Joint User Scheduling and UAV Height Control for Smart Wearable Device Charging Network

Hongjing Ji[1], Xiaojie Wang[2](✉), and Zhaolong Ning[2]

[1] School of Software Engineering, Dalian University of Technology, Dalian, China
jihongjing@mail.dlut.edu.cn
[2] School of Communication and Information Engineering, Chongqing University of Posts and Telecommunications, Chongqing, China
{xiaojie.kara.wang,z.ning}@ieee.org

Abstract. This paper studies the user device time slot scheduling and Unmanned Aerial Vehicle (UAV) height control problem in the UAV-assisted smart wearable charging network. In contrast to traditional studies that only consider UAVs to serve user devices at a fixed height and ignore the flexibility and mobility of UAVs. We consider the UAV coverage and limited battery energy constraints as well as the charging demand of wearable devices; aiming to maximize network throughput. Specifically, first we formulate the problem as a Constrained Markov Decision Process (CMDP), and then propose a Proximal Policy Optimization (PPO)-CMDP algorithm for solving the formulated problem based on the Lagrangian original pairwise strategy optimization. Finally, the results from simulation evaluations show that our proposed algorithm can learn the mobility policy of UAV and the time slot scheduling policy of wearable devices to maximize the throughput of the achieved network while ensuring that the power of the UAV satisfies the constraint, and outperforms the baseline scheme.

Keywords: Wearable networks · wireless power transfer (WPT) · user scheduling · UAV altitude control · constrained deep reinforcement learning

1 Introduction

As Internet-of-Things (IoT) devices grow by leaps and bounds [1], the IoT is redefining the way we live, while laying the foundation for the rapid development of smart wearables [2]. The advancement of smart wearables will not only

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improve the quality of life level, but also play an important role in medical emergencies [3]. The global rampage of the novel coronavirus pneumonia outbreak has had a huge impact on healthcare systems and economic development in countries around the world [4]. According to the World Health Organization (WHO), as of March 6, 2022, more than 433 million diagnosed patients and more than 5.9 million dead cases have been reported worldwide. To counter the further spread of the virus [5], the use of smart wearable devices can monitor various health data of patients in real time [6], thus reducing the contact with patients. However, the batteries in smart wearable devices have limited energy and direct replacement or rechargeable batteries can extend the battery life, but this is much time consuming and inconvenient when there are a large number of wearables.

The emergence of Wireless Power Transfer (WPT) technology has made it possible to wirelessly charge smart wearable devices. In addition, with the fast-growing advancement of 5G and the improving regulations related to UAVs in recent years, more UAVs are being utilized in various fields [7]. Unlike traditionally deployed fixed network infrastructure, UAVs have the advantage of easy deployment and flexibility to provide short-term temporary expansion to underserved areas lacking extensive Internet coverage [8]. Therefore, it makes sense to deploy UAVs on-demand at cost-effective prices and use them as carriers of WPT to provide real-time charging services for smart wearable devices to extend their duration of use.

The joint optimization of UAV altitude changes and user device slot scheduling is challenging. On the one hand, this is caused by the change in user devices allowed to be served due to the change in UAV altitude. On the other hand, it is difficult to allocate services to user devices in different time slots to satisfy their needs. In this paper, we consider a UAV-assisted IoT network for smart wearable charging. Specifically, a UAV is dispatched from the charging station to the user cluster area, and then it provides charging services to the smart wearable devices within the coverage area by adjusting the altitude position, and finally returns to the charging station. The main contributions of this paper are summarized as follows:

- We propose a novel model that employs UAV wireless charging technology to assist in real-time charging of wearables. Under the premise of ensuring non-negative UAV energy, we consider the limited coverage of UAVs and the service demand of wearable devices to schedule user time slots and adjust UAV height positions, with the objective of maximizing network throughput.
- To solve the problem of time slot scheduling of wearable devices and height control of UAVs in energy-constrained UAV-assisted networks, it is transformed into a Constrained Markov Decision Process (CMDP), and a Proximal Policy Optimization (PPO)-CMDP algorithm is proposed based on the Lagrangian original pairwise strategy optimization, in which the UAV decides to adjust the moving distance of the altitude and the selected wearable devices for service within the current coverage.

