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Goal-Oriented UAV Communication Design and Optimization for Target Tracking: A Machine Learning Approach

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Abstract—To accomplish various tasks, safe and smooth control of unmanned aerial vehicles (UAVs) needs to be guaranteed, which cannot be met by existing ultra-reliable low latency communications (URLLC). This has attracted the attention of the communication field, where most existing work mainly focused on optimizing communication performance (i.e., delay) and ignored the performance of the task (i.e., tracking accuracy). To explore the effectiveness of communication in completing a task, in this letter, we propose a goal-oriented communication framework adopting a deep reinforcement learning (DRL) algorithm with a proactive repetition scheme (DeepP) to optimize C&C data selection and the maximum number of repetitions in a real-time target tracking task, where a base station (BS) controls a UAV to track a mobile target. The effectiveness of our proposed approach is validated by comparing it with the traditional proportional integral derivative (PID) algorithm.

Index Terms—Task-oriented, UAV, DRL, K-repetition scheme, C&C data, real-time target tracking.

I. INTRODUCTION

DUE to the high mobility, low cost, and line-of-sight communication, unmanned aerial vehicles (UAVs) have been widely used to accomplish various tasks, including image classification, parcel delivery, target detection, IoT management, and base station (BS) substitution [1–6]. In order to successfully complete the task, the smooth and safe control of the UAV is important, which demands stringent quality of service (QoS) requirements (i.e., high reliability) for the downlink control and command (C&C) data transmission. However, the ultra-reliable low-latency communications (URLLC) provided by the existing fifth-generation (5G) mobile communication network cannot meet such requirements.

This challenge has raised increasing research interest from the communications field, where most existing research mainly focused on enhancing communication performance, such as latency, reliability, and data rate [7–9]. In [7], the optimal response delay was theoretically derived with close-form solutions for a swarm of three-dimensional distributed UAVs. In [8], the closed-form analytical expressions of the average packet error probability and effective throughput in the control link of UAV communications were formulated. To guarantee the data rate requirement and motion control performance of UAV, a data rate triggered sensing-control pattern activation in cellular-connected UAV networks was designed and its closed-form expression was obtained [9]. However, in a practical

robotic task, the goal-oriented performance metric (i.e., tracking accuracy) is more important than communication metric. And there is a lack of research focused on improving it.

To fill this gap, goal-oriented communication (a new communication paradigm focuses on how the transmitted bits affect the goal) has been proposed in [10] to design the communication system with a focus on the effectiveness of communication (the impact of the communication on the goal) in accomplishing a specific task. One promising approach to optimizing robotic task performance (i.e., classification accuracy [11]) is deep reinforcement learning (DRL). To generate optimal C&C data in the UAV waypoint transmission task, DRL was applied at the BS to minimize the distance between the UAV’s actual positions and the UAV’s target positions at the end of each transmission time interval (TTI) [12]. To reduce the redundant downlink C&C data transmissions for the UAV, DRL was utilized at the BS with a focus on maximizing the task-oriented semantic-aware information [13]. Though this framework has recently been proposed, there is only a little research using it to optimize goal-oriented performance metrics in a practical robotic control task.

Motivated by this, in this letter, we first propose a goal-oriented communication framework for the UAV downlink C&C data transmission in a real-time target tracking task, where a BS controls a UAV to track a mobile target in real time. With the goal of maximizing the probability of successful tracking for this task, we propose a DRL algorithm along with a proactive repetition scheme (DeepP) to optimize the generation of the C&C data and maximum repetition number. Compared with the traditional proportional integral derivative (PID) algorithm [14], our proposed DeepP algorithm can increase the probability of successful tracking by 5.4 times.

The rest of this paper is organized as follows. Section II presents the system model and problem formulation. Section III introduces the DeepP algorithm. Section IV provides the simulation results. Finally, Section V concludes the paper.

II. SYSTEM MODEL AND PROBLEM FORMULATION

In this section, a real-time target tracking task is introduced, where a BS sends C&C data to control a UAV to track a mobile target in real time. Subsequently, we model the communication environment and introduce the proactive repetition scheme to transmit the downlink C&C data. According to it, the problem formulation is presented.

