Energy-aware Goal Selection and Path Planning of UAV Systems via Reinforcement Learning

Amir Niaraki, Jeremy Roghair, Ali Jannesari

Abstract- Smart data collection via UAV systems is an attractive topic in various disciplines. Disturbances such as intense wind can significantly hinder the operational time of drones. This work demonstrates a reinforcement learning approach for the optimization of power consumption in a UAV system for data collection in sparse locations. Two common reinforcement learning algorithms, Q-learning and SARSA, are implemented in a simulation environment, utilizing a combination of robot operating system (ROS) and Gazebo. The effect of time-varying wind fields and time-dependency of the tasks were simulated and the developed framework showed reliable adaptability in various scenarios. This framework can result in 30% power consumption improvement for intense wind conditions in comparison to naïve control algorithms.

I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) are employed in variety of disciplines, for applications such as target search and data collection. Today, although UAVs are popularly in use for such applications, they suffer from limited battery life. Sufficient aerial imagery in large fields is typically achieved by multiple drone flights, which beside long wait time for recharging, are decelerating the applicability of these drones. Generally, wind plays the most significant role in power consumption of areal vehicles. It is shown that, by only changing the yaw of a quadrotor with respect to wind vector, we can improve the covered path by 30% on the same battery life.[1] Therefore, simultaneous path planning of the UAVs and monitoring of power consumption with respect to wind is an attractive research topic during any autonomous task completion mission.

There are two folds to UAV control while addressing an autonomous task completion problem. Firstly, flight control inherently implies stabilization and position control of aircraft, which is executed by an onboard Flight Control Unit (FCU) in an “inner loop” level. Secondly, a control unit in “outer loop” level, is typically responsible for mission level objectives such as path planning, collision avoidance and navigation.[2] Let us define the problem of periodic (i.e. daily) crop monitoring by covering the farm demonstrated in Figure 1. The task is to provide aerial imagery of the whole field, frequent enough to reliably monitor the health of the crops, but not through redundant visits, which results in power depletion of the drone. While wind can assist the drone to reach certain far spots, it may increase the power cost of covering other paths. Importantly, disturbances like wind are time varying, so tackling this problem requires constant re-planning. Thus far, Bezzo et al. have comprehensively studied the goal scheduling problem under wind, with a model predictive control algorithm.[3] A benchmark study on energy-aware coverage path planning of UAVs by Di Franco and Buttazzo[4] have tackled the path planning problem to minimize energy consumption while satisfying other requirements. Considerations on the objective is vital for optimal operation of autonomous UAV agent. For instance, the behavior of the objective function, health or color-map of the crops in this case, is time dependent and will vary from case to case. Therefore, it is preferred to utilize a framework, which simultaneously addresses the objective requirements and the optimal path planning. Thus, we employed a reinforcement learning (RL) approach to utilize the history of objective’s behavioral data to develop a sense of priority. In this proposed framework, the UAV agent interacts with its environment to collect sufficient power consumption information concerning varying wind fields.

Figure 1. Adapting to wind condition can significantly reduce the power cost of UAV system in large fields with sparse goals.
In the studied case here, the agent starts with no knowledge of its power cost function, disturbance information, and behavior of objective function and achieves a path planning policy through solving a power optimization problem through interacting with a simulation environment. Model-based RL has been utilized to address the path planning problem for a single start to goal case without the wind effect.[5] To the knowledge of the authors, this is the first time that RL is used for goal-selection and path planning on varying wind conditions.

The rest of this article is organized as follows: Section II presents a high-level description of UAV flight dynamic and general RL framework. In Section III, the proposed framework is described besides its implementation in two relevant task completion scenarios. The simulation results and a discussion on its expansion to real-world cases is given in Section IV and the closing remarks are provided in Section V.

II. BACKGROUND

Here, a generalized explanation for quadrotor flight dynamic is provided to create the background required to understand this work. Next, a brief overview of reinforcement learning (RL) and two commonly known RL algorithms: Q-learning and SARSA are presented.

A. UAV Flight Dynamic

The problem here is simplified to we define a planar motion with 3 degrees of freedom which includes position in x and y axis and the heading angle \( \psi \) while the altitude of the quadrotor (position in z axis) remains constant. It is reasonable to consider the quadrotor as a rigid body, which accelerates by the torques and forces applied form its four rotors.

