ASEN 6519-006 Project Proposal

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1 Project Overview

Small unmanned aircraft systems (sUAS) have been utilized by CU Boulder researchers to investigate severe storms and better understand the formation of tornadoes. However, flying sUAS in supercell thunderstorms presents a significant risk to the safety and efficacy of the aircraft due to high winds, hail, and rain inside of the storm. As an alternative approach, "drifter" weather balloons can be deployed from sUAS to take in-situ measurements of relevant atmospheric quantities [1]. Drifters have been used for decades to sample Earth's atmosphere. **This project will conduct autonomous decision making for use on board sUAS to deploy drifters in a stochastic wind field.**

Figure 1: Pictures of a drifter unit being deployed by CU Researchers from the ground. We aim to autonomously deploy drifters from the sUAS platform.

Figure 2: Mistral Aircraft, the sUAS platform from which the drifters will be deployed.

2 Model Information

For the purposes of this project, we will assume a 2D (in x-y plane), discretized environment. This assumption is valid, as lateral winds in supercell thunderstorms are often much faster than vertical. Predicted wind vector field data sets can be acquired from various government agencies in order to predict balloon dynamics once deployed. As the prediction of the wind field has inherent uncertainty, we will treat the winds as stochastic. Balloon dynamics will be treated in continuous space, while the sUAS dynamics and action space will be discretized. Wind vectors at any location in continuous space will be found using interpolation between measured values in the discretized space. Figure 3 below demonstrates this problem formulation.

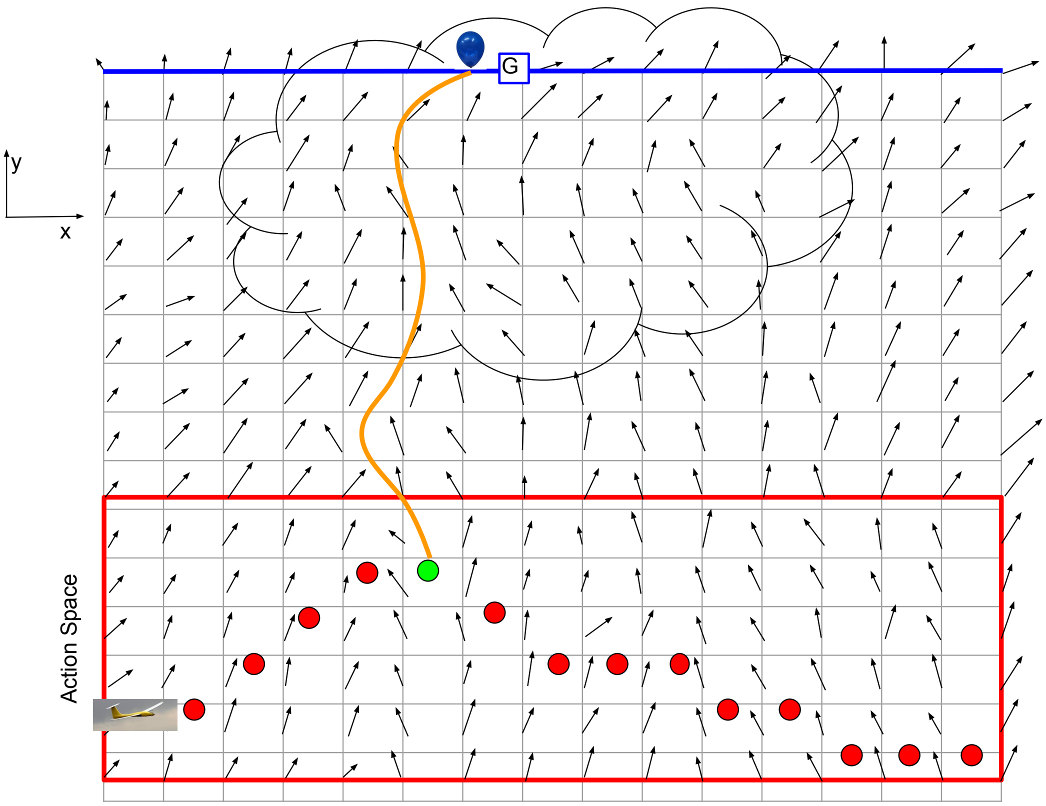

Figure 3: A figure demonstrating our problem setup. The Mistral sUAS (located in the bottom left corner) can take discrete actions within the action space. The goal of our autonomous decision making algorithm will be to find the optimal set of actions (movement and deployment) to maximize a utility function. The circles within the action space portray an optimal set of actions, with the green circle being the state at which the drifter is deployed. The action set should minimize expected the distance between the goal point (labeled "G") and the balloon after it has traveled to some y value. These desired behaviours will be encoded into the utility function.