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A. Real-time Target Tracking Task

Without loss of generality, we adopt a fundamental goal-oriented communication design in the real-time target tracking task shown in Fig. 1, where a BS controls a UAV to track a mobile target (i.e., vehicle) moving alongside a random trajectory in real-time. This design can extend to multiple BS, UAV and mobile target scenarios. We assume the mobile target can send its real-time positions to the BS correctly all the time without error and the UAV's onboard sensor captures its real-time positions, forwarding them to the BS. Upon receiving these positions, the BS generates C&C data to manipulate the UAV to track the target, which is achieved by managing the distance d between the UAV and the target. If d is not larger than a distance threshold d^{th} ($d \leq d^{\text{th}}$), the UAV successfully tracks the target. Otherwise, the UAV fails to track the target.

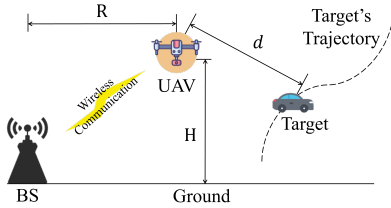


Fig. 1: System model

B. Channel Model

As shown in Fig. 1, the BS is assumed to be in a fixed position and the UAV is envisaged to navigate a circular horizontal disk defined by radius R and height H , where the C&C data is transmitted via downlink transmission from the BS to the UAV. Incorporating both potential line-of-sight (LoS) and non-line-of-sight (NLoS) scenarios, we employ free-space path loss and Rayleigh fading to formulate the path loss from the BS to the UAV as

$$h^{\text{DL}} = \begin{cases} \left(\frac{4\pi d^{\text{UB}} f^{\text{DL}}}{c}\right)^\alpha \eta_{\text{LoS}} \beta, & P_{\text{LoS}} \\ \left(\frac{4\pi d^{\text{UB}} f^{\text{DL}}}{c}\right)^\alpha \eta_{\text{NLoS}} \beta, & P_{\text{NLoS}}, \end{cases} \quad (1)$$

where d^{UB} represents the UAV-BS distance, f^{D} is the downlink transmission frequency, c denotes the light's speed, α is path loss exponent, and $\beta \sim \mathcal{CN}(0, 1)$ represents the Rayleigh small-scale fading. The η_{LoS} and η_{NLoS} are the path loss coefficients in LoS and NLoS scenarios, respectively. By calculating the angle of the UAV as $\theta^{\text{U}} = \frac{180}{\pi} \arcsin \frac{H}{d^{\text{UB}}}$, we formulate the probability of LoS case P_{LoS} as

$$P_{\text{LoS}} = \frac{1}{1 + C_1 e^{-C_1(\theta - C_2)}}, \quad (2)$$

where C_1 and C_2 are positive constants corresponding to the environment. Then, we can derive the downlink channel as

$$h^{\text{DC}} = (P_{\text{LoS}} \eta_{\text{LoS}} + P_{\text{NLoS}} \eta_{\text{NLoS}}) \left(\frac{4\pi d^{\text{UB}} f^{\text{DL}}}{c}\right)^\alpha \beta. \quad (3)$$

According to it, the signal to noise ratio (SNR) is derived by

$$\text{SNR} = \frac{P h^{\text{DC}}}{\sigma^2}, \quad (4)$$

where the BS transmits the C&C data in power P and the Additive White Gaussian Noise (AWGN) power is σ^2 . By using Eq. (4), the delay of the C&C data with size N^{CC} and bandwidth B^{CC} is formulated as

$$t^{\text{Tr}} = \frac{N^{\text{CC}}}{B^{\text{CC}} \log(\text{SNR} + 1)}. \quad (5)$$

At the UAV, the C&C data is able to be successfully decoded when its SNR exceeds the threshold γ^{th} , which is decided by the parameter δ^{CC} defined as

$$\delta^{\text{CC}} = \begin{cases} 0, & \text{SNR} \leq \gamma^{\text{th}} \\ 1, & \text{SNR} > \gamma^{\text{th}}. \end{cases} \quad (6)$$

If δ^{CC} is 1, the C&C data is successfully decoded with the assumption that it can be fully recovered.

