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Reinforcement Learning-Based Intelligent Resource Allocation for Integrated VLCP Systems

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Abstract—In this letter, an intelligent resource allocation framework based on model-free reinforcement learning (RL) is first presented for multi-user integrated visible light communication and positioning (VLCP) systems, in order to maximize the sum rate of users while guaranteeing the users' minimum data rates and positioning accuracy constraints. The learning framework can learn the optimal policy under unknown environment's dynamics and the continuous-valued space, and a reward function is proposed to take into account the strict communication and positioning constraints. Moreover, a modified experience replay actor-critic (MERAC) RL approach is proposed to improve the learning efficiency and convergence speed, which efficiently collects the reliable experience and utilizes the most useful knowledge from the memory. Numerical results show that the MERAC approach can effectively learn to satisfy the strict constraints and achieve the fast convergence speed.

Index Terms—Visible light communication and positioning, intelligent resource allocation, reinforcement learning, experience replay, actor critic.

I. INTRODUCTION

WHITE light emitting diodes (LEDs) have achieved much attention recently for the long lifetime, low power consumption and reliability [1]. Besides illumination, LEDs are used for visible light communications (VLC), which have the abundant bandwidth and high security properties [1]. In addition, visible light positioning (VLP) based on LEDs has become an attractive research topic due to the high positioning accuracy as compared with radio frequency (RF)-based localization systems [2]. Recently, resource allocation has also been widely investigated in VLC and VLP systems [3]–[10] to satisfy quality-of-service (QoS) constraints of users and improve the system performance.

On the one hand, the works [3]–[6] investigated the resource allocation approaches in VLC systems, where the authors of [3] and [4] designed optical resource optimization schemes aiming to enhance the sum rate of users under the practical optical power and users' QoS constraints. In addition, the optimal power allocation for a considerable number of

multiplexed users was derived in non-orthogonal multiple access (NOMA) VLC systems [5], [6]. On the other hand, the literatures [7]–[9] proposed power allocation approaches among LED lamps in VLP systems to improve the positioning accuracy. Especially, the experimental results were presented to indicate the effectiveness of power allocation based on received signal strength (RSS) in VLP systems [8]. So far, several works [8]–[10] deployed the integration of VLC and VLP (called integrated VLCP) in indoor scenarios, so both communication and positioning can be achieved at the same time, but the works [8]–[10] did not investigate the different QoS requirements in multi-user integrated VLCP systems.

The practical integrated VLCP systems indicate the uncertainty in the accurate channel information and the complete model of the systems evolution due to the mobility of users, different QoS requirements, as well as the user arrival and departure dynamics. Furthermore, the above optimization technologies [3]–[9] are usually non-convex and NP-hard, leading to a difficult search of the optimum. Hence, the model-free reinforcement learning (RL) technique is adopted to solve optimization problems in wireless RF or VLC systems [11]–[15], where the optimal policy is learned for decision making by interacting with the environment. So far, the works [12] and [13] applied experience replay to enhance the learning speed, but they did not study how to collect the reliable experience and utilize the most useful policy from historical experience.

To address the above mentioned issues, this letter firstly investigates the resource allocation in multi-user integrated VLCP systems under the different users' QoS and positioning accuracy requirements, where the system uses filter bank multi-carrier-based subcarrier multiplexing (FBMC-SCM) [10] and RSS [8]. The decision making problem for power and subcarrier allocation is modelled as a Markov decision process (MDP), and a reward function is proposed to consider users' requirements. To improve the learning efficiency and convergence speed, a modified experience replay actor-critic (MERAC) RL approach is proposed to efficiently collect the reliable experience and utilize the most useful knowledge. Numerical results verify that the proposed MERAC approach can efficiently deploy intelligent resource allocation for multi-user integrated VLCP systems.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. Integrated VLCP System Model

We consider a downlink multi-user integrated VLCP system, which consists of four LED lamps, and K users are randomly distributed on the floor, as shown in Fig. 1. There exists a central controller to connect all LED lamps and the uplink feedback is offered by the Wi-Fi links. Each user is

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Fig. 1. An indoor multi-user integrated VLCP system.

equipped with a single photodetector (PD). The total bandwidth is equally allocated to N subcarriers, and there are four subcarriers being used for RSS positioning. Let $\mathcal{L}$, $\mathcal{N}$, and $\mathcal{K}$ denote the sets of LED lamps, subcarriers and users, respectively. The transmitted signal z_l at LED lamp $l \in \mathcal{L}$ is given by

$$z_l = \sum_{k \in \mathcal{K}} \sum_{n \in \mathcal{N}} \rho_{k,n} \sqrt{P_{n,l}} x_{k,n} + b_l > 0 \quad (1)$$

where $\rho_{k,n}$ is a binary variable and $\rho_{k,n} \in \{0, 1\}$, $\rho_{k,n} = 1$ represents that the n -th subcarrier is allocated to user k ; otherwise, $\rho_{k,n} = 0$. $P_{n,l}$ denotes the allocated transmit electrical power on the n -th subcarrier at the l -th LED lamp. In addition, let $P_{n',l}$ denotes the n' -th ($n' \in \mathcal{N}$) subcarrier which is assigned for positioning and modulated into the l -th LED lamp. $x_{k,n}$ is the data symbol for user k on the n -th subcarrier and we set that the mean of $x_{k,n}$ is zero, and it is in the range of $[-\sigma, +\sigma]$ with $\sigma > 0$ [4], [9]. b_l denotes the direct current (DC) offset of the l -th LED lamp and it is used to ensure the transmitted signal (shown in Eq. (1)) is positive.