The velocity and applied wind is simplified in order to reduce the complexities derived by the physics of the UAV, and shown schematically in Figure 2. For the given velocities, we can have:

\[
\begin{align*}
X_G &= V_w \sin(\psi) + W_x \\
Y_G &= V_w \cos(\psi) + W_y \\
\psi &= \frac{V_w}{R_{\text{min}}} U (-1 < U < 1)
\end{align*}
\]

Equation 3 can be integrated, to give

\[
\psi = \psi_0 + \frac{V_w}{R_{\text{min}}} Ut
\]

\[
X_G = V_w \sin(\psi_0 + \frac{V_w}{R_{\text{min}}} Ut) + W_x
\]

\[
Y_G = V_w \left[ \cos\left(\frac{V_w}{R_{\text{min}}} Ut\right) \sin(\psi_0) \right] + \cos\left(\frac{V_w}{R_{\text{min}}} Yt\right) \cos(\psi_0) Ut] + W_x
\]

Equation 6 is integrated giving:

\[
X_G = -\frac{R_{\text{min}}}{U} \cos\left(\psi_0 + \frac{V_w}{R_{\text{min}}} Ut\right) + W_xt + X_{G_0}
\]

Similarly, Equation 4 is substituted into Equation 2 and then integrated to give:

\[
Y_G = \frac{R_{\text{min}}}{U} \sin\left(\psi_0 + \frac{V_w}{R_{\text{min}}} Ut\right) + W_yt + Y_{G_0}
\]

The variables \( X_G \) and \( Y_G \) represent the UAV’s total velocity in the x and y direction respectively, relative to the ground. \( W_x \) and \( W_y \) are the wind speeds in the x and y directions, respectively. \( \psi \) gives the angular velocity, \( R_{\text{min}} \) and \( V_w \) represents the UAV’s minimum turning radius and speed. Finally, \( X_G, Y_G \) gives x and y coordinate of the UAV while \( \psi \) describes its heading angle.[6]

B. Reinforcement Learning: Q-Learning and SARSA

Robot reinforcement learning is an increasingly popular method that can offer the capability of learning the previously missing abilities. These can include behaviors that are priory unknown are not facile to code or optimizing problems without an accepted closed solution.[7] The behavior optimization occurs through repetitive trial and error interaction with its environment. This machine
The learned action value function, $Q$, directly approximates $Q^*$ independent of the followed policy
\[
Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha [R_{t+1} + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)]
\]
(10)

Where, $\alpha \in (0,1)$ is the learning rate, which is a hyper-parameter to tune the significance of the most recent rewards.

SARSA is an On-Policy temporal difference (TD) learning method which uses the following algorithm to update its action value function, $Q$:
\[
Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha [R_{t+1} + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)]
\]
(11)

The major difference between SARSA and Q-learning lies upon the method for updating the Q-value. SARSA uses every element of these five events: $(s_t, a_t, R_{t+1}, s_{t+1}, a_{t+1})$ that creates the transition from one state-action pair to the next.[9]

III. Adaptive Goal Selection and Path Planning

Presented here, the objective of power-optimized data collection from sparse locations under disturbance is considered in two scenarios.

A. Architecture

The experiments were implemented through a combination of ROS and Gazebo. Gazebo is equipped with a robust physics engine, which paves the way for taking in actual wind history and resulting in realistic power responses in various conditions. We utilized Hector Quadrotor, a drone model developed by Meyer et al.[10] to obtain the power consumption data from the movement of drone between consecutive states. The wind field was published to the simulation environment and the power consumption was obtained and normalized based on based on motor voltages for the four motors, given as a pulse width in the range of 0 to 255. For simplicity, the entire surveillance domain is broken down to equally-sized cells, while their center-point corresponds to the $(x, y)$ coordinate. To define the case in RL paradigm, the state of the agent comprises its $x,y$ location on the grid $(s_x \in [0, WorldWidth], s_y \in [0, WorldHeight])$ its battery-level ($s_b$) and the wind field it experiences at each location. At all states, the agent can chose from

Figure 3. Standard network structure for reinforcement learning algorithm.

The expected return (sum of discounted rewards) can consequently be used to give the optimal state-action value function for a given state-action pair $(s, a)$:
\[
Q^*(s_t, a_t) = R(s_t, a_t) + 
\gamma \sum_{s_{t+1} \in S} P(s_{t+1} | s_t, a_t) \max_{a_{t+1} \in A} Q^*(s_{t+1}, a_{t+1})
\]
(9)

Where $t$ can be an iteration numerator (or time-step), $\gamma \in (0,1)$ is a pre-defined discount factor. Therefore, the agent learns to modify his action policy based on the cumulative rewards over iteration. The agent’s policy is essentially a mapping from each state to its corresponding action. Using this state-action value function, we can calculate the optimal policy, $\pi^*$ by:
\[
\pi^*(s, a) = \arg \max_a Q^*(s_t, a_t)
\]

Various RL algorithms mostly vary in terms of trade-off between exploration and exploitation in creating and updating the value function.[9] Here we will describe Q-learning and SARSA and further implement them in the experimental scenarios.

