Emerson Hall

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Project Kickoff & Literature Review

Introduction

Unmanned Aerial Vehicles (UAVs) are widely used in aerospace for delivery, surveillance, and environmental monitoring. A major challenge for UAV deployment is trajectory optimization, which means finding a safe and efficient flight path. Traditional methods such as A* and Rapidly Exploring Random Trees (RRT) work in static environments, but they are not flexible when conditions change. Machine Learning (ML) is a promising way to improve UAV decision-making. It can make flight paths more efficient and adaptive in real time.

This week focused on setting the scope, objectives, and success metrics of the project. A literature review was also completed to study current methods in UAV trajectory optimization and ML applications.

Project Scope and Objectives

Scope:

This project will study ML methods for UAV trajectory optimization in simulation. It will compare ML approaches with traditional algorithms like A* and RRT. Performance will be measured in terms of efficiency, safety, and adaptability.

Objectives:

1. Define trajectory optimization as an engineering problem.
2. Implement A* and RRT for baseline performance.

3. Develop ML models such as reinforcement learning and supervised learning.
4. Test and compare results in simulation with static and moving obstacles.

Success Metrics

Efficiency: At least 10 percent shorter paths compared to baseline.

Safety: At least 90 percent success in avoiding collisions.

Computation: Less than one second per decision step in simulation.

Adaptability: Robust performance under different terrains and weather.

Literature Review

Traditional Approaches

- A*: Finds optimal paths in grid environments. It is slower in large or continuous spaces.
- RRT/RRT*: Works well in continuous spaces with obstacles. Paths are often longer and need smoothing.
- Limitations: These methods do not adapt well to unexpected changes in the environment.

Machine Learning Approaches

- Reinforcement Learning (RL): Methods like Deep Q-Network (DQN) and Proximal Policy Optimization (PPO) allow UAVS to learn from trial and error. RL adapts well to moving obstacles
- Imitation Learning (IL): Uses expert data to train models quickly. It is less effective in new situations.

- Hybrid Approaches: Combine planning algorithms with ML to balance safety and adaptability

Simulation Tools

- MATLAB/Simulink: For UAV modeling and algorithm testing.
- ROS2 and Gazebo: For realistic 3D simulation and physics-based UAV behavior.
- PX4 Autopilot SITL: For realistic UAV control and testing.

Peer Review Articles

- Federated deep reinforcement learning based trajectory design for UAV-assisted networks with mobile ground devices
  - Authors: Yunfei Gao, Mingliu Liu, Xiaopeng Yuan, Yulin Hu, Peng Sun, Anke Schmeink (Scientific Reports 2024)
  - Main idea: Employs federated DRL for multi-UAV coordination in data collection tasks, optimizing 3D trajectories while satisfying constraints like no-fly zones and collision avoidance.
  - https://doi.org/10.1038/s41598-024-72654-y
  - https://www.nature.com/articles/s41598-024-72654-y
- Reinforcement learning-based dual-UAV trajectory optimization for secure communication
  - Authors: Zhouyi Qian, Zhixiang Deng, Changchun Cai, Haochen Li (Electronics 2023)

- Main idea: Uses double-DQN (a form of deep Q-learning) to jointly optimize trajectories and transmit power in UAV-enabled secure communication settings, achieving fast convergence and improved secrecy rates.
  - https://doi.org/10.3390/electronics12092008
  - https://www.mdpi.com/2079-9292/12/9/2008
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- Deep reinforcement learning for UAV trajectory design considering mobile ground users
  - Authors: Wonseok Lee, Young Jeon, Taejoon Kim, and Young-II Kim (Sensors 2021)
  - Main idea: Applies DQN to allow UAV base stations to adaptively follow mobile users in 3D which enhances energy efficiency, user experience and coverage compared to static planning.
  - https://doi.org/10.3390/s21248239
  - https://www.mdpi.com/1424-8220/21/24/8239
- Optimal formation tracking control via actor-critic reinforcement learning for multi-UAV systems
  - Authors: Weizhen Wang, Xin Chen, Jiangbo Jia, Kaili Wu, Mingyang Xie (Control Engineering Practice 2023)
  - Main idea: Employs an adaptive sliding-mode control combined with actor-critic RL to maintain UAV formations despite disturbances, demonstrated in a ROS/Gazebo simulation
  - https://doi.org/10.1016/j.conengprac.2023.105735

