2[n] \ge 0,\ \forall n, \tag{16}$$
$$\|\mathbf{q}[n+1] - \mathbf{q}[n]\|^2 \le D^2, \quad n = 1, \ldots, N-1, \tag{17}$$

where $\bar{p}_r$ denotes the average power of the UAV within the horizon time T, while $p_r^{\max}$ is the maximum power that can be radiated by the UAV. Eq. (14) and (15) represent the average transmit power constraint over T and maximum power one at the UAV, respectively. Obviously, (P1) is particularly challenging since the objective function (13) and the inequality constraint (14)-(15) are not convex. In the following, we present an efficient algorithm for maximizing the throughput under the UAV's power and maximum speed constraints.

B. SOLUTION

Since (P1) is a non-convex programming, which can't be directly solved with standard convex optimization techniques. Therefore, we adopt IBCD technique to eliminate the coupling between $\mathbf{Q}$ and $\mathbf{G}$, which can provide a computationally efficient algorithm. More specifically, we consider two sub-problems of (P1), namely power optimization with fixed relay's trajectory and trajectory optimization with fixed power allocation, respectively. Based on the solutions obtained, an iterative algorithm is then proposed for (P1) via alternately optimizing the power dividing factors and UAV's trajectory.

1) SUB-PROBLEM 1: OPTIMIZING THE TRANSMIT POWER DIVIDING FACTORS GIVEN THE UAV's TRAJECTORY

The first sub-problem of (P1) for optimizing the power dividing factors by assuming that the relay's trajectory variables $\mathbf{Q}$ is fixed. For ease of description, we denote $\phi_1[n] = p_b h_{ar}[n]h_{br}[n]/N_0$, $\phi_2[n] = p_a h_{ar}[n]h_{br}[n]/N_0$, $\varphi_1[n] = p_b h_{br}[n]$, $\varphi_2[n] = p_a h_{ar}[n]$. Due to the constraints in (16) and the channel coefficients are positive, the left inequality in (15) is obviously true. Thus, (P1) can be equivalently reformulated as

$$(\text{P1.1}): \max_{\mathbf{G}} \sum_{n=1}^{N} R[n] \tag{18}$$
$$\text{s.t.}\ \bar{p}_r - \frac{1}{N}\sum_{n=1}^{N}(G_1[n]\varphi_1[n] + G_2[n]\varphi_2[n]) \ge 0, \tag{19}$$
$$p_r^{\max} - (G_1[n]\varphi_1[n] + G_2[n]\varphi_2[n]) \ge 0, \quad \forall n, \tag{20}$$
$$G_1[n] \ge 0, G_2[n] \ge 0, \forall n. \tag{21}$$

It's easy to verify that (P1.1) is convex with respect to $\{G_1[n], G_2[n]\}$, thus (P1.1) can be efficiently solved by standard convex optimization techniques. To obtain more detailed properties of the optimal solution to (P1.1), we adopt Lagrange dual method to analyze it.

(P1.1) satisfies the Slater's condition and holds strong duality as its convexity so that the optimal solution can be acquired by solving the dual problem [38]. Furthermore, the UAV's power allocations for UAV to node A and B in (P1.1) are coupled via both the objective function and unequal constraints in (18)-(20), which can be decoupled by studying its partial Lagrangian [25].

Assuming $\lambda_n \ge 0, n = 1, \ldots, N+1$, are the Lagrange dual variables to (P1.1), thus the partial Lagrangian of (P1.1) can be defined as

$$\begin{aligned} &L\left(\{G_1[n], G_2[n], \lambda_n\}\right) \\ &= \sum_{n=1}^{N} \frac{W}{2}\left[\log_2(1+\phi_1[n]G_1[n])+\log_2(1+\phi_2[n]G_2[n])\right] \\ &\quad + \sum_{n=1}^{N} \lambda_n \left[p_r^{\max} - (G_1[n]\varphi_1[n]+G_2[n]\varphi_2[n])\right] \\ &\quad + \lambda_{N+1}\left[\bar{p}_r - \frac{1}{N}\sum_{n=1}^{N}(G_1[n]\varphi_1[n]+G_2[n]\varphi_2[n])\right]. \end{aligned} \tag{22}$$