– Simulation results show that the proposed PPO-CMDP algorithm is capable of fast convergence and dynamic adaptive solutions. Compared with two competing existing deep reinforcement learning algorithms, PPO-CMDP has better service completion rate and energy saving performance.

The rest of the paper is organized as follows: the system model is described in Sect. 2. The PPO-based algorithm is proposed in Sect. 3. Simulation results are given in Sect. 4. Finally, the paper is concluded in Sect. 5.

2 System Model

We consider a downlink UAV-assisted system for wireless charging of smart wearable devices networks. There are $\mathcal{I} = \{1, ..., i, ..., I\}$ smart wearables and a UAV. Before the task starts, the UAV is loaded full of energy at the charging station [9]. When the smart wearable device sends a charging request, the UAV flies to a given position (e.g., directly above the center of the user cluster) for serving, as shown in Fig. 1. Taking into account the limited coverage of the UAV [10], it can serve smart wearables in the hotspot area by adjusting its altitude. The energy demand of smart wearable devices in the user cluster is denoted by g_i. We suppose that most of the UAV's transmission power is concentrated directly below the UAV within an aperture angle of α.

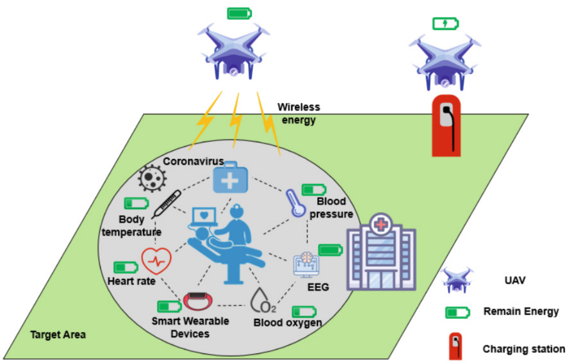

Fig. 1. Illustration of system architecture.

Since charging smart wearable devices is a delay-sensitive task, for example, in medical emergencies where patients' various physiological data need to be monitored in real time [11], it is important to charge smart wearable devices that can ensure their long-term health monitoring. A time-slot-frame structure is used to divide the time domain into set $\mathcal{L} = \{1, ..., l, ..., L_{max}\}$ in terms of frames, and the energy transfer should be done in L_{max}. Each frame consists of K time slots [12], $\mathcal{K}$ represents the set of time slots and every time slot has a period δ. As the change of the UAV's altitude position [13], the set of wearable devices currently covered by the UAV is $\mathcal{C}_{k,l} \in \mathcal{I}$ and the number is $C_{k,l} \leq I$. In addition, the smart wearable devices scheduled in that time slot are defined as a service device group. The possible candidate service device groups are noted as $\mathcal{Z}_{k,l} = \{1, ..., z, ...Z_{k,l}\}$, and the maximum number is $Z_{k,l} = 2^{C_{k,l}-1}$ [14]. The number and set of the current service devices of the group z at time slot k in frame l is denoted by $C_{k,z,l}$ and $\mathcal{C}_{k,z,l}$.

Suppose the smart wearable devices are randomly distributed in the hotspot area and their location coordinates are $(x_i, y_i, 0)$ [15] . The charging pile is outside the UAV coverage cluster. In addition, the 3D position coordinates of the UAV are $(X^u, Y^u, H^u_{k,l})$, where $H^u_{k,l}$ is the altitude of the UAV in the user cluster [16]. Then, the UAV covers a disc region with a radius of $\psi = H^u_{k,l} tan(\frac{\alpha}{2})$. Thus, the 3D distance from a UAV to a smart wearable device $i \in \mathcal{C}_{k,z,l}$ can be expressed as $d_{i,u} = \sqrt{(X^u - x_i)^2 + (Y^u - y_i)^2 + (H^u_{k,l})^2}$.