The end-goal is to determine an optimal control policy π^* for an sUAS that releases drifters to collected data at a desired location within a storm. A Markov decision process (MDP) will be used to model sUAS dynamics and control decisions, and a discrete wind field will propagate the balloons after they are released. The control policy π^* will be computed offline given initial conditions of the sUAS, the target states of the drifters, and an estimate for the wind field. π^* will be computed using a Monte-Carlo particle method to find the best control actions and balloon release points.

The MDP uses a discrete state space $X = \{1, \ldots, M \times N\}$ which corresponds to grid numbers in an $M \times N$ 2-dimensional grid space. The sUAS action space A is made of two discrete sets $A_1 = \{\text{turn right, turn left, continue straight}\}$ and $A_2 = \{\text{release balloon, do not release balloon}\}$ with $A = A_1 \times A_2$. Actions are executed simultaneously at every state. For example, the action pair $\mathbf{a}_k = (a_1, a_2) =$(turn right, release balloon) executed at state $x_k \in X$ means the sUAS will execute a right turn and transition to x_{k+1} and release the balloon at x_{k+1}. There is a transition probability associated with the control action $P(x_{k+1}|x_k, a_1)$ that could cause the sUAS to deviate from its intended course. The reward function $R(\mathbf{b}(t), x_k, \mathbf{a}_k)$ to calculate the utility of future actions is dependent on the final estimated position of the drifter and is discussed below.

A discrete $P \times N$ wind field is used to model the motion of the uncontrolled drifter. For Level 1, the field will be deterministic with a wind vector $W_{i,j}$ at every node (i, j) with $i \in \{1, \ldots, P\}$ and $j \in \{1, \ldots, N\}$. Given an initial position $\mathbf{b}(0) \in \mathbb{R}^2$, the drifter's predicted position $\hat{\mathbf{b}}(t)$ can be found using numerical integration methods along the wind field. The integration continues until $\hat{b}_y(t) \approx g_y$ (the y-component of the goal position). The distance $||\hat{\mathbf{b}}_T - \mathbf{g}||_2$ will be used in the MDP's reward function.

For Level 2, the field will be probabilistic with the wind vector represented by a normal distribution at every node i.e. $W_{i,j} \sim \mathcal{N}(\boldsymbol{\mu}_{i,j}, \Sigma_{i,j})$. For predicting $\hat{\mathbf{b}}(t)$, the wind vectors will be realized and interpolated to the current position prediction. Then, the new position will be found with numerical integration. A Level 3 task involves estimating the wind vector distribution parameters $(\boldsymbol{\mu}_{i,j}, \Sigma_{i,j})$ at every node after a drifter is released and is broadcasting position data.

The reward function $R(\mathbf{b}(t), x_k, \mathbf{a}_k)$ will incorporate the drifter's estimated distance from the target $||\hat{\mathbf{b}}_T - \mathbf{g}||_2$ as the main objective, while imposing costs on sUAS actions. Level 1 will consider a single drifter and target state, while our Level 2 objectives involve designing a reward function for multiple drifters and target positions.

3 Project Objectives

3.1 Level 1

- Build the sUAS MDP and discrete, deterministic wind field framework
- Define a reward function for a single drifter and goal position
- Implement a brute-force Monte-Carlo particle solver to find π^*

3.2 Level 2

- Use a probabilistic wind field for particle propagation
- Define a reward function for a an arbitrary number of drifters and goal positions
- Implement smarter solvers (tree truncation?)

3.3 Level 3

- Learn the distributions for the probabilistic wind field using drifter trajectories
- Update the control policy online as the wind field is updated
- Model sUAS transitions using a POMDP, and change transition probabilities after a drifter is released

4 Project Timeline

Table 1: Timeline for completing major tasks.

Week	**Tasks**
Week 1	Refine Problem, Build Necessary Tools
Week 2	Complete Level 1 Tasks
Week 4	Complete Level 2 Tasks, Write Report

References

[1] Sara Swenson, Brian Argrow, Eric Frew, Steve Borenstein, Jason Keeler, and Adam Houston. DEVELOPMENT OF UAV-DEPLOYED AIR-LAUNCHED DRIFTERS FOR ABOVEGROUND THERMODYNAMIC MEASUREMENTS IN SUPERCELLS. In *29th Conference on Severe Local Storms*, 2018.