Consequently, the corresponding Lagrange dual function of (P1.1) is expressed as

$$f\left(\{\lambda_n\}\right) = \begin{cases} \max\limits_{\mathbf{G}} & L\left(\{G_1[n], G_2[n], \lambda_n\}\right) \\ \text{s.t.} & G_1[n] \geq 0, G_2[n] \geq 0, \quad \forall n. \end{cases} \tag{23}$$

According to (23), the Lagrange dual problem of (P1.1) is then defined as

$$\text{(P1.1-D)}: \min_{\{\lambda_n\}} f\left(\{\lambda_n\}\right) \tag{24}$$

$$\text{s.t. } \lambda_n \geq 0, \quad n = 1, \cdots, N+1. \tag{25}$$

Because of the strong duality, optimal solution to (P1.1) can be obtained by equivalently solving (P1.1-D). Therefore, we first solve (P1.1-D) to obtain optimal dual solutions $\{\lambda_n^*\}$ with any initial given power dividing factors $\mathbf{G}^0$. Then the optimal power dividing factors $\mathbf{G}^*$ are obtained based on the dual optimal solutions.

Let us first consider the problem (P1.1-D) of minimizing the dual function over $\{\lambda_n\}$ with fixed $\{G_1^0[n]\}$ and $\{G_2^0[n]\}$. For (P1.1-D), it can be done by the subgradient-based method [25]. And the subgradient of $f(\{\lambda_n\})$ at point $\{\lambda_n\}$ is given by $\mathbf{g} = [g_1, g_2, \ldots, g_{N+1}]^T$, with $g_n = p_r^{\max} - \left(G_1^0[n]\varphi_1[n] + G_2^0[n]\varphi_2[n]\right), \forall n$, and $g_{N+1} = \bar{p}_r - \frac{1}{N}\sum_{n=1}^{N}\left(G_1^0[n]\varphi_1[n] + G_2^0[n]\varphi_2[n]\right)$. The procedures to obtain the optimal dual solutions $\{\lambda_n^*\}$ are shown in Algorithm 1.

The optimal primal variables for Lagrangian maximization in (23) can be obtained by solving two parallel sub-problems with obtained dual variables $\{\lambda_n^*\}$, which are shown as follows [25]

$$\max_{\{G_1[n]\}} L\left(\{G_1[n], \lambda_n^*\}\right) \tag{26}$$

$$\text{s.t. } G_1[n] \geq 0, \quad \forall n, \tag{27}$$

and

$$\max_{\{G_2[n]\}} L\left(\{G_2[n], \lambda_n^*\}\right) \tag{28}$$

$$\text{s.t. } G_2[n] \geq 0, \quad \forall n, \tag{29}$$

where

$$\begin{aligned} L\left(\{G_1[n], \lambda_n^*\}\right) &= \sum_{n=1}^{N} \frac{W}{2}\log_2(1+\phi_1[n]G_1[n]) \\ &\quad + \sum_{n=1}^{N} \lambda_n^*\left[p_r^{\max} - G_1[n]\varphi_1[n]\right] \\ &\quad + \lambda_{N+1}^*\left[\bar{p}_r - \frac{1}{N}\sum_{n=1}^{N} G_1[n]\varphi_1[n]\right], \end{aligned} \tag{30}$$

$$\begin{aligned} L\left(\{G_2[n], \lambda_n^*\}\right) &= \sum_{n=1}^{N} \frac{W}{2}\log_2(1+\phi_2[n]G_2[n]) \\ &\quad - \sum_{n=1}^{N} \lambda_n^* G_2[n]\varphi_2[n] \\ &\quad - \lambda_{N+1}^*\frac{1}{N}\sum_{n=1}^{N} G_2[n]\varphi_2[n]. \end{aligned} \tag{31}$$

Note that the above-mentioned two parallel sub-problems are both convex optimization problems with a single variable. We can apply Karush-Kuhn-Tucker (KKT) conditions for the optimal solution, and the detailed algorithm for completeness is provided as follows.