For user k , its received electrical power on the n' -th positioning subcarrier from the l -th LED lamp is $P_{i,l}^{\text{rec}} = G_{i,l}^2 P_{i,l}$, where $G_{i,l}$ is the line-of-sight (LOS) channel gain from the l -th LED lamp to the k -th user. Then, the distance between the l -th LED lamp and the k -th user is calculated by [8]

$$d_{l,k} = \sqrt[4]{\frac{(m+1)A_r T_s(\psi_{k,l})g(\psi_{k,l})h^2}{2\pi} \sqrt{\frac{P_{n',l}}{P_{i,l}^{\text{rec}}}}} \quad (2)$$

where A_r is the physical area of the PD, $d_{l,k}$ and $\phi_{l,k}$ denote the distance and the angle of incidence from the l -th LED lamp to the k -th user, respectively, $\psi_{k,l}$ is the incident angel. m is the order of Lambertian emission and h is the height. $T_s(\psi_{k,l})$ and $g(\psi_{k,l})$ are the gain of the optical filter and the optical concentrator gain at the PD, respectively. The user's position can be estimated based on the RSS algorithm [8]. The positioning root square error (RSE) of the k -th user is

$$RSE_k = \sqrt{(x_{k,e} - x_k)^2 + (y_{k,e} - y_k)^2} \quad (3)$$

where (x_k, y_k) and $(x_{k,e}, y_{k,e})$ are the real position and the estimated position of the k -th user, respectively.

At the receiver, the received signal-to-noise-ratios (SNRs) of the k -th user on the n -th communication subcarrier and the n' -th positioning subcarrier can be written as

$$SNR_{k,n} = \mu^2 \sum_{l \in \mathcal{L}} P_{n,l} (G_{l,k,n})^2 / \delta_{\text{total}}^2 \quad (4)$$

$$SNR_{k,n'} = \mu^2 P_{i,l} (G_{l,k,n'})^2 / \delta_{\text{total}}^2 \quad (5)$$

respectively, where μ denotes the PD's responsivity. $G_{l,k,n}$ and $G_{l,k,n'}$ represent the channel gain from the l -th LED lamp

to user k on the n -th and n' -th subcarrier [3], respectively. δ_{total}^2 is the total noise power, which contains the shot noise as well as the thermal noise [2]. For the k -th user, the data rate on the n -th subcarrier can be expressed as

$$R_{k,n} = \frac{B_{\text{sub}}}{2} \log_2(1 + SNR_{k,n}) \quad (6)$$

where the factor $\frac{1}{2}$ is due to the Hermitian symmetry [3], [5]. B_{sub} is the subcarrier bandwidth $B_{\text{sub}} = B/N$ with B being the system transmission bandwidth.

In practical integrated VLCP systems, users also have both the QoS and positioning accuracy requirements. These requirements can be guaranteed by controlling the probability of the unsatisfied communication service (p_k^{co}) and positioning service (p_k^{po}), where each user's data rate $R_k = \sum_{n \in \mathcal{N}} \rho_{k,n} R_{k,n}$ is below its minimum (min.) rate threshold R_k^{min} , and RSE_k exceeds its maximum (max.) positioning error threshold RSE_k^{max} , which can be expressed as

$$p_k^{\text{co}} = \Pr\{R_k < R_k^{\text{min}}\}, \quad p_k^{\text{po}} = \Pr\{RSE_k > RSE_k^{\text{max}}\}. \quad (7)$$

B. Problem Formulation

The policy learning problem of resource allocation in integrated VLCP systems can be modelled as a MDP with a tuple $(\mathcal{S}, \mathcal{A}, \mathcal{P}, r, \gamma)$ [11], where $\mathcal{S}$ is the state space, $\mathcal{A}$ denotes the action space, $\mathcal{P}$ denotes the transition probability: $\mathcal{P}(s'|s, a)$ if the agent selects the action $a \in \mathcal{A}$ from the system state $s \in \mathcal{S}$ to the new state $s' \in \mathcal{S}$, r represents the reward, and $\gamma \in [0, 1)$ means the discount factor.

1) *Agent*: Each communication and positioning service.

2) *State*: For each service (agent), the system state can be defined by the received SNR on the communication and positioning subcarriers as well as the subcarrier occupy status (ρ), which is given by $s = \{SNR_1, \dots, SNR_N, \rho_1, \dots, \rho_N\}$.