The UAV backhaul link and the UAV-user device link occupy portions of the spectrum that do not generate mutual interference, and are vulnerable to the environment in the communication link from the UAV to the user device[17]. The path loss between the UAV and the smart wearable device is denoted as $PL_{i,u} = 20 \lg(\frac{4\pi f_c d_{i,u}}{c}) + \varphi$, where f_c, c and φ represent the carrier frequency, speed of light, and path loss, respectively [18]. In addition, since a UAV may serve multiple smart wearable devices in the same time slot, there is unavoidable interference among devices, defined as $\mathcal{F}_{i,j} = \sum_{j \in \mathcal{C}_{k,z,l} \setminus \{i\}} P_t G_{j,u}$, where P_t denotes the transmission power and $G_{i,u} = 10^{-PL_{i,u}/20}$ is the channel gain [19]. Then, the Signal-to-Interference-plus-Noise-Ratio (SINR) from the UAV to the smart wearable device is denoted as $SINR_{i,u} = \frac{P_t G_{i,u}}{\mathcal{F}_{i,j} + \sigma^2}$, where σ^2 is the noise power. The total throughput of a wearable device network is defined as: $T_l = \sum_{k=1}^{\mathcal{K}} \sum_{i \in \mathcal{I}} B log_2(1 + SINR_{i,u})$, where B is the system bandwidth.

UAV is powered by a battery with an initial energy of E_{init}. In each time slot k in frame l, UAV moves $h^u_{k,l} \in [-h_{max}, h_{max}]$ a distance in the vertical direction at a certain speed η, and then interacts with the environment while hovering at a new position. The propulsive power of the UAV flight $P_f(\eta)$ and UAV hovering energy consumption P_h are given according to [20]. Then UAV flying energy consumption is $E^f_l = \sum_{k \in \mathcal{K}} P_f l_f$, where l_f is the flight time for the UAV to adjust its altitude, denoted as $l_f = \frac{|h^u_{k,l}|}{\eta}$.

Assuming that the UAV is hovering while charging in parallel to wearable devices [21], then the UAV's hovering time l_h is equal to the charging service time l_c, the total energy consumption of the UAV charging and hovering can be expressed as $E^s_l = \sum_{k \in \mathcal{K}} (P_h + P_c) l_c$, where P_c is the UAV's communication power when charging the smart wearables. In summary, the battery energy of the UAV at time frame l is $E^u_l = E_{init} - E^f_l - E^s_l$, and the energy collected is given by $E^c_{i,z,l} = \sum_{k \in \mathcal{K}} \mu P_c G_{i,u} l_c$, where μ is the WPT energy conversion factor.

We define the decision variable $p_{z,k,l}$ to be a wearable scheduling indicator, where $p_{z,k,l} = 1$ indicates that the wearable group $z \in \mathcal{Z}_{k,l}$ is selected for service by UAV at time slot k on frame l. Another decision variable $h^u_{k,l}$, represents the distance the UAV travels to adjust its height on frame l at time slot k, and the positive or negative sign indicates the direction of movement. Changes in the height position of the drone affect the service quality of the wearable devices and therefore the throughput of wearable network. Since UAV has a limited battery capacity, the optimization problem with the objective of maximizing the throughput is formulated as:

$$\mathcal{P}_1 : \quad \max_{p_{z,k,l}, h^u_{k,l}} \quad \sum_{l=1}^{\mathcal{L}} T_l, \tag{1}$$

$$s.t.$$

$$p_{z,k,l} \in \{0,1\}, \quad \forall i \in \mathcal{C}_{k,z,l}, z \in Z_{k,l}, k \in \mathcal{K}, l \in \mathcal{L}, \tag{1a}$$

$$h^u_{k,l} \in [-h_{max}, h_{max}], \quad \forall k \in \mathcal{K}, l \in \mathcal{L}, \tag{1b}$$