We assume that $\boldsymbol{\omega}$ is a Lagrange multiplier column vector corresponding to the inequality constraints. The optimal solution for problem (26-27) must satisfy the following KKT conditions

$$\begin{aligned} &\frac{W\phi_1[n]}{2\ln 2\left(1+\phi_1[n]G_1^*[n]\right)} - \left(\lambda_n^* + \frac{1}{N}\lambda_{N+1}^*\right)\varphi_1[n] \\ &= \omega^*[n], \quad \forall n, \end{aligned} \tag{32}$$

$$G_1^*[n] \geq 0, \quad \forall n, \tag{33}$$

$$\omega^*[n]\, G_1^*[n] \geq 0, \quad \forall n, \tag{34}$$

$$\omega^*[n] \geq 0, \quad \forall n, \tag{35}$$

where $G_1^*[n]$ and $\omega^*[n]$ represent the optimal value for $G_1[n]$ and $\omega[n]$. According to (32)-(35), we can get the closed solution for problem (26-27), which can be written as

$$G_1^*[n] = \left[\frac{W}{2\ln 2\left(\left(\lambda_n^* + \frac{1}{N}\lambda_{N+1}^*\right)\varphi_1[n] + \omega^*[n]\right)} - \frac{1}{\phi_1[n]}\right]^+. \tag{36}$$

Similarly, as (31) has the same form with (30) after derivation, we can easily get the optimized solution for (28-29) by (36) as

$$G_2^*[n] = \left[\frac{W}{2\ln 2\left(\left(\lambda_n^* + \frac{1}{N}\lambda_{N+1}^*\right)\varphi_2[n] + \mu^*[n]\right)} - \frac{1}{\phi_2[n]}\right]^+, \tag{37}$$

where $\boldsymbol{\mu}^*$ is the optimal value of the Lagrange multiplier column vector $\boldsymbol{\mu}$ corresponding to the inequality constraints in (29), and $[x]^+ \triangleq \max\{0, x\}$. Furthermore, the complete procedures for solving (P1.1-D) is summarized in Algorithm 1.

Algorithm 1 Alternating Optimization for (P1.1)

1: Initialize $G_1^0[n] \geq 0$, $G_2^0[n] \geq 0$, $\forall n$.
2: **Repeat**
3: Compute the subgradient of $f(\{\lambda_n\})$ at point $\{\lambda_n\}$.
4: Obtain λ_n^*, $\forall n$ with given $\left\{G_1^0[n]\right\}, \left\{G_2^0[n]\right\}$.
5: Update $\{G_1[n]\}, \{G_2[n]\}$ by KKT conditions.
6: **Until** converge or the preset number of iterations has been reached.
7: Output $\left\{\lambda_n^*\right\}$, $\left\{G_1^*[n]\right\}$ and $\left\{G_2^*[n]\right\}$.

2) SUB-PROBLEM 2: OPTIMIZING THE UAV's TRAJECTORY GIVEN THE TRANSMIT POWER

Secondly, for any given UAV's power allocation scheme $\mathbf{G}$, the trajectory optimization problem can be written as

$$(\text{P1.2}): \max_{\mathbf{Q}} \sum_{n=1}^{N} \frac{W}{2}\left[\log_2(1+\xi_1[n]) + \log_2(1+\xi_2[n])\right] \tag{38}$$

$$\text{s.t.} \sum_{n=1}^{N} \left(\frac{G_1[n]p_b\beta_0}{\kappa_2[n]} + \frac{G_2[n]p_a\beta_0}{\kappa_1[n]}\right) \leq N\bar{p}_r, \tag{39}$$

$$0 \leq \frac{G_1[n]p_b\beta_0}{\kappa_2[n]} + \frac{G_2[n]p_a\beta_0}{\kappa_1[n]} \leq p_r^{\max}, \quad \forall n, \tag{40}$$

$$\|\mathbf{q}[n+1]-\mathbf{q}[n]\|^2 \leq D^2, \quad n=1,\ldots,N-1, \tag{41}$$

where $\xi_1[n] = G_1[n]p_b\beta_0^2 / (N_0\kappa_1[n]\kappa_2[n])$, $\xi_2[n] = G_2[n]p_a\beta_0^2 / (N_0\kappa_1[n]\kappa_2[n])$, while $\kappa_1[n] = H^2 + \|\mathbf{q}[n]\|^2$, $\kappa_2[n] = H^2 + \|\mathbf{q}[n] - \mathbf{s}_B\|^2$.

