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Sum-Rate Optimization for Visible-Light-Band UAV Networks Based on Particle Swarm Optimization

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***Abstract*—The mobility nature of unmanned aerial vehicles (UAVs) takes them into high consideration in military, public, and civilian applications in recent years. However, scaling out millions of UAVs in the air will inevitably lead to a more crowded radio frequency (RF) spectrum. Therefore, researchers have been focused on new technologies such as millimeter-wave, Terahertz, and visible light communications (VLCs) to alleviate the spectrum crunch problem. VLC has shown its great potential for UAV networking because of its high data rate, interference-free to legacy RF spectrum, and low-complex frontends. While the physical layer design of the VLC system has been extensively investigated, visible-light-band networking is still in its infancy because of the intermittent link availability caused by blockage and miss-alignment among transceivers. Fortunately, drones can be deployed dynamically at network runtime to establish line-of-sight (LOS) links to users in blockage-rich environments. In this article, we first formulate a sum-rate optimization problem for visible-light-band UAV networks by jointly control the real-time position and orientations of drones. We then propose a solution algorithm based on particle swarm optimization (PSO). The simulation results show that the proposed algorithm can converge in 10 to 20 iteration time and can result in up to 24% performance gain compared to that in heuristic-central-point drone deployment.**

***Index Terms*—Visible Light Network, Unmanned Aerial Vehicles, Throughput Optimization, Particle Swarm Optimization.**

I. Introduction

Unmanned aerial vehicles (UAVs) are playing an increasingly important role in the military, public, and civilian applications [1] [2] [3]. More recently, UAVs have become a hot topic in the wireless communication research community. The mobility and the on-demand deployment nature of the UAVs have enabled a set of new applications such as UAV-assisted cellular communications and cellular-assisted UAV sensing (e.g., battlefield, corp, or environment monitoring). Despite the many benefits due to their mobility, UAV networks still suffer from some practical constraints. For example, densely deployed UAVs as aerial BSs in tomorrow's ultra-dense wireless networks will interfere with ground users, thus degrading the performance of the ground networks. In addition, the limited battery power prohibits drones in the RF domain to provide high-speed communication services. These challenges can be addressed by equipping drones with visible light communication (VLC) capabilities [4] [5]. Moreover, the dynamically changed altitude of drones can more likely establish line-of-sight (LOS) links to users especially in blockage-rich environments. Therefore, using VLC can be a promising approach to provide high-speed UAV communications with a large portion of the unregulated visible-light spectrum.

In the past few years, significant research has been focused on addressing challenges in wireless UAV networks such as optimal deployment [6] and energy efficiency [7]. However, most of the existing work is focused on the crowded radio frequency (RF) spectrum which may not allow the drones to meet the high data rate demands of users. Therefore, more recently, visible-light-enabled drone networks have started to attract researchers' attention to provide high-speed communication [4] [8]. In [8], an integrated VLC and UAV framework has been proposed that can simultaneously provide communication and illumination, where the power consumption of UAVs is minimized by controlling the locations of drones. However, the orientation of the users is not considered which plays an important role in transmitter-receiver alignment and thus channel gain.

The main contribution of this work is to propose a novel framework to optimize the sum throughput of ground users served by VLC-enabled drones by adjusting their positions and orientations in a real-time fashion. Our key contributions include:

- We first formulate mathematically the control problem in a VLC-based UAV network, where the objective is to maximize the network-wide throughput of ground users by jointly determining the positions and orientation of the drone hot-spots.
- We design a fast solution algorithm based on particle swarm optimization (PSO) to solve the resulting optimization problem, where the heuristic optimal solution can be found within 20 iterations as shown in Sec. V.

Simulation results show that the proposed approach can achieve up to 24% throughput gain compared to the heuristic-central-point UAV deployment among ground users. To the best of our knowledge, this is the first work that studies the sum-rate optimization in VLC-enabled UAV communication by jointly considering the positions and orientations of drones and ground users.

The rest of the paper is organized as follows. We review the related work in Section II, and then present the system model in Section III. The optimization solution algorithm is then described in Section IV. Then, the results are discussed in Section V, and finally, we draw main conclusions in Section VI.