$$\sum_{l=1}^{\mathcal{L}} \sum_{z=1}^{Z_{k,l}} \sum_{k=1}^{\mathcal{K}} p_{z,k,l} E^c_{i,z,l} \geq g_i, \quad \forall i \in \mathcal{I}, \tag{1c}$$

$$\sum_{z=1}^{Z_{k,l}} p_{z,k,l} \leq 1, \quad \forall i \in \mathcal{C}_{k,z,l}, l \in \mathcal{L}, \tag{1d}$$

$$H_{min} \leq H^u_{k,l} \leq H_{max}, \quad \forall k \in \mathcal{K}, l \in \mathcal{L}, \tag{1e}$$

$$\sum_{l=1}^{\mathcal{L}} (E^u_{l+1} - E^u_l) \leq E_{thre}, \quad \forall l \in \mathcal{L}. \tag{1f}$$

Constraints (1a) and (1b) limit the range of decision variables $p_{z,k,l}$ and $h^u_{k,l}$. Constraint (1c) indicates that no more than one group of wearable devices can be scheduled in a time slot. Constraint (1d) ensures that the charging demand of all wearable devices is satisfied within L_{max}. Constraint (1e) restricts the height position of the UAV to the allowed range. Constraint (1f) makes sure that the UAV's battery energy changes below the threshold E_{thre}. The height position of the UAV in the considered problem is tightly coupled with wearable device scheduling, and the problem has energy constraints on the agent's actions. We formulate the wearable device time slot scheduling and UAV height decision problem as a CMDP model.

3 CMDP Problem Formulation

3.1 State Definition

The status of the system is made up of three components: the current altitude of the UAV, the remaining battery capacity of the UAV, and the unserved energy demand of the smart wearable device.

- When the UAV serves smart wearables, we only care about the UAV's altitude position at time slots k on frame $l < L_{max}$. The UAV flies with a movement boundary within the altitude limit, thus $H^u_{k,l} \in [H_{min}, H_{max}]$.
- The agent will learn from experience to ensure that the change in battery energy of the UAV when serving smart wearables is within the limit, i.e., $E^u_l \in [E_{thre}, E_{init}]$.

- The remaining energy demand of the smart wearable is also part of the environment state and the unserved energy that will charge the smart wearable, when on time frame l is $D_{l+1} = D_l - o_l^{\pi}$, where $D_0 = \sum_{i=1}^{\mathcal{I}} g_i$ and o_l^{π} is the energy delivered by the UAV to the smart wearable at time frame l under policy $\pi(S_l|A_l)$.

To sum up, the state S_l can be defined as, $S_l = [H_{k,l}^u, E_l^u, D_{1,l} \cdots, D_{\mathcal{I},l}]$.

3.2 Action Definition

The action of the UAV consists of two parts, one is the height moving distance at time frame l, $h_l^u = \{h_{1,l}^u, \cdots, h_{K,l}^u\}$, where $h_{k,l}^u \in [-h_{max}, h_{max}]$. Another is the user time slot allocation for the UAV at time frame l, $p_l = \{p_{1,l}, \cdots, p_{K,l}\}$, where $p_{k,l} \in \{1, \cdots, z, \cdots Z_{k,l}\}$, $p_{k,l} = z$ represents the z user device candidate group at the k time slot on l time frame to be selected for service. Thus, the action space is defined as: $A_l = \{h_l^u, p_l\}$.