Since $\xi_1[n]$ is a concave function with respect to $\mathbf{q}[n]$, and its value is always greater than zero, and $\log_2(1+\xi_1[n])$ is a concave function. Besides, Eq. (38) can be proved to be concave since any positive linear combination of the concave function is also concave. Nevertheless, (P1.2) is still non-convex due to the constraints (39) and (40) are non-convex. To handle this problem, the successive convex optimization technique can be applied. It can be observed that $h_{ar}[n]$ is concave with respect to $\mathbf{q}[n]$, which can be globally upper-bounded by its first-order Taylor expansion at any local point. Define $\mathbf{Q}^{(k)} = \left\{\mathbf{q}^{(k)}[n]\right\}$ as a given initial trajectory in the k-th iteration, $h_{ar}[n]$ is upper-bounded by

$$h_{ar}[n] \leq E^{(k)}[n], \tag{42}$$

where $E^{(k)}[n] = \frac{\beta_0 H^2 + 3\beta_0\left\|\mathbf{q}^{(k)}[n]\right\|^2 - 2\beta_0\mathbf{q}^{(k)}[n]^T\mathbf{q}[n]}{\left(\kappa_1^{(k)}[n]\right)^2}$, $\forall n$. Similarly, $h_{br}[n]$ can be upper-bounded by

$$h_{br}[n] \leq F^{(k)}[n], \tag{43}$$

where $F^{(k)}[n] = \frac{\beta_0\kappa_2^{(k)}[n] - 2\beta_0\left(\mathbf{q}^{(k)}[n]-\mathbf{s_B}\right)^T\left(\mathbf{q}[n]-\mathbf{q}^{(k)}[n]\right)}{\left(\kappa_2^{(k)}[n]\right)^2}$, $\forall n$.

Given an initial trajectory $\mathbf{Q}^{(k)}$, the approximate problem of (P1.2) can take the following form by referring to (42) and (43) as

(P1.2.1) :

$$\max_{\mathbf{Q}} \sum_{n=1}^{N} \frac{W}{2}\left[\log_2(1+\xi_1[n]) + \log_2(1+\xi_2[n])\right] \tag{44}$$

$$\text{s.t.} \sum_{n=1}^{N} (G_1[n]p_bF^{(k)}[n] + G_2[n]p_aE^{(k)}[n]) \leq N\bar{p}_r, \tag{45}$$

$$0 \leq G_1[n]p_bF^{(k)}[n] + G_2[n]p_aE^{(k)}[n] \leq p_r^{\max}, \quad \forall n, \tag{46}$$

$$\|\mathbf{q}[n+1] - \mathbf{q}[n]\|^2 \leq D^2, \quad n=1,\ldots,N-1. \tag{47}$$

With the above detailed analysis, (P1.2.1) is a convex optimization problem, which can be efficiently solved by the interior-point method. The first-order Taylor expansions in (42) and (43) suggest that the inequality of the constraints in (P1.2) are strictly satisfied, and the optimal solution to primal problem (P1.2) can be obtained by approximately solving (P1.2.1).

Algorithm 2 Alternating Optimization for (P1)

1: Initialization: Let iteration number $l = 0$ and initialize the power dividing factors $\left\{G_{1,l}[n], G_{2,l}[n]\right\}$ and UAV's trajectory $\left\{\boldsymbol{q}_l[n]\right\}$.
2: **Repeat**
3: Solve (P1.1) with the given trajectory $\left\{\boldsymbol{q}_l[n]\right\}$ by standard convex optimization techniques.
4: Update the power dividing factors.
5: Solve (P1.2.1) with updated power dividing factors $\left\{G_{1,l+1}[n], G_{2,l+1}[n]\right\}$.
6: Update the trajectory $\left\{\boldsymbol{q}_{l+1}[n]\right\}$.
7: **Until** converge or the preset number of iterations has been reached.
8: Output UAV's trajectory $\{\boldsymbol{q}[n]\}$, power dividing factors $\{G_1[n], G_2[n]\}$ and end-to-end sum-rate.

3) OVERALL ALGORITHM

In summary, the non-convex problem (P1) can be solved by applying the block coordinate descent method, which solves two sub-problems (P1.1) and (P1.2.1) alternately in an iterative manner. The details of the proposed algorithm are summarized in Algorithm 2. Since the sub-problem (P1.1) for power optimization can be solved by KKT conditions, which implies that Algorithm1 provided a globally optimal solution. However, since the sub-problem (P1.2) for trajectory optimization cannot be guaranteed to be optimally solved, no optimality can be theoretically declared for Algorithm 2.