C. Proactive repetition scheme

At the start of n^{th} TTI t_{n-1} , where n ranges in $\{1, 2, \dots, N\}$ with $N \in \mathbb{N}$ is the index of the final TTI, the C&C data \mathbf{m}_n is generated and transmitted from the BS to the UAV. Meanwhile, at the end of n^{th} TTI t_n , the UAV and target send their position $\mathbf{p}_n^{\text{U}} = (x_n^{\text{U}}, y_n^{\text{U}}, z_n^{\text{U}})$ and $\mathbf{p}_n^{\text{TG}} = (x_n^{\text{TG}}, y_n^{\text{TG}}, z_n^{\text{TG}})$ to the BS, respectively. The length of one TTI is T , and the C&C data \mathbf{m}_n is represented as

$$\mathbf{m}_n = (\mathbf{v}_n, \tau_n^{\text{E}}), \quad (7)$$

where $\mathbf{v}_n = (v_n^x, v_n^y, v_n^z)$ is the planned UAV's velocity vector for n^{th} TTI consisting of the velocities on the x , y , and z axis, respectively. After receiving \mathbf{m}_n , the UAV is assumed to execute this command for a fixed τ_n^{E} period, with $\tau_n^{\text{E}} = T$.

To achieve reliable C&C data transmission, we introduce the proactive repetition scheme [15], where the BS transmits the same C&C data for a maximum number of K^{max} repetitions and the time duration between two adjacent repetitions is T^{rep} . Concretely, for the C&C data \mathbf{m}_n , its j^{th} repetition ($j \in \{1, \dots, K^{\text{max}}\}$) is transmitted at $t_{n,j} = t_{n-1} + (j-1)T^{\text{rep}}$. For each repetition, the UAV will feedback the corresponding acknowledgement (ACK) or negative acknowledgement (NACK) to the BS, defined as

$$\delta_{n,j}^{\text{ACK}} = \begin{cases} 0, & \delta_{n,j}^{\text{CC}} = 0 \\ 1, & \delta_{n,j}^{\text{CC}} = 1, \end{cases} \quad (8)$$

where $\delta_{n,j}^{\text{CC}}$ is the detection state (i.e., success or failure) of the j^{th} repetition for \mathbf{m}_n . If $\delta_{n,j}^{\text{ACK}} = 1$, the UAV transmits an ACK back. Otherwise, the UAV sends a NACK. If the BS receives ACK, it will terminate repetitions earlier. With an emphasis on the downlink communication design, the uplink transmission (i.e., the target's position) is assumed to be ideal without packet loss or delay. Once the UAV successfully decodes one repetition, it will ignore other repetitions.

D. Problem Formulation

At the time t in whole process $[0, TN]$, we denoted the UAV's position and the target's position as \mathbf{p}_t^{U} and \mathbf{p}_t^{TG} , respectively. For each TTI, we uniformly split it into L parts with the timestamp of the l^{th} ($l \in \{1, \dots, L\}$) part in n^{th} TTI as $[(n-1)T + \frac{T}{L}l]$. According to it, we can obtain the UAV's

position $\mathbf{p}_{(n-1+\frac{T}{L})}^U$ and the target's position $\mathbf{p}_{(n-1+\frac{T}{L})}^{TG}$, respectively. Based on that, we formulate the distance $d_{n,l}$ between the UAV and the target at the timestamp $[(n-1)T + \frac{T}{L}l]$ as

$$d_{n,l} = \|\mathbf{p}_{(n-1+\frac{T}{L})}^U - \mathbf{p}_{(n-1+\frac{T}{L})}^{TG}\|, \quad (9)$$

where $\|\cdot\|$ is the Frobenius norm. Then, we define a function $V(d_{n,l})$ to value the distance $d_{n,l}$. If $d_{n,l}$ is not larger than the threshold d^{th} (successful tracking), $V(d_{n,l})$ reaches its maximum value of 1. Otherwise (failed tracking), $V(d_{n,l})$ decreases as the distance $d_{n,l}$ increases and its range is from -1 to 0. According to it, the function $V(d_{n,l})$ is formulated as

$$V(d_{n,l}) = \frac{[-f(d^{\text{th}} - d_{n,l}) + 1](e^{d^{\text{th}} - d_{n,l}} - 2)}{2} + 1, \quad (10)$$

where the function $f(\cdot)$ is expressed as

$$f(x) = \begin{cases} 1, & x \geq 0 \\ -1, & x < 0. \end{cases} \quad (11)$$

To achieve the tracking task effectively, we aim to maximize the long-term value function $V(d_{n,l})$. Based on that, we can formulate the problem as

$$\begin{aligned} \mathcal{P}1 : \max \lim_{L \rightarrow \infty} \frac{1}{NL} \sum_{n=1}^N \sum_{l=1}^L V(d_{n,l}) \\ \text{s.t. } N, L \in \mathbb{N}. \end{aligned} \quad (12)$$

