

Glider MDP

The Outliers

Gary Ellingson & Dan Koch



Problem Statement

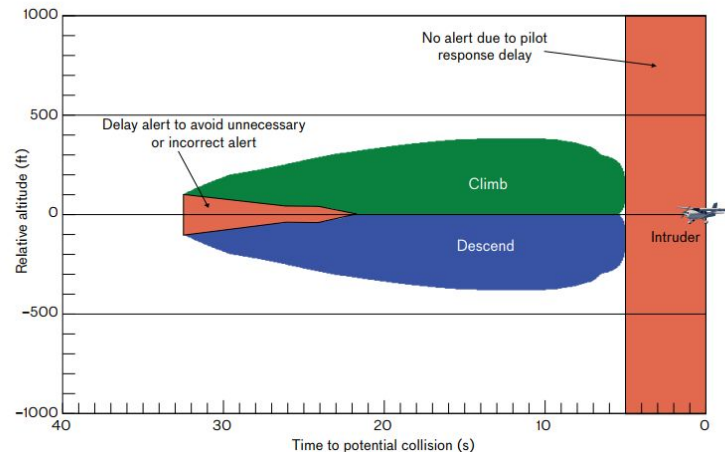
- Markov decision process
- Longitudinal control of a glider to reach a target
- Target: 1 meter above ground at the end of the room
- States observed with motion capture



Objectives & Motivation

- Learn about Markov Decision Processes
- Apply them to a “real” problem

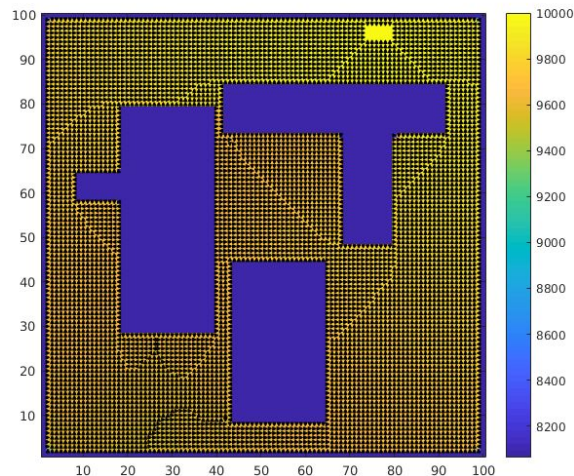
$$V_{\infty}(\mathbf{x}) = \gamma \max_{\mathbf{u}} \left[r(\mathbf{x}, \mathbf{u}) + \sum_j V(\mathbf{x}_j) p(\mathbf{x}_j | \mathbf{x}, \mathbf{u}) \right]$$





Challenges

- Transition probability model
 - Based on UAV book dynamics
 - Use distributions of points to represent uncertainty
- Computational tractability
 - State dimensionality
 - Pre-compute transition probabilities
 - Position-invariant computation
- Hardware / delay
 - Arduino PPM trainer port setup





State space

$$\mathbf{x} = \begin{bmatrix} x \\ h \\ u \\ w \\ \theta \\ q \end{bmatrix}$$

$$\mathbf{u} = \delta_e$$

- State space: longitudinal states
- Action space: elevator deflection
- Discretize state space into coarse grid
 - x and h: 0.25m step size, u and w: 1.0m/s step size, θ : 10deg step size
 - Resulting grid: $23*10*7*5*5*5 = 201,250$ elements
- Discretize action space
 - $\delta_e \in \{-30^\circ, -15^\circ, 0^\circ, 15^\circ, 30^\circ\}$
 - Resulting search space: $201,250*5 = 1,006,250$ elements



System dynamics

Assuming $\phi = p = r = v = 0$ and with $\alpha = \arctan(w/u)$, $V_a = \sqrt{u^2 + w^2}$:

$$\dot{u} = -qw - g \sin \theta + \frac{\rho V_a^2 S}{2m} \left[C_{X_0} + C_{X_\alpha} \alpha + C_{X_q} \frac{cq}{2V_a} + C_{X_{\delta_e}} \delta_e \right]$$

$$\dot{v} = qu + g \cos \theta + \frac{\rho V_a^2 S}{2m} \left[C_{Z_0} + C_{Z_\alpha} \alpha + C_{Z_q} \frac{cq}{2V_a} + C_{Z_{\delta_e}} \delta_e \right]$$

$$\dot{q} = \frac{1}{2J_y} \rho V_a^2 c S \left[C_{m_0} + C_{m_\alpha} \alpha + C_{m_q} \frac{cq}{2V_a} + C_{m_{\delta_e}} \delta_e \right]$$