However, only the convex optimization technique is required at each iteration as shown in the proposed iterative algorithm. Furthermore, since the overall computational complexity of Algorithm 2 mainly lies in Step 3 and 5, the complexity is polynomial in the worst situation. Specifically, since it can be verified that (P1.1) fulfills Slater's condition, to obtain the structural properties of the optimal solution, the convex problem (P1.1) can be solved by applying the

Lagrange duality. Then, the dual problem can be solved by using the ellipsoid method. The complexity for updating the dual variables by the ellipsoid method is in the order of $O(N^2)$ and for convergence, it takes $O(N^2)$, where N is the number of time slots. So, the complexity for solving (P1.1) is $O(N^4)$ [39], which accounts for the complexity of one iteration in the Algorithm 1. Also, (P1.2.1) is a standard convex optimization problem, which can be solved by the interior point method with the complexity of $O(N^3)$ [38]. Thus, denoting L as the number of iterations for convergence of the proposed algorithm, the total complexity can be expressed as $O(LN^4)$.

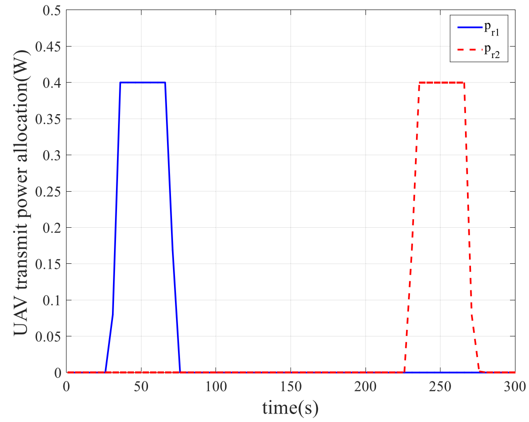
IV. SIMULATION RESULTS AND DISCUSSIONS

In this section, numerical results are provided to evaluate the performance of our proposed trajectory and power optimization scheme for the UAV-aided two-way relaying system. We consider a system where the terminal A and B are separated by $L = 2000$m, the location of two nodes are $A = (0, 0, 0)^T$, $B = (2000, 0, 0)^T$ [25], and the initial/final x-y coordinates of the UAV's trajectory are given by $\mathbf{q}_0 = (-500, 500)^T$, $\mathbf{q}_F = (2500, 500)^T$, respectively. The UAV's flying altitude is fixed to $H = 120$m, which corresponds to the minimum altitude required in moderate mountainous area. For the mobile relaying system, the maximum UAV speed is assumed to be $V_{\max} = 20$m/s, which corresponds to the future high speed fixed-wing or hybrid fixed-and-rotary-wing UAVs. To ensure that the placement of the UAV is barely changed within δ_t, we set the elemental slot to $\delta_t = 0.1$s. Without loss of generality, we assume that the reference channel coefficient $\beta_0 = -30$dBm, noise power spectrum density at two ground terminals and UAV are equal, i.e. $N_0 = -160$dBm/Hz. The communication bandwidth of per link is 10MHz with a carrier frequency of 2GHz [26]. Unless otherwise specified, the maximum average transmit power at UAV is assumed to be $p_r^{\max} = 0.4$W, and the average power is $\bar{p}_r = 0.1$W. Besides, the transmit power of two ground terminals are constant and which equal to $\bar{p}_r = 0.1$W, and the threshold of given algorithm is set as $\varepsilon = 10^{-4}$ [21], [25].

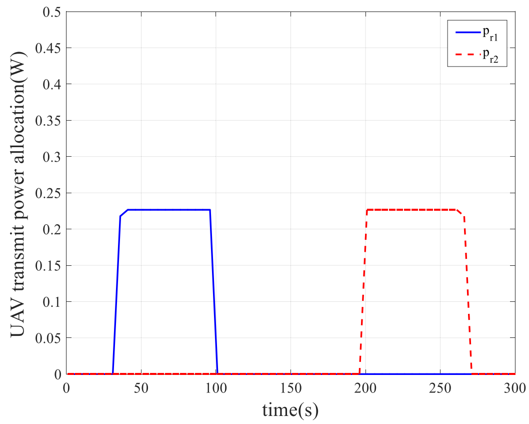
In this paper, three schemes are considered for comparisons.