3.3 Reward and Penalty Definition

Immediate reward is defined as the total throughput of the wearable device network, i.e., $\mathcal{R}(s_l, a_l) = T_l$. The penalty constraint is defined as the difference in the remaining energy of the UAV between adjacent time slots, i.e., $\mathcal{Q}(s_l, a_l) = E_{l+1}^u - E_l^u$. Considering the maximization of long-term discount network throughput, a discount factor β is introduced, so that the CMDP problem can be formulated as follows:

$$\mathcal{P}_2: \quad \max_{\pi_\zeta} \quad \mathbb{E}_{\pi_\zeta}\left[\sum_{l=0}^{\infty} \beta^l T_l\right], \tag{2}$$

$$s.t. \quad \mathbb{E}_{\pi_\zeta}\left[\sum_{l=0}^{L} (E_{l+1}^u - E_l^u)\right] \leq E_{thre}. \tag{2a}$$

In this paper, we propose a nested PPO-CMDP algorithm to solve the problem by constructing Lagrangian-based reward and penalty functions to relax the constrained optimization problem. In this algorithm, an Actor-Critic scheme is used to improve the strategy for updating the parameters of a given Lagrangian on a faster time scale, and updating the Lagrangian parameters on a slower time scale.

4 Numerical Results

In this section, we conduct simulation experiments to evaluate the performance of PPO-CMDP-based UAV-assisted user time slot allocation and height control algorithms. We consider a square area of 1 km × 1 km. The training is performed on a Windows 10 server with intel(R) Core(TM) i7-10700 CPU @ 2.90 GHz and 16.0 GB RAM. The algorithm is based on Actor-Critic network architecture implemented using Tensorflow. Both the critic and actor DNNs contain two fully connected hidden layers with 500 and 300 neurons, respectively. In the simulation experiments, we compare our algorithm with two baseline algorithms, the Trust region policy optimization (TRPO) algorithm and the Actor-Critic algorithm, respectively.

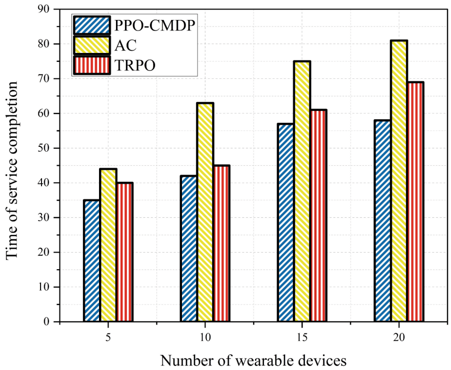

Fig. 2. Service completion time vs devices number.

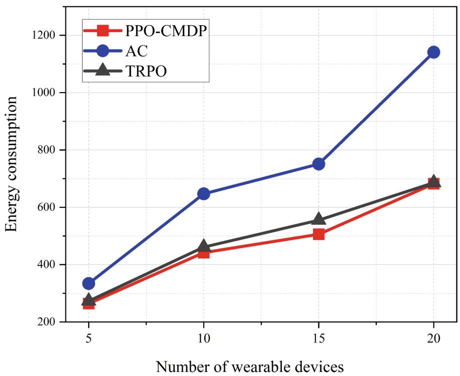

Fig. 3. Energy consumption vs devices number.

Figure 2 shows the relationship between service completion time and number of smart wearable devices. We can see that in all three scenarios, as the number of smart wearable devices increases, the total service time also prolongs. However, our solution has the shortest total service time, due to the increase in the number of smart wearables. The randomness of the number of smart wearables currently covered by the UAV and the selection of the devices to be served, and the need to charge different devices in order to meet them lead to the extension of the service time.

Figure 3 illustrates relationship between total energy consumption and number of wearable devices. We can see that total energy consumption is less than baseline algorithm using our PPO-CMDP-based algorithm. In addition, the total energy consumption increases as the number of wearable devices increases. This is because as the number of wearable devices increases, the more charging energy is required and more charging time is needed to obtain more energy to ensure the sustainable use of the wearable devices.

5 Conclusion

This paper solved the problem of height position adjustment and user device time slot allocation for charging smart wearable devices by UAV-assisted wireless power technology. We formulated the problem as a constrained Markov decision process, and designed a PPO-CMDP-based algorithm to find the optimal height adjustment strategy for UAVs and service wearable device decisions. In addition, we conducted simulation experiments, and the simulation results showed that as the number of wearable devices increases, the service completion time and energy consumption increase. Moreover, it is found that the performance of our scheme is much better than the competing schemes.

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