    - https://www.sciencedirect.com/science/article/pii/S0967066123003040?via%3Dihub
- UAV motion control using deep reinforcement learning
    - Authors: Zifei Jiang and Alan F. Lynch (Canadian Journal of 2021)
    - Main idea: Uses PPO (a deep RL algorithm) to train a neural network controller for hovering stability. Achieves performance comparable to manually tuned PD controllers without requiring a model.
    - https://doi.org/10.1139/juvs-2021-0010
    - https://cdnsciencepub.com/doi/10.1139/juvs-2021-0010
- Real-time UAV route planning with improved Soft Actor-Critic (SAC)
    - Authors: Yuxiang Zhou, Jiansheng Shu, Xiaolong Zheng, Hui Hao, Huan Song (Frontiers in Neurorobotics 2022)
    - Main idea: Combines SAC with artificial potential field information for efficient reward shaping and path smoothing in real-time UAV navigation tasks.
    - https://doi.org/10.3389/fnbot.2022.1025817
    - https://www.frontiersin.org/journals/neurorobotics/articles/10.3389/fnbot.2022.1025817/full

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Literature Review

Trajectory optimization for UAVs has advanced significantly through reinforcement learning (RL). Traditional methods such as A* and RRT are useful for finding collision-free paths, but they struggle in dynamic environments. Recent studies show that deep reinforcement learning (DRL) can improve UAV adaptability and performance in complex missions. Researchers have tested different RL algorithms for challenges such as secure communication, mobile user tracking, formation control, and real-time navigation.

One important area of research is multi-UAV coordination. Yunfei Gao, Mingliu Liu, Xiaopeng Yuan, Yulin Hu, Peng Sun, and Anke Schmeink studied federated DRL for UAV networks. Their system optimized three-dimensional flight paths for multiple UAVs while respecting restrictions such as no-fly zones and collision avoidance. By using federated learning, their method let UAVs train collaboratively without sharing raw data, which improves both privacy and scalability (Gao, Liu, Yuan, Hu, Sun, and Schmeink).

Reinforcement learning has also been applied to secure UAV communication. Zhouyi Qian, Zhixiang Deng, Changchun Cai, and Haochen Li developed a Double Deep Q-Network (Double DQN) model that optimizes both UAV trajectories and transmit power. Their method improved secrecy rates and converged faster compared to baseline strategies. This work highlights how RL can be applied not only for navigation but also for missions where data security is essential (Qian, Deng, Cai, and Li).

In another study, Wonseok Lee, Young Jeon, Taejoon Kim, and Young-Il Kim applied DQN for UAVs acting as base stations. Their system allowed UAVs to follow mobile users in three dimensions. This improved energy efficiency, coverage, and overall user experience compared to static UAV planning. Their results suggest that RL could play a major role in wireless communication systems by allowing UAVs to adapt in real time to user movement (Lee, Jeon, Kim, and Kim).

Formation control for UAV groups is also an active area of research. Weizhen Wang, Xin Chen, Jiangbo Jia, Kaili Wu, and Mingyang Xie proposed a hybrid control method that combined adaptive sliding-mode control with actor-critic RL. Their system successfully maintained UAV formations even when disturbances were present. They tested the method in a ROS and Gazebo simulation environment, showing that hybrid designs may be effective for practical use (Wang, Chen, Jia, Wu, and Xie).

Some researchers focus on low-level UAV stability. Zifei Jiang and Alan F. Lynch trained a neural network controller using Proximal Policy Optimization (PPO). Their RL controller was able to keep a UAV stable during hovering, performing at the same level as a proportional-derivative (PD) controller. Unlike PD controllers, their PPO method did not need a detailed system model, which makes it more flexible and easier to apply to different UAV designs (Jiang and Lynch).

Finally, Yuxiang Zhou, Jiansheng Shu, Xiaolong Zheng, Hui Hao, and Huan Song improved the Soft Actor-Critic (SAC) algorithm for real-time UAV path planning. They added artificial potential field information to improve reward shaping and produce smoother paths. Their system generated safer and more efficient trajectories compared to standard SAC, showing the value of combining reinforcement learning with domain knowledge (Zhou, Shu, Zheng, Hao, and Song).

Together, these studies demonstrate how reinforcement learning can address many different UAV challenges, from data collection to secure communication to real-time stability. They also show that RL can outperform traditional methods in adaptability and safety. However, challenges remain, such as the need for large amounts of training data and the difficulty of transferring models from simulation to the real world. Even with these challenges, the literature shows that reinforcement learning is a powerful and flexible tool for UAV trajectory optimization.

Work Cited

Gao, Yunfei, Mingliu Liu, Xiaopeng Yuan, Yulin Hu, Peng Sun, and Anke Schmeink. "Federated Deep Reinforcement Learning-Based Trajectory Design for UAV-Assisted Networks with Mobile Ground Devices." *Scientific Reports*, vol. 14, no. 1, 2024, p. 72654. Nature, https://doi.org/10.1038/s41598-024-72654-y.

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