Q-learning is an Off-Policy algorithm for temporal difference (TD) learning. While not requiring a model of the environment, based on an exploratory or random policy, Q-learning learns to optimize the policy when the actions are selected. In Q-learning,
a set of actions to move to adjacent cells horizontally, vertically or diagonally ($a_e \in [1,8]$). It is assumed that the UAV moves in constant altitude and at constant speed. Thus, $s_b$ is dependent on the change of location in consecutive time-steps and wind vector at that location and time. In order to maintain the generality of the framework, no battery model was used. Consequently, the agent can receive updates on its battery level solely by experimenting, provided by the simulation.

The generality of task completion is defined by a stochastic objective function $\Phi$. The task is successfully completed at each episode if $\Phi(x, y, t) > \Phi_c$, while $\Phi_c$ is a critical constant threshold value ($0 < \Phi < 1$). Meanwhile, the value of objective function can degrade with an arbitrary function as a characteristic of environment $\partial \Phi(x, y, t)/\partial t$. The value of degradation rate can be constant in a very basic case and can vary to a fully stochastic model.

In large farms, the task areal imaging of the crop can be achieved through constant and frequent coverage of the entire domain by drone flights. Such task completion policy is tedious and results in extreme power cost. Moreover, the images collected in frequent intervals may not bear new information for a pattern recognition machine. This can be influence by several factors such as the type of the crop, temperature, wind direction and the location of each goal point in the domain. Therefore, $\Phi$ and its first derivative are considered here as a feature of the environment which can be tuned for various applications. To mimic the crop degradation as an example of $\Phi$, and create the sense of urgency for the drone, a classification task was performed on well-known MNIST dataset for Hand-written digit recognition. The convolutional neural net was trained on 5500 input train data, with batch size of 512 on $28p \times 28p$ images. The model was compiled with Adam optimization algorithm,[11] and categorical cross entropy loss function. The overall accuracy of the model was equal to 91.6%.

In the start of each episode, the environment draws 1000 test data for each goal state. However, the classification is postponed until the time agent visits each goal. In order to model the degradation rate of the objective function at each goal state, we utilized a time dependent filter that adds noise randomly to the 784 pixels of each image data (See Figure 4). The number of altered pixels $n_f$ and the rate at which the new pixels are added to the images at each episode, the degradation factor $r_f$ are set by equation 12, which is the tunable variable for the characterization of the environment. Large values of $r_f$ can represent a rapidly changing environment while urgent requires no prioritization in goal selection when $r_f = 0$. $T_{avg}$ is the average number of overall time-steps in each episode.

$$n_f = (7.84)r_f T; \quad 0 < r_f \sim \frac{1}{T_{avg}} < 1$$

![Figure 4. Samples of noisy test data for episodes with average duration of $T_{avg} = 65$ and filtering rate of $r_f = 0.15$. Red pixels represent the added noise at A) t=32 and B) t=65.](image)

Now the case can be reduced to the task of providing an accurate map of $\Phi_{goal}(x,y)$ with the least consumed power. Therefore, the reward function in non-terminal states based on the accuracy of classification results at goal states.

$$\begin{align*} R(x,y)_{goal} &= 100 & \Phi_{goal} > \Phi_c \\ R(x,y)_{goal} &= 0 & \Phi_{goal} \leq \Phi_c \end{align*}$$

The battery level at each state is calculated based on the battery level at previous state and the power cost, which is calculated by the simulation engine $p_t$ (equation 14).

$$s_b(t) = s_b(t-1) - p_t$$

Each episode starts from the initial state at ground control station with full battery. Termination occurs in either of three conditions: (1) The agent reaches to one of the goal states resulting in the reward given by equation 13. (2) The agent runs out of battery ($s_b = 0$) with the reward of -100. (3) The agent takes an action that cause the drone to leave the domain, which is allowed, but will result in the reward of -100.
At the start of each episode, the environment generates multiple goals, \( g_i \) which are required to be visited \( v_i \) times and are located at \( (x_i, y_i) \), where \( i \in [1, N_g] \). An additional negative reward for charging was set to -30 for each time that the agent visits the ground stations to recharge the battery \( (s_b = s_{b_{max}}) \).

**B. Baseline Scenario: goal selection and path planning.**

The initial state is set to the origin \((0,0)\), and the goals \((N_g = 2)\) are spread in sparse locations of the domain far from the initial state each are required to be visited only once \( V = 1 \) (Figure 5). The agent starts in the initial state with full battery, aiming to first, discover these goals and second, find the path that minimizes its power consumption under the applied constant wind vector \( \vec{W}(x, y, t) = \text{const} \). In order to, evaluate the ability of the agent to adapt to the conditions; there exists an additional charging spot which might be beneficial to visit depending on the experienced power loss in severe wind. For the ease of representation, 5 constant wind intensities were applied:

\[
W_x \in \left[ -W_{\text{max}}, -\frac{W_{\text{max}}}{2}, 0, \frac{W_{\text{max}}}{2}, W_{\text{max}} \right],
\]

\( W_y = 0 \). The degradation rate of the objective function was set to zero \( (r_f = 0) \).