II. Related Work

Drone-assisted Network. The drone-assisted network has drawn significant research attention [9] [10] [11] [12] [13]. For example, in [9], the authors propose a new coordinate multi-point (CoMP) based network architecture for UAV-assisted

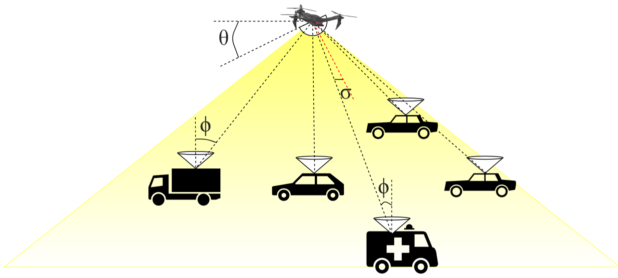

Fig. 1: Visible light communication based UAV to vehicles communication system, where σ is the irradiance angle, θ is the rotation angle of the UAV, and ϕ represents the incidence angle.

wireless communication, which harnesses both the benefits of interference mitigation via CoMP and high mobility of UAVs to achieve effective multi-UAV multi-user communications. [10] investigates the radio propagation characteristics of ground-to-air channels. Field measurements show that a height-dependent parameter is necessary to describe the channel for UAVs at different altitudes. The authors in [11] present the use of mobile UAVs for energy-efficient data collection in a static and time-varying Internet of Things (IoT) network. The proposed framework minimizes the total transmit power of the IoT devices while providing sustainable connectivity, by jointly optimizing the 3D locations of UAVs, device-UAV associations, and transmit power of each IoT device.

VLC-enabled UAV networks. A few works focusing on visible-light-based UAV networking have been proposed [14] [15] [16] [17] [4]. In [14], the authors discuss different use-cases for VLC on drones and the corresponding main research challenges in realizing the technology. The authors in [15] propose an algorithm to minimize the power consumption in by jointly control the locations of UAVs and the cell association with the constraints of illumination. In [17], the authors formulate an optimization problem to jointly optimizes UAV deployment, user association, and power efficiency while meeting the communication and illumination requirements. In [4], the author presents a frame for programmable visible-light-band UAV networking. To the best of our knowledge, we for the first time investigate the location- and orientation-aware sum throughput optimization for VLC-based UAV network.

III. System Model and Problem Formulation

A. Model Description

Consider a wireless network composed of one VLC-enabled UAV [1] that serve a set $\mathcal{U}$ of U ground users distributed over a geographical area $\mathcal{A}$. The UAV provides downlink transmission to ground users as shown in Fig. 1. We assume that the information of location and orientation of the users can be obtained by the devices themselves [18] and share with the drones. Please also note that the UAV does not serve ground users until it moves to the resulting optimal location.

[1]It can be easily extended to multiple UAV scenarios in future work.

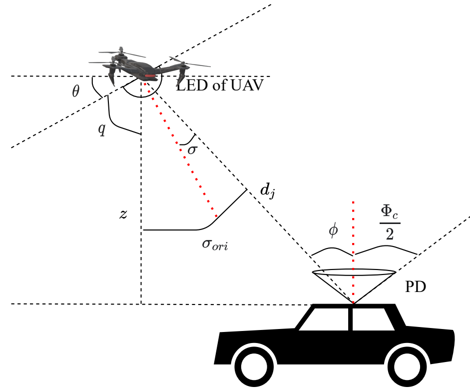

Fig. 2: Geometry LOS propagation model with visible light communication light transmitter (LED), and receiver (PD), where z represents the height of the UAV, d_j is the distance between the UAV and the user j, $\varPhi_c$ is the field of view of PD, σ_{ori} represents the irradiance angle when UAV is facing straightly downwards.