III. DRL-BASED VELOCITY AND MAXIMUM REPETITION NUMBER SELECTION

Due to the varying significance of C&C data in accomplishing our task and the diverse channel conditions for transmission, it is feasible to set different maximum repetition numbers K_n^{max} for each C&C data \mathbf{m}_n . As a result, to address the problem in Eq. (12), we define the downlink C&C data transmission action $A_n = \{v_n^x, v_n^y, v_n^z, K_n^{\text{max}}\}$ to optimize the C&C data $\mathbf{m}_n = (v_n^x, v_n^y, v_n^z)$ and K_n^{max} selection at the beginning of n^{th} TTI t_{n-1} . At the BS, the action A_n is chosen by accessing all prior historical observations $O_{n'}$ from the previous TTIs $n' \in \{1, \dots, n-1\}$. The set $O_{n'}$ includes the UAV's position $\mathbf{p}_{n'-1}^U$ and the target's position $\mathbf{p}_{n'-1}^{TG}$. By incorporating all histories of the measurement $O_{n'}$ and the action $A_{n'}$, the observation in n^{th} TTI can be denoted as $O_n = \{A_1, O_1^H, \dots, A_{n-1}, O_{n-1}^H\}$.

To select the optimal action A_n at the start of n^{th} TTI, we aim to maximize the long-term average reward R_n associated with the distance d_n between the UAV and the target at the end of n^{th} TTI t_n , which is formulated as

$$d_n = \|\mathbf{p}_n^U - \mathbf{p}_n^{TG}\|, \quad (13)$$

Based on that, R_n is formulated as

$$R_n = V(d_n). \quad (14)$$

The optimization depends on choosing the action parameter A_n based on the observation history O_n concerning the stochastic policy π , and it is derived as

$$\mathcal{P}2 : \max_{\pi(A_n|O_n)} \sum_{k=n}^{\infty} \gamma^{k-n} \mathbb{E}_{\pi} [R_k], \quad (15)$$

where $\gamma \in (0, 1]$ represents the discount factor, accounting for the weighting of future TTIs. This process is a Markov decision process because its state $S_n = \{x_{n-1}^{TG} - x_{n-1}^U, y_{n-1}^{TG} - y_{n-1}^U, z_{n-1}^{TG} - z_{n-1}^U\}$ is only associated with its previous state and past action. Since the channel situation cannot be obtained, this introduces a partially observable markov decision process (POMDP) problem, which is generally intractable.

Algorithm 1: DQN

Input: Action space \mathcal{A} , N^I , N^θ , training parameters.

- 1 Initialization: θ , θ^* , replay memory M .
- 2 **for** Iteration $\leftarrow 1$ to N^I **do**
- 3 **for** $n \leftarrow 1$ to N **do**
- 4 Obtain \mathbf{p}_{n-1}^U and \mathbf{p}_{n-1}^{TG} .
- 5 Generate probability p_ϵ .
- 6 **if** $p_\epsilon < \epsilon$ **then**
- 7 | A_n is random chosen from \mathcal{A} .
- 8 **else**
- 9 | $A_n = \arg \max_A Q(S_n, A; \theta_n)$.
- 10 **end**
- 11 **for** $j \leftarrow 1$ to K^{max} **do**
- 12 **if** there is ACK back **then**
- 13 | Break.
- 14 **end**
- 15 Update the positions of the UAV and target.
- 16 **end**
- 17 Obtain \mathbf{p}_n^U and \mathbf{p}_n^{TG} , get S_{n+1} and R_n .
- 18 Store the transition (S_n, A_n, R_n, S_{n+1}) in M .
- 19 Sample transitions randomly from M .
- 20 Calculate $\nabla L(\theta_n)$ and update θ .
- 21 **end**
- 22 Update $\theta^* = \theta$ every N^θ episodes.
- 23 **end**