**C. Prioritization Scenario.**

In this case, the agent starts in the middle of the environment and four goals are generated randomly, in the 25 cells that are located at each corner of the domain (Figure 6). Each goal \( i \) is required to be visited \( V_i = 10 \) times the location of goals and number of required visits do not change between the episodes. In contrast with baseline scenario, the wind magnitude changes throughout each episode \( w_x \in (0, W_{\text{max}}), w_y = 0 \) wind with respect to time-steps is given in Figure 7 and the degradation rate is set to \( r_f = 0.15 \). We are interested to see the agent visiting the goals that cost the least, by leveraging the wind direction. However, postponing a visit for too long can cause the accuracy of the objective function to drop under the desired criteria \( \Phi_c = 0.7 \). In order to measure the power cost improvement, a Naïve path-planning algorithm, was defined which choses the shortest path to each goal regardless of wind field at each time-step. The Naïve planner selects the goals in constant order \((1,2,3,4,1,\ldots)\) until \( V_i \) is met. The Naïve planner does not perform the classification task on goals.

**IV. Results and Discussion**

The baseline scenario was designed to evaluate the ability of Q-learning and SARSA for target search and path planning, while preventing severe power cost under various disturbance conditions.
Particularly, in this case we are interested to evaluate the adaptability of the two algorithms to the wind intensity. Figure 8A, demonstrates the reward of both algorithms, upon finding the optimal path for each goal across all wind intensities. The reported rewards are an average of accumulated rewards of each episode for the last 10% of overall episodes prior to the convergence of policy. The results suggest that, goal 1 could be reached with minimal cost via both RL algorithms in a single battery life. However, we are interested in the head-wind fields \( \left( \frac{w_{\text{max}}}{2}, w_{\text{max}} \right) \) that cause a fast drop in battery level due to the drag force. When the wind reached to its maximum amount, any path that did not visit the charging spot ended with a termination due to battery loss. The interesting case however, is for \( w_x = \frac{w_{\text{max}}}{2} \): SARSA generated the path to visit the charging spot resulting in lower rewards and lower overall cost, in comparison with the path of Q-learning. In contrast, Q-learning found a path to reach the goal 2 without recharging. If we look at other accumulated rewards, often SARSA generated a more conservative path. The reason behind this discrepancy is the greedier nature of Q-learning. Once the goal state is found, the value of state-action pairs that lead to the goal state increases due to the embedded maximization, in value update rule (equation 11).

It is commonly known that, it is challenging to implement RL for tasks with sparse goals. For the case with maximum head-wind, we observed that, moving the charging location form what is given in Figure 5, to \((x_c, y_c) = (20,0)\) can increase the number of episodes by a factor of 10 for a reliable convergence. The exploration strategy was shown to be the prominent factor in the case of discovering the charging location. \(\epsilon\)-greedy algorithm is a common exploration technique for policy improvement.[12] For the scenarios with multiple goals in the same environment (no new instance of wind field, degradation factor or power model) we witnessed a significant improvement in convergence rate by updating \(\epsilon_{\text{episodic}}\) exponentially via equation 14, once an estimate of overall number of required episodes is available. Where, \(E\) is the average number of required episodes for all the previously found goals.

\[
\epsilon_{\text{episodic}} = \left( \epsilon_{\text{init}} \right)^{1 - \frac{e}{E}}; \quad (14)
\]

In order to initialize \(Q\)-learning, value update was performed for each wind scenario to train the RL planner, with constant \(\epsilon\). After the first convergence, the RL planner was trained on all wind fields until convergence using \(\epsilon_{\text{episodic}}\).

A comparison of the average power cost of two planner algorithms is given in figure 9 for 10 runs. It was resulted that as the wind intensity increases the RL planner performs better in comparison to the Naïve planner, where at \(w_x = w_{\text{max}}\), the RL algorithm can completely out-perform the Naïve.
controller and reduce the power consumption to up to 30%.

Goal selection and path planning with the proposed RL framework with can significantly increase the diameter of operation of the quadrotor and can pave the way

V. Conclusion and Future Work

Energy-aware goal selection and path planning via autonomous UAVs is addressed here through two scenarios. The proposed algorithm is particularly robust, for spars goals with the challenge of limited battery life. RL can be a suggested as a planning tool which adjusts to various disturbance conditions. The ability of a properly tuned RL-based agent to learn the effect of newly emerged wind field (for the cases with time variant wind), and to observe the degradation of the objective itself, suggests the applicability of this algorithm for fully autonomous task completion in large fields.

VI. References