1) *Scheme I* : We assume that UAV's power applied for transmitting to A/B is equal across different time slots, and UAV flies unidirectionally from $(-500, 500, 120)^T$ to $(2500, 500, 120)^T$ with the constant speed at 10 m/s.
2) *Scheme II* : The trajectory scheme in *Scheme I* is still considered, while the power allocation is optimized by solving problem (P1.1) iteratively until convergence.
3) *Proposed method* : The power allocation and UAV's trajectory are jointly designed in a best-effort manner.

Figure 2 illustrates the power allocations of UAV over different time slots while the flight period is $T = 300$s.



(a) *Scheme II*



(b) *Proposed method*

FIGURE 2. UAV's power allocation results by Algorithm 1.

Furthermore, as previously mentioned, $\mathbf{p_{r1}}$ and $\mathbf{p_{r2}}$ represent the transmit power of the UAV for link UAV-A and UAV-B, respectively. It is observed from Figure 2(a) that when the UAV is close to node A, that is, roughly from 25s to 75s, $p_{r1}[n]$ is much bigger than $p_{r2}[n]$. When the UAV flies near to node B, the value of $p_{r1}[n]$ is approaching zero, whereas $p_{r2}[n]$ is relatively high. Additionally, there is no data transmission when the UAV's transmission power is zero. This is because when UAV is close to A, the channel gain $h_{ar}[n]$ is large, thus $p_{r1}[n]$ should be much bigger to get a great sum-rate, which also follows the water-filling method. In Figure 2(b), to maximally employ the good channel condition for link UAV-node A induced by trajectory optimization, all the power is allocated to $p_{r1}[n]$ from 30s to 100s, whose value is 0.225W limited by the sum-power of the UAV.

Figure 3 shows the UAV's trajectories versus the flight period T, while the transmission power of UAV for link UAV-A and UAV-B is fixed. For illustration, node A, node B, and initial and final relay locations are marked by square, circle, plus sign, and product sign, respectively. It is observed that when $T = 150$s, which is the minimum required time for the UAV to fly from the initial location

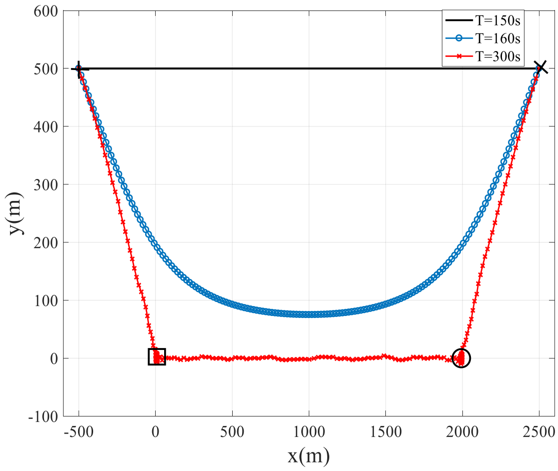


FIGURE 3. UAV's trajectories versus the flight period *T*.

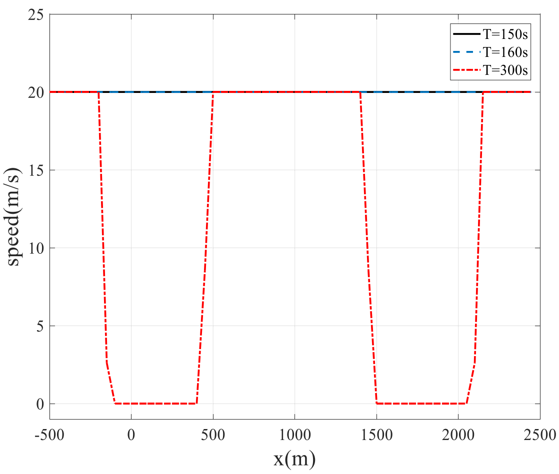


FIGURE 4. The speed of the UAV over time for three different trajectories from Figure 3.

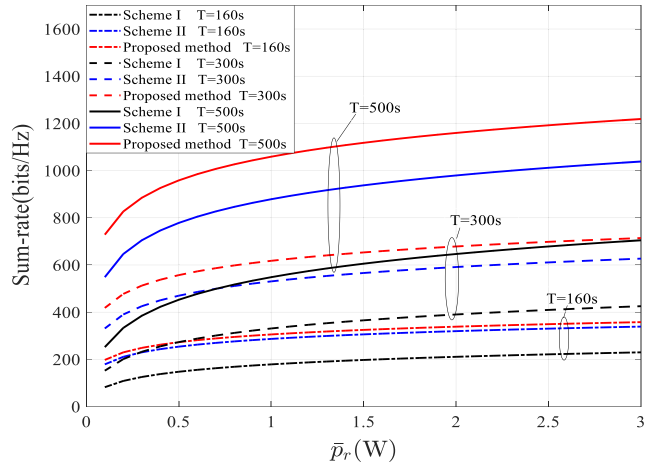


FIGURE 5. Sum-rate versus the average power of UAV.