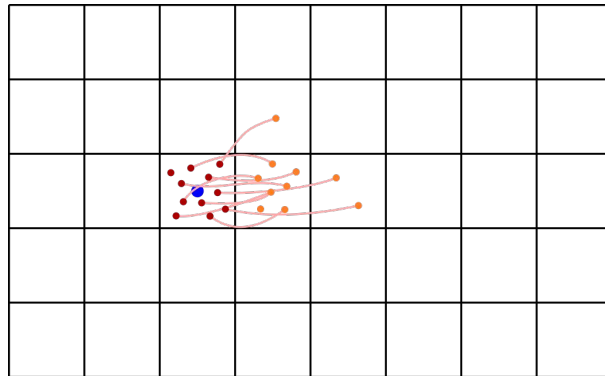
$$\dot{\theta} = q \cos \theta$$

$$\dot{h} = u \sin \theta - w \cos \theta$$



Transition probability model

- Propagate collection of noisy points through dynamics
 - Uncertainty on aerodynamic coefficients
 - Uncertainty on actual state value within grid cell
- Probability equal to fraction of points that end up in a given grid cell
- Used 500 sample points



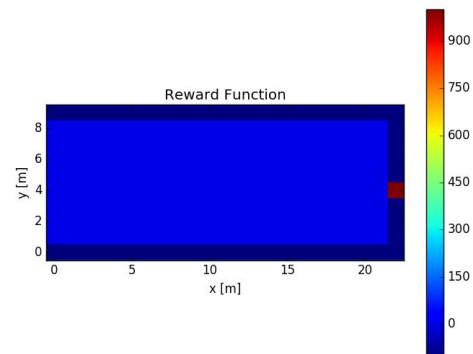


Value iteration

- Standard value iteration

$$V_{\infty}(\mathbf{x}) = \gamma \max_{\mathbf{u}} \left[r(\mathbf{x}, \mathbf{u}) + \sum_j V(\mathbf{x}_j) p(\mathbf{x}_j | \mathbf{x}, \mathbf{u}) \right]$$

- Reward function:
 - -100 at walls and ceiling
 - +1000 for hitting target

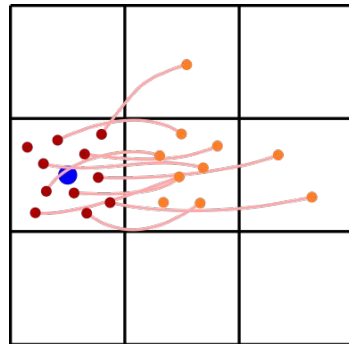




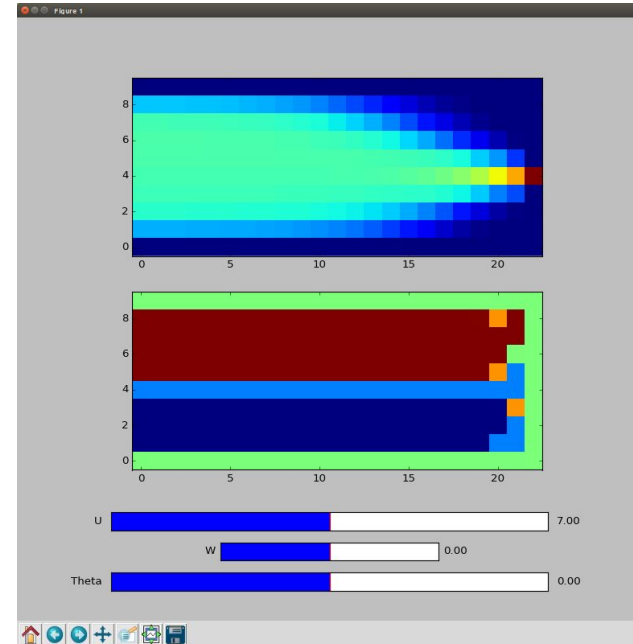
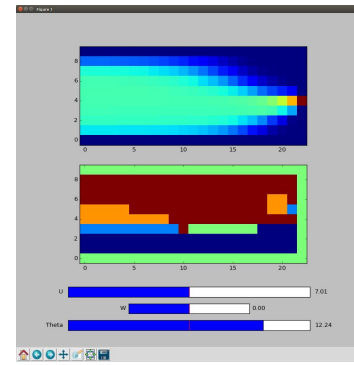
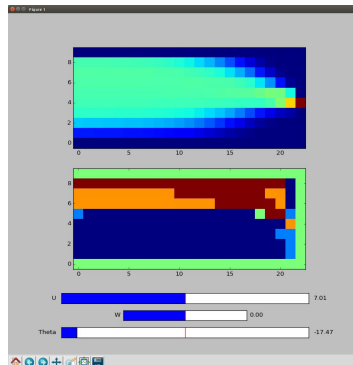
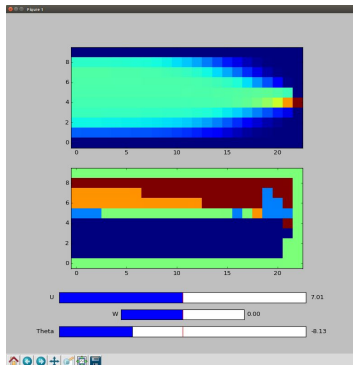
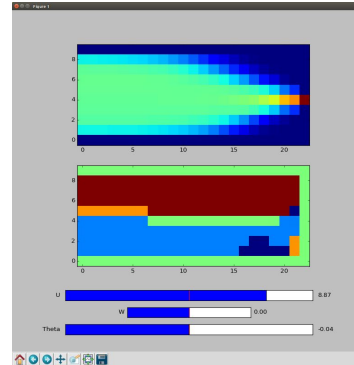