B. Transmission Model

Given a UAV located at $\mathbf{a} = (x, y, z, \theta^a)$ representing the 3D position and orientation of UAV and a ground user $j \in \mathcal{U}$ located at $\mathbf{u}_j = (x_j, y_j, 0, \theta_j^u) \in \mathcal{A}$ denoting the position of the orientation of ground user j. Without loss of generality, in our problem, we consider the scenario that the receivers of the users on the ground are facing straightly upwards, i.e., $\theta_j^u = 0$. The intensity modulation and direct detection (IM/DD) model is considered in the paper. For simplicity, we do not consider the diffusion of visible light in outdoor environments. Therefore, the LoS and non-line-of-sight (NLoS) channel gain of the VLC link between UAV and user j can be given by:

$$h_j^{LoS} = \begin{cases} \frac{A(m+1)}{2\pi d_j^2}\ P_t cos^m(\sigma_j) T_s(\phi_j) g(\phi_j)\cos(\phi_j) & 0 \leq \phi \leq \frac{\Phi_c}{2}, \\ 0 & otherwise, \end{cases} \quad (1)$$

$$h_j^{NLoS} = 0, \quad (2)$$

where A is the physical area of the PD on the receiver, and m is the order of Lambertian emission and is determined by the semi-angle $\phi_{1/2}$ at half illuminance power of an LED as $m = \frac{\ln 2}{\ln(\cos\phi_{1/2})}$. d_j is the distance between a transmitter and a receiver, which is calculated as $d_j = \sqrt{(x-x_j)^2 + (y-y_j)^2 + z^2}$. P_t is the transmitted power of UAV. σ_j is the irradiance angle to user j, ϕ_j is incidence angle of user j, and $\varPhi_c$ is the field of view of the PD. $T_s(\phi_j)$ represents the optical filter gain, and $g(\phi_j)$ is the optical concentrator gain, $g(\phi_j) = \frac{n^2}{\sin^2(\varPhi_c/si2)}$. We denote the rotation angle of the UAV as θ. σ_j^{ori} represents the irradiance angle to user j when UAV is facing straightly downwards, which can be obtained base on the geometric relationship as shown in Fig. 2, calculated as $\sigma_j^{ori} = \arccos(\frac{z}{d_j})$. The geometric relationship among UAV rotation angle θ, the original irradiance angle σ_j^{ori}, and the new irradiance angle σ^j can be derived as below:

$$\theta + q = q + \sigma_j^{ori} + \sigma_j = 90°. \quad (3)$$

Finally, we can calculate the new irradiance angle σ_j with respect to θ and σ_j^{ori} as

$$\sigma_j = |(\theta - \sigma_j^{ori})|. \tag{4}$$

We denote the field of view of the LED transmitter equipped on the UAV as Σ_c. If σ_j is greater than $\frac{\Sigma_c}{2}$, the ground users are out of the field of view of the UAV, which further means that the ground user cannot be served by the UAV. Then the channel gain h_j^{LoS} is set to 0.

Next, we formulate the channel capacity C_j of user j as:

$$C_j(\mathbf{a}) = B\log_2\left(1 + \frac{e}{2\pi}\left(\frac{\xi P_t h_j^{LoS}}{\sigma_j^w}\right)^2\right) \tag{5}$$

where B is the bandwidth, e is the Euler's number, ξ is the illumination target, and σ_j^w is the standard deviation of the additive white Gaussian noise at user j.

C. Problem Formulation

The objective of the network control problem is to maximize the sum-rate of the UAV visible-light downlink access network by jointly determining the position and orientation of the UAV, i.e., $\mathbf{a}$. The network control problem can then be formulated as

$$\begin{aligned}
&\text{Problem 1: Given: } \mathbf{u_j}, P_t, \Phi_c, \Sigma_c \\
&\underset{\mathbf{a}}{\text{Maximize}} \;\; f = \sum_{j\in\mathcal{U}} C_j(\mathbf{a}) \\
&\text{Subject to: } \arccos\frac{z}{d_j} \le \frac{\Phi_c}{2}, \\
&\qquad |(\theta - \sigma_j^{ori})| \le \frac{\Sigma_c}{2}, \\
&\qquad 0 \le x_j \le 10, \;\; j \in \mathcal{U}, \\
&\qquad 0 \le y_j \le 10, \;\; j \in \mathcal{U}.
\end{aligned} \tag{6}$$

