Final Project Proposal: Rocket Landing Guidance under Wind and Sensor Uncertainty

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1. Goal

The automated landing of launch vehicles for later booster reuse has seen a boom in the past decade with its successful introduction by SpaceX and its further (hopeful) implementation by companies such as Blue Origin, Rocket Lab, and Relativity. The automated landing process is extraordinarily stochastic in nature, with external disturbances such as wind or sensor imperfection influencing our decision making process. Our goal is to model this procedure with these incorporated imperfections to help our simulated rocket successfully land upright during an approach burn.

Zhao et al. (2020) provides helpful dynamics models for modeling our rocket's descent burn. Krishnamurthy and Djonin (2007) provides useful POMDP models for incorporating sensor noise and inaccuracy into our holistic rocket landing model.

2. Decision Making

Rocket Landing Guidance under Wind Uncertainty

We model powered descent and landing as a **sequential decision problem in a two-dimensional environment with uncertain lateral winds and noisy sensors**. At discrete time steps $t = 0, 1, \ldots, T$, a guidance policy selects thrust magnitude and gimbal angle to minimize landing error and propellant usage while avoiding crash. The state can be represented as $s_t = (x_t, z_t, v_{x,t}, v_{z,t}, \theta_t, \dot{\theta}_t, f_t)$, where x_t, z_t denote position, $v_{x,t}, v_{z,t}$ velocities, θ_t the attitude angle, $\dot{\theta}_t$ the angular rate, and f_t the remaining fuel. Actions $a_t = (u_t, \phi_t)$ specify the main-engine throttle $u_t \in [0, 1]$ and gimbal angle ϕ_t (optionally discretized). Transitions follow simplified rigid-body dynamics with gravity and thrust, plus stochastic disturbances w_t modeling winds and actuation lag: $s_{t+1} = f(s_t, a_t) + w_t$. The reward encourages accurate, gentle touchdowns with low fuel burn, for example,

$$r_t = -\alpha \|a_t\|_1 - \beta \|(x_t, z_t) - (0, 0)\|^2 - \gamma \|(v_{x,t}, v_{z,t})\|^2,$$

with a large terminal penalty for tipping or high-impact landing. We optimize the discounted return $\sum_t \gamma^t r_t$. Decision making is inherently sequential: each thrust vector change reshapes the future state distribution (position, velocity, fuel), trading immediate correction against later maneuverability and fuel reserves.

If sensors are imperfect, the problem can be modeled as a POMDP with noisy observations of altitude, velocity, and attitude. We use a short-horizon forward search (rollout) controller that simulates candidate actions under sampled wind disturbances and selects the action with the best expected reward. This formulation captures key uncertainty sources and provides a tractable testbed for studying decision making under uncertainty in rocket landing.

3. Sources of Uncertainty

Several key sources of uncertainty come up during powered descent and landing. The most significant external factor is atmospheric wind disturbance, which introduces random lateral accelerations and can vary spatially and temporally during descent. We model this as an additive stochastic process $w_t \sim \mathcal{N}(0, \Sigma_w)$ acting on the vehicle's translational dynamics, capturing both gust-like fluctuations and steady biases.

Sensor uncertainty is another major contributor. Altimeters and velocity sensors produce noisy or biased measurements, particularly during engine ignition. This motivates a partially observable formulation, where the state s_t is estimated from noisy observations $o_t = h(s_t) + \nu_t$, with $\nu_t \sim \mathcal{N}(0, \Sigma_\nu)$. Actuation uncertainty also plays a role, as thrust response to commanded throttle or gimbal angle is subject to lag. Together these disturbances can lead to trajectory deviations that must be compensated for. Modeling them explicitly allows us to evaluate controller resilience under realistic uncertainty conditions.

4. Sketches of Solution

Our proposed approach begins with implementing a simplified 2D vertical takeoff and landing dynamic model capturing position, velocity, attitude, and fuel dynamics. We will first validate deterministic trajectory tracking using nominal parameters before introducing stochastic disturbances. Wind uncertainty will be incorporated as Gaussian noise in the translational equations of motion, while sensor uncertainty will be modeled as observation noise added to position, velocity, and attitude measurements.

To address decision making under uncertainty, we plan to model the rocket landing problem as a Partially Observable Markov Decision Process (POMDP), where the true system state is not directly known due to sensor noise and estimation errors. The controller will maintain a belief distribution over possible states, updated through noisy observations of altitude, velocity, and attitude. We will implement a rollout-based planner that samples potential actions and simulates future trajectories under varying wind and sensor disturbances, selecting the action that maximizes expected reward over a finite horizon. The resulting policy will balance landing precision and fuel efficiency while mitigating sensing and environmental uncertainties. Its robustness and stability will be evaluated under varying noise levels during descent and touchdown.

References

Vikram Krishnamurthy and Dejan Djonin. Structured threshold policies for dynamic sensor scheduling – a partially observed markov decision process approach. *IEEE Transactions on Signal Processing*, 55(10):4938–4957, 2007. doi: 10.1109/TSP.2007.897078. URL `https://doi.org/10.1109/TSP.2007.897078`.

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