To address the problem in (15), we propose the DRL-based approach with its ability to select the optimal C&C data and K^{max} to achieve the task by considering the dynamic communication environment. The training process involves multiple episodes with every episode containing N TTIs. In each episode, the selected action A_n and current state S_n are fed into the Q-network with the parameter vector θ_n , where the predicted value is calculated by using the function $Q(S_n, A_n; \theta_n)$. After that, the next state S_{n+1} and the reward R_n are forwarded to the network which has the same structure as Q-network, namely target Q-network with the parameter vector θ_n^* , to calculate the target value. Subsequently, these results are processed to calculate the gradient of the loss function which derived as

$$\begin{aligned} \nabla L(\theta_n) = \mathbb{E}_{S_n, A_n, R_n, S_{n+1}} [(R_n + \gamma \max_A Q(S_{n+1}, A; \theta_n^*) \\ - Q(S_n, A_n; \theta_n)) \nabla_{\theta} Q(S_n, A_n; \theta_n)], \end{aligned} \quad (16)$$

where θ_n is updated by

$$\theta_{n+1} = \theta_n - \lambda_{\text{RMS}} \nabla L(\theta_n), \quad (17)$$

where λ_{RMS} is the RMSprop learning rate. It is crucial to note that the DQN updates θ^* by copying θ every N^θ episodes. To achieve the trade-off between exploration and exploitation, the

ϵ -greedy approach is employed with $\epsilon \in [0, 1]$. In each TTI, a probability is randomly generated by the agent and compared with ϵ . If the probability is less than ϵ , the agent randomly chooses an action. Otherwise, the agent chooses the optimal action. The implementation of the DQN algorithm is shown in **Algorithm 1**, which has the time complexity of $O(NN^1)$.

IV. SIMULATION RESULTS

In this section, we present the simulation results of our proposed DeepP algorithm and compare it with the PID algorithm. The location of the BS is (0m, 0m, 0m). The initial positions of the UAV and the target are $\mathbf{p}_0^U = (69\text{m}, 70\text{m}, 50\text{m})$ and $\mathbf{p}_0^{\text{TG}} = (70\text{m}, 70\text{m}, 50\text{m})$. The values of T and N are 1 ms and 100. f^{DL} , γ^{th} , σ^2 , and P are set as 5 GHz, 5.5 dB, -104 dBm, and 18 dBm, respectively. In the DQN algorithm, ϵ is 1, the batch size is 32, λ_{RMS} is 10^{-4} and γ is 0.1. The size of one C&C data N_{CC} is set as 100 bytes. The velocities v_n^x , v_n^y , and v_n^z are selected from the sets $\{-2000, -1500, \dots, 2000\}$, $\{-2000, -1500, \dots, 2000\}$, and $\{0\}$, respectively. The maximum repetition number K_n^{max} is selected from $\{1, 2, \dots, 10\}$. For the PID algorithm, we only use the proportional term with the proportional gain of 0.5. We obtain the results through the average value of 1000 simulations for each algorithm.

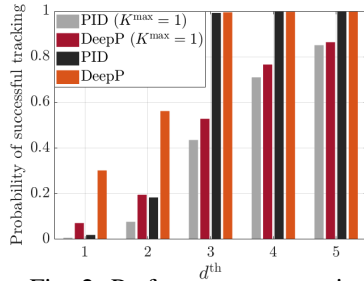


Fig. 2: Performance comparison.

Fig. 2 plots the probability of successful tracking of the traditional PID algorithm when $K^{\text{max}} = 1$ and the K^{max} which approaches the performance limit, and also plots our proposed DeepP algorithm when $K^{\text{max}} = 1$ and K^{max} optimized by the DQN agent among different values of the threshold distance d^{th} . We can obtain that as d^{th} increases, the probability of successful tracking of all algorithms in all cases increases. This is because the target tracking task can tolerate more packet loss when d^{th} is larger. It can also be observed that our proposed DeepP algorithm outperforms the traditional PID algorithm in all cases, especially when there is a stringent d^{th} requirement. For example, when $d^{\text{th}} = 2$, our proposed DeepP algorithm can increase the probability of successful tracking by 1.54 times than the traditional PID algorithm when $K^{\text{max}} = 1$ and its probability of successful tracking is even higher than the traditional PID algorithm with the K^{max} approaching the performance limit. When DQN optimizes K^{max} , our proposed DeepP algorithm can increase the probability of successful tracking by 2.06 times. The results validate the effectiveness of our proposed DeepP algorithm.

V. CONCLUSION

In this letter, we designed a goal-oriented communication framework for the real-time target tracking task, where a BS controls a UAV to track the target in real-time. To increase

the tracking success, we proposed a DeepP algorithm to select optimal C&C data and K^{max} for the task. Our results shed light on that our proposed task-oriented communication framework can achieve a higher probability of successful tracking than the traditional PID algorithm.

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