3) *Action*: The power and subcarrier allocation strategy is considered as the action of each agent in the RL framework, which can be defined as $a = \{P_{n,l}, \rho_{k,n}\}_{l \in \mathcal{L}, n \in \mathcal{N}, k \in \mathcal{K}}$.

4) *Reward*: The RL framework makes decisions by maximizing the immediate reward by interacting with the environment. Due to the requirements of users, a reward function is presented to consider the above requirements in multi-user integrated VLCP systems, which is calculated as follows

$$r = \sum_{k \in \mathcal{K}} \sum_{n \in \mathcal{N}} \rho_{k,n} R_{k,n} - c_1 \sum_{k \in \mathcal{K}} p_k^{\text{co}} - c_2 \sum_{k \in \mathcal{K}} p_k^{\text{po}} \quad (8)$$

In (8), the first part is the utility (the sum data rate), and the second and third parts are the cost functions (unsatisfied QoS and positioning accuracy constraints). The coefficients c_1 and c_2 are the costs for the unsatisfied probabilities, and they are also used for balancing the utility and the costs.

The objective is to search a policy strategy π to maximize the reward of agents. Let $Q^\pi(s, a)$ denotes the state-action value function for starting the system state s with a given policy strategy π under action a , which is an accumulative discounted reward [11], and it is expressed as

$$Q^\pi(s, a) = r(s, a) + \gamma \int_{s' \in \mathcal{S}} P(s'|s, a) Q^\pi(s', a) \quad (9)$$

Algorithm 1 MERAC Based Intelligent Resource Allocation

Input: Learning rate factor β_a and β_c , discount parameter γ , all integrated VLCP environment simulators.

- 1: **Initialize:** Initialize s_0 , $Q(s_t, a_t)$ and $\pi_t(s_t, a_t)$
- 2: **for** each time stage $t=0, 1, 2, \dots$, **do**
- 3: Select an action a_t^{na} at state s_t based on $\pi_t(s_t, a_t)$ by (12);
- 4: Calculate the reward r_t in (8) and update state s_{t+1} ;
- 5: Find the historical learned action a^{er} with the highest similarity, execute a^{er} if the agent is new or has poor performance;
- 6: Update (13), (14), (15) and (16), respectively;
- 7: Update the policy function $\pi_{t+1}(s_t, a_t^{ov})$ by (12).
- 8: **end for**

Fig. 3. The performance evaluations and comparisons. (a) Reward vs. training. (b) Unsatisfied services vs. training. (c) Sum rate of users vs. $R^{\min}$. (d) Unsatisfied services vs. $R^{\min}$. (e) Sum rate of users vs. $RSE^{\max}$. (f) Unsatisfied services vs. $RSE^{\max}$.

We consider a $5m \times 5m \times 3m$ indoor room with the receiving plane $0.5m$ above the floor. The locations of four LED lamps are $(1.25, -1.25, 3)$, $(1.25, 1.25, 3)$, $(-1.25, -1.25, 3)$ and $(-1.25, 1.25, 3)$ in meter. $K = 5$, $A_r = 0.5 \text{ cm}^2$, $B = 20 \text{ MHz}$ and $T_s(\psi_{k,l}) = 1$. The LED lamp's semi-angle at half power is 60° , and the field of view of PD is of 120° . The PD responsivity is 0.5 A/W . The system transmission bandwidth $B = 20 \text{ MHz}$ with 64 subcarriers, but only 31 subcarriers are used for data transmission due to Hermitian symmetry [3]. The transmit electrical power per LED lamp is 20 mW . All users have $R^{\min} = 8 \text{ Mbps}$ and $RSE^{\max} = 3 \text{ cm}$. We set $c_1 = c_2 = 3 \times 10^8$ to balance the utility and the costs in (8) [12], [13]. Other relevant parameters can be found in [6], [12], and [14].

As shown in Fig. 3 (a) and (b), the MERAC approach has the best reward and satisfied services performance with the fastest convergence speed compared with other RL approaches. From Fig. 3 (c) and (d), we can observe that the performance of all approaches decreases as the minimum rate

threshold $R^{\min}$ increases. This is due to that under the limited resource, more resource needs to be allocated to users with poor channel gains to guarantee their increased QoS requirements, consequently leading to the performance degradation. Fig. 3 (e) and (f) depict that the sum rate enhances and the probability of unsatisfied links reduces when the maximum positioning error threshold $RSE^{\max}$ increases. Such the performance improvement results from the looser requirement on the positioning accuracy as $RSE^{\max}$ increases, the requirement is easy to be satisfied in the case. From Fig. 3 (c) to (f), the approach in [4] can achieve the comparable sum rate performance to the RL approaches (except MERAC and greedy), but it obtains the lower probability of the satisfied services, especially when users have higher communication or positioning accuracy requirements.

V. CONCLUSION

This letter has studied the intelligent resource allocation based on RL in integrated VLCP systems. Moreover, the MERAC approach was presented to effectively learn the optimal policy by utilizing the historical learning knowledge. Numerical results verify the effectiveness of the presented MERAC approach compared with other approaches.

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