IV. PSO Optimization Algorithm

As stated in Sec. III, the objective of the UAV visible-light network control problem is to maximize the sum throughput of the users by controlling the position and the orientation of the UAV, as presented in Problem 1. In (6), the channel gain h_j^{LoS} is nonconvex with respect to $\mathbf{a}_j$. Therefore, the resulting network control problem is a nonlinear nonconvex NP-hard problem. An intuitive proof is given in the Appendix. Classical mathematical methods that are widely used such as gradient methods and Lagrange relaxation methods, are not suitable for such complex optimization problems [19]. Thus, it requires a heuristic algorithm to find the optimal value. Recent studies have shown that the particle swarm optimization (PSO) based methods outperform the other modern metaheuristic search techniques [20] [21], such as genetic algorithms (GAs), biogeography-based optimization (BBO), differential evolution (DE), ant colony optimization (ACO), artificial bee colony (ABC), and hybrid swarm intelligent based harmony search algorithm (HHS) according to its several advantages in terms of simplicity, convergence speed, and robustness [22].

Algorithm 1 Solution Algorithm

```
Data: Predefine u_j, P_t, Φ_c, Σ_c. Initialize {pop_size} = 100,
      {W}, {c_1}, {c_2}.
Result: Obtain {f} and {a} when stopping criterion is met.
Initialize the Swarm
iter = 1
while true do
    for all (particles i) do
        Compute V_i(iter), X_i(iter) based on (7) (8)
        Compute sum data rate f_i(iter) based on X_i(iter)
        if f_i(iter) ≥ f_i^* then
            f_i^* = f_i(iter)
            pbest = X_i(iter)
        end
    end
    for all (particles i) do
        if f_i^* ≥ f^* then
            gbest = pbest(i)
            f^* = f_i^*
        end
    end
    iter++
    if {a}, the (Global.Sol), meet the stopping criterion then
        f = f^*
        Output {f} and {a} and iter
        break
    end
end
```

Therefore, we propose a solution algorithm to solve (6) based on particle swarm optimization because PSO is easy to be implemented and can result in high precision and fast convergence speed [23].

Next, we discuss the proposed PSO-based algorithm in detail. The basic design principle of PSO algorithm is to start from a random initialization with a set of candidates (i.e., initialized positions) and finally find a global optimal solution of the fitness function via iteration based on the position and velocity updating. Let X_i represent the solution provided by particle $i, i \in \mathcal{P}$, with $|\mathcal{P}|$ denoting the number of the particles we use. We then define V_i as velocity, which represents the searching or the moving direction of the solution vector X_i at the next iteration time. $V_i(t+1)$ can then be updated as:

$$\begin{aligned}
V_i(t+1) = {} & W \times V_i(t) \\
& + r1 \cdot c1 \cdot (pbest_i(t) - X_i(t)) \\
& + r2 \cdot c2 \cdot (gbest(t) - X_i(t)),
\end{aligned} \tag{7}$$

where $c1$ and $c2$ are learning factors, $r1$ and $r2$ are uniform random numbers in the range of [0,1]. $pbest_i(t)$ and $gbest(t)$ represent the personal best position of particle i at iteration time t, and the global best position at iteration time t, respectively.

Then, we can calculate the solution of the particle i at iteration time $t{+}1$, i.e., $X_i(t{+}1)$, based on the newly generated

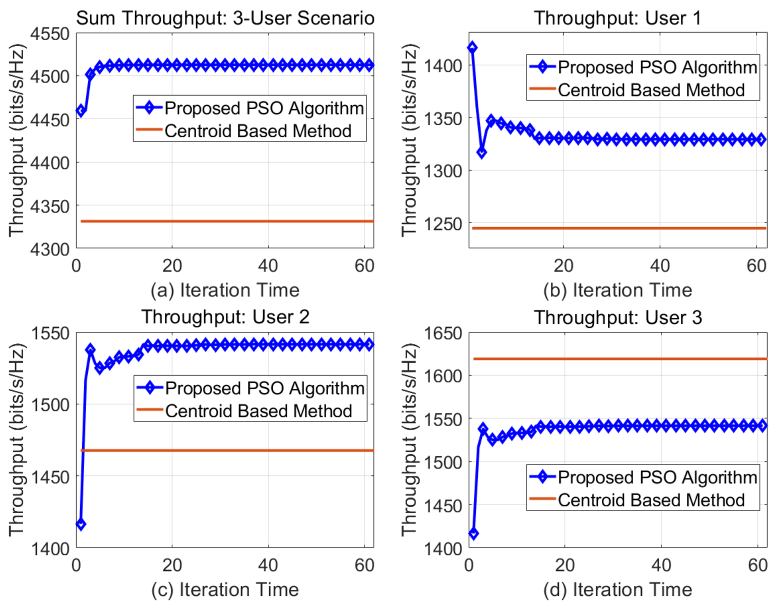

Fig. 3: Sum throughput and individual throughput comparison for the 3-user scenario.

