UAV Trajectory Optimization With Machine Learning

Independent Study – Fall 2025

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Project Overview

- Semester long study of UAV planning and control
- Compared a classical A* system to a machine-learning enhanced controller
- Tested across 3 terrains and 4 wind profiles
- Final goal: measure reliability, safety and performance

Motivation

- UAVs must navigate cluttered, windy environments
- Classical planners are predictable but conservative
- Machine learning can improve efficiency but may reduce reliability
- This project studied how the two approaches behave under identical scenarios

Background

- A* grid-based path planning on an inflated occupancy map
- Frenet-frame controller with repulsion and braking logic
- Behavior cloning model trained on expert trajectories
- Multi-UAV coordination using dilation and reserved corridor logic

Simulation Environment

- 2D 20x20 m world
- Urban, Natural and Manmade terrain layouts
- Thick/Thing occupancy masks for safe planning
- Wind modeled with Ornstein-Uhlenbeck gusts
- 4 wind profiles: calm, breeze, gusty, storm

Baseline Controller

- A* planner and smoothed path (string-pull and shortcuts)
- Frenet-frame tracking with lateral correction
- Repulsion forces using distance gradients
- Braking when rays detect nearby obstacles
- Very stable in wind and narrow corridors

Machine Learning Controller

- Dataset from baseline expert trajectories
- Features: goal direction, velocity, obstacle distance, wind terms
- Model: Ridge Regression (multi-output)
- Near-zero training and validation error
- Replaces the baseline’s local tracking step

Multi-UAV and Wind Handling

- Up to 3 UAVs at once
- Each treats others as moving obstacles
- Reserved corridor dilation to reduce path overlap
- Wind feedforward and airspeed capping
- Minimum ground progress rule prevents stalling

Validation Framework

- Deterministic scenarios for fairness
- 3 terrains x 4 winds x 2 modes
- Metrics:
  - Time to goal, Path length, Minimum clearance, Replans, Success flag
- Generated bar charts, CDFs and scenario videos

Results: Key Finds

- Calm Wind:
  - ML ≈ Baseline in all terrains
- Breeze Wind:
  - ML often faster (urban and manmade)
- Gusty Wind:

  Baseline more reliable

  ML failed in manmade terrain
- Storm Wind:

  Both modes fail as wind was too strong

Performance Summary

- Urban: ML faster in breeze, both fail in high wind
- Natural: Both strong in all but storm
- Manmade: ML best in breeze; ML fails early in gusty

- Minimum clearance nearly identical across all cases

Discussion

- ML controller imitates baseline very well in mild conditions
- ML is less reliable when it leaves the distribution of its training data
- Baseline more robust to crosswind drift and narrow corridors
- Safety margins mainly depend on planning and occupancy inflation

Future Work

- Larger and more diverse training dataset
- Add perturbations and failure recovery behavior
- Reinforcement learning to optimize long-term performance
- Hybrid controller that switches between ML and Baseline based on wind
- Extend to 3D UAV dynamics

Conclusion

- ML can outperform classical control in mild wind
- Baseline remains more reliable under difficult geometry and high wind
- Planning and inflated safety masks dominate the safety behavior
- Project shows both the potential and the limitations of ML in UAV trajectory control