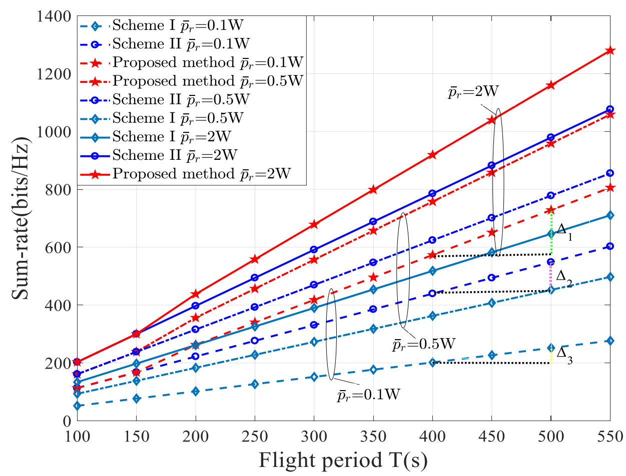


FIGURE 6. Sum-rate versus the flight period T.

to the final location at the maximum speed $v = 20$m/s. It shows an apparent difference as T increases. Specifically, when $T = 160$s, the UAV will fly with a curve route, it flies to the two terminals as near as possible, and between two nodes, an approximately direct path is employed. In particular, when $T = 300$s, the UAV hovers at $(0, 0, 120)^T$ and $(2000, 0, 120)^T$ as long as it can afford. At these two positions, the system seems to have the highest energy efficiency. Meanwhile, when the UAV hovers, the transmission power allocation remains constant as shown in Figure 2(b). To get more insight, Figure 4 shows the UAV's speed versus the flying position for different period T shown in Figure 3. It is observed that, when T is small, the UAV will fly with the maximum speed to finish the journey. When T is long enough, the UAV will employ a binary speed, i.e., it remains stationary for certain duration when it reaches A and B and moves at the maximum speed otherwise.

In Figure 5, the proposed scheme is compared to the other two benchmark ones, where the system sum-rate versus the average transmission power of UAV with different period T is investigated. Obviously, the sum-rate of all the schemes increases with an increasing $\bar{p}_r$, while the proposed scheme performs better than the baseline schemes for all $\bar{p}_r$ since it optimizes the transmit power and the UAV's trajectory jointly and concentrates most of the power to time slots with the best link qualities. Specifically, as the $\bar{p}_r$ increases, the power constraints become active, which makes $\mathbf{p_{r1}}, \mathbf{p_{r2}}$ and the sum-rate of each scheme get increased.

Figure 6 shows the corresponding sum-rate of different schemes versus flight period T when $\bar{p}_r = 0.1$W, 0.5W and 2W. It is observed that the sum-rate of all algorithms increase significantly with T, as expected. Additionally, the proposed method always achieves the highest sum-rate than the other two benchmark schemes. Furthermore, it is worth pointing out that the increment versus flight period T of three schemes exist huge difference (e.g. when $\bar{p}_r = 0.1$W, the flight period T varies from 400s to 500s, the increment $\Delta_1 > \Delta_2 > \Delta_3$), which shows that the trajectory adaption with increasing T is essential for the sum-rate improvement.

V. CONCLUSION

In this paper, we have investigated a UAV-aided mobile two-way relaying system to connect two isolated robot swarms. The DF relay strategy has been employed to reduce the complexity of the analysis. The UAV's transmission power and trajectory have been jointly optimized to achieve the maximum end-to-end throughput. We have also proposed an alternating iterative algorithm and utilized the successive convex optimization technique to solve the associated non-convex optimization problem. From the numerical results, we have demonstrated that compared to the fixed power and trajectory schemes, significant improvement of the throughput can be achieved by the proposed joint power and trajectory optimization scheme. As future works, extension to different UAV-ground channel models [17] is worth pursing. Also, throughput-delay tradeoff over the all system could be an important research direction.

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