TABLE I: Summary of Parameters

Parameter	Value
Bandwidth (B)	B = 20MHZ
Transmitted electrical power (Pt)	Pt = 1W
Optical filter gain (Ts(ϕ))	Ts(ϕ) = 1
Field of view of the PD	π
Optical concentrator gain ($g(\phi)$)	$g(\phi) = 2.25, 0 \leq \phi \leq \pi/2$; $g(\phi) = 0, \phi \geq \pi/2$
Area of PD (A)	A = 1cm^2
Particle population size	100

velocity value $V_i(t+1)$ as:

$$X_i(t+1) = \ X_i(t) + V_i(t+1). \tag{8}$$

Next, we explain how to combine PSO into the proposed problem (6). We define the sum rate objective function in (6) $f = \sum_{j \in \mathcal{U}} C_j(\mathbf{a})$ as fitness function of the PSO algorithm. Let $f_i(t)$ be the sum data rate of the network at time t with the assumption that the drone is placed exactly at the position $X_i(t)$ of the particle (i). If $f_i(t+1)$ is greater than the best personal solution to time t, i.e., $f_i^*(t)$, then we assign $X_i(t+1)$ as the new best personal position $pbest_i(t+1)$ of particle i. Next, we compare the $pbest_i(t+1)$ of all the $|\mathcal{P}|$ particles, the location $X_i(t+1)$ that can result in the maximal f is assigned as the new best global position $gbest(t+1)$. Then the maximized sum-rate of the network at iteration time $t+1$ can be obtained, denoted as $f^*(t+1)$. Finally, the algorithm will stop when the adopted stopping criteria is met. The detailed algorithm for UAV position and orientation optimization is summarized in Algorithm 1.

V. PERFORMANCE EVALUATION

In this section, we evaluate the proposed solution algorithm through simulations. We consider that 1 UAV simultaneously serves multiple users (the number of users ranging from 1 to 10), where the users' positions are randomly generated within the predefined area. We assume the bandwidth for each user j is 20 MHz. The transmission power of UAV to each user j is 1 W. The field of view of the UAV and the users are π and $\frac{2\pi}{3}$ [2], respectively. Table I summarizes the parameters used in the simulation. To evaluate the proposed PSO algorithm, we compare it with a heuristic algorithm (referred to as Centroid based Method), i.e., the position of the UAV is determined as the centroid of the users from the geometric perspective.

Figures 3 and 4 illustrate the sum throughput and the individual throughput comparison between the proposed PSO algorithm and the centroid based method for networking scenarios with 3 users and 5 users, respectively. We can see that the proposed PSO algorithm outperforms the centroid based method in both scenarios. From Figs. 3 and 4, it can also be seen that the proposed PSO algorithm can converge very fast to the global optimum of the nonconvex problem formulated in (6), in around 10 to 20 iterations for 3-user and 5-user scenarios, respectively. The stopping criteria we use is $|f^*(t+1) - f^*(t)| \leq s_t$ with s_t denoting the predefined threshold for acceptable fluctuation. To further enhance the stability of the algorithm, we also define a parameter T and only when the stopping criterion is satisfied for T times, the algorithm will stop. In our simulation, we set $T = 10$ and $s_t = 0.05\%$, respectively. Figure 8 shows the detailed convergence procedure of the proposed PSO algorithm in the 5-user scenario with respect to the UAV's x and y coordinates (z is eliminated for simplicity because it doesn't change in our problem.) and orientation θ^a. We can see that, after approximately 12-time iteration, the UAV's location and orientation are not changed drastically anymore, which is

[2]Without loss of generality, we assume the field of view of each user is the same and our proposed algorithm can be easily adapted to the scenario where users have different field of views.

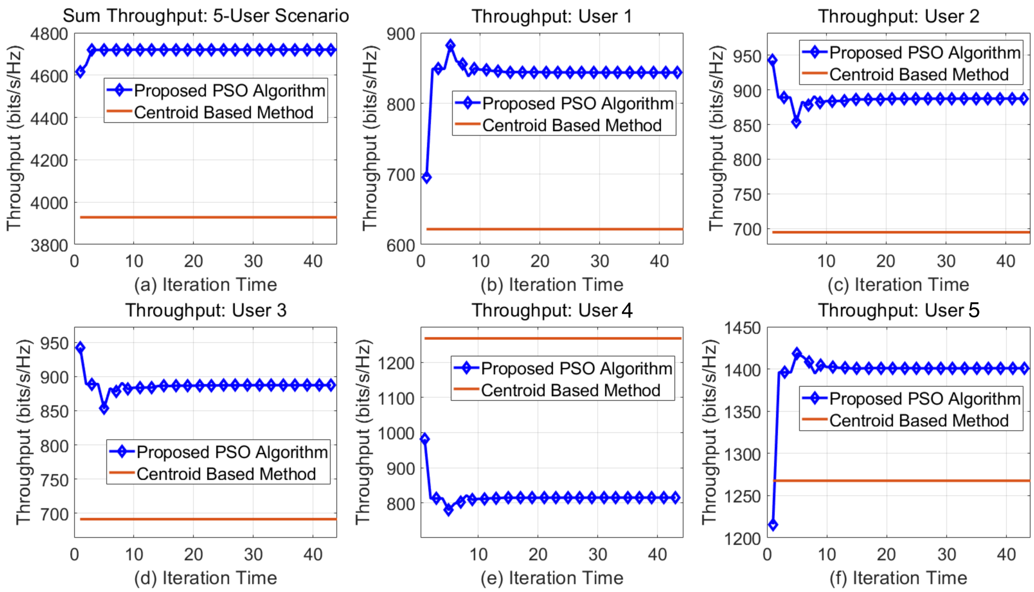

Fig. 4: Sum throughput and individual throughput comparison for the 5-user scenario.

almost approaching the convergence point.

To further validate the effectiveness of the proposed PSO algorithm, we also compare the performance in 8 different network instances for 3-user and 5-user scenarios, as shown in Figs. 5 and 6. It can be observed that the proposed PSO algorithm outperforms the centroid based method by up to 24% in all network instances which we randomly generate. In Fig. 7, we further compare the performance for scenarios with different user numbers, ranging from 1 to 10. For the 1-user scenario, the proposed method and the centroid method perform the same because the UAV straightly aligns with the only user is the best solution for both methods. For all of the remaining scenarios with 2 to 9 users, the proposed PSO algorithm results in higher sum throughput compared to the centroid based method.

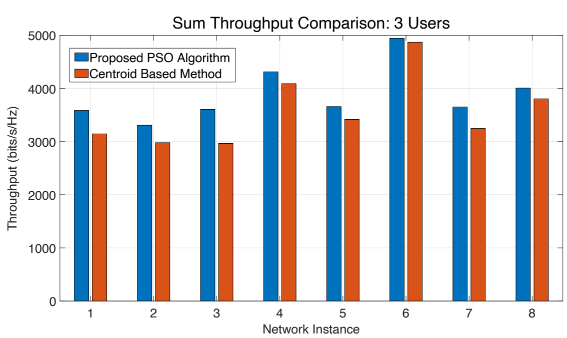

Fig. 5: Sum throughput comparison for the 3-user scenario.

VI. Conclusions

In this paper, we have proposed a network control problem in the UAV visible-light network to maximize the sum throughput by jointly controlling the position and orientation of the UAV. We then design a solution algorithm based on

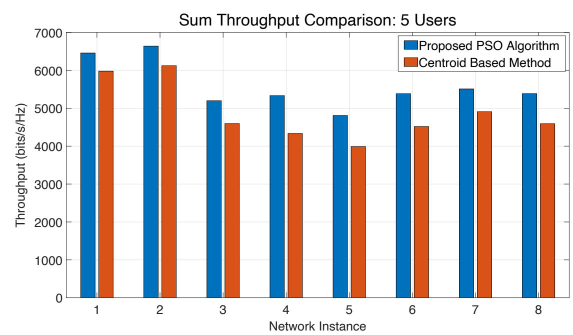

Fig. 6: Sum throughput comparison for the 5-user scenario.

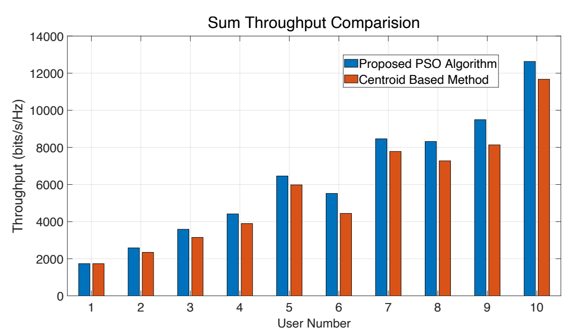

Fig. 7: Sum throughput comparison for scenarios with different user numbers.

PSO. Finally, we conduct simulations to validate the effectiveness of the proposed PSO algorithm and compare it with the heuristic centroid point method. The simulation results show that the proposed PSO algorithm can improve the sum throughput up to 24%.

In the future, we plan to apply advanced machine learning methods to solve the optimization problem based on the real-time trajectory prediction of the users, thus reducing the

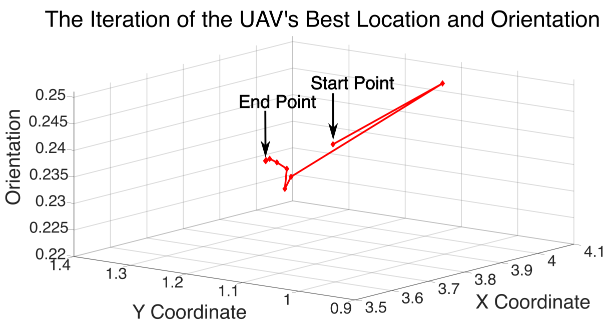

Fig. 8: The convergence with respect to the UAV's location and orientation (5-User scenario).

influence of the response time of the algorithm and achieving a fast association between the UAV and the users. We will also consider a dynamic environment rather than the static one in our future work.

Appendix

Proof of Convexity of the Channel Gain Function

First, we prove the LoS channel gain of VLC link between the UAV and the user in (1) is a non-convex function. We convert the function in (1) into a function with two independent variables σ_j and ϕ_j. This is because except for the parameter d_j, all the other parameters are predefined with fixed values and d_j can be expressed in the form of $\lambda\phi_j$, with λ being a real number. In addition, without loss of generality, we set the orientation of the LED of the UAV to straightly point down, then we have $\theta = 0$, $\sigma_j = \phi_j$. In this case, we further convert the function in (1) into a one parameter function with respect to ϕ_j as $h(\phi_j) = \frac{1}{(\phi_j)^2} cos^{m+1}(\phi_j)$ with $m = 1$ and ϕ_j ranging from 0 to $\frac{\Phi_c}{2}$ continuously. This can be further rewritten in a simplified form as:

$$h(x) = \frac{1}{(x)^2} cos^2(x), 0 \le x \le \frac{\Phi_c}{2}, \tag{9}$$

with x representing ϕ_j. We then can calculate the second derivative of (9) with respect to x as:

$$h^{''}(x) = \frac{-2x^2cos(2x) + 4xsin(2x) + 6cos^2(x)}{x^4}, 0 \le x \le \frac{\Phi_c}{2}. \tag{10}$$

$h^{''}(x)$ is not always greater than 0 nor less than 0 in $[0, \frac{\Phi_c}{2}]$. According to the definition in [24] that a twice-differentiable function of a single variable is convex if and only if its second derivative is nonnegative on its entire domain. Therefore, $h(x)$ is not convex in $[0, \frac{\Phi_c}{2}]$. Because (1) is equivalent to (9), then we can obtain that (1) is also not a convex function. According to the definition of a convex optimization problem in [24], where objective function and constraints are both required to be convex, we can further conclude that the proposed problem in (6) is not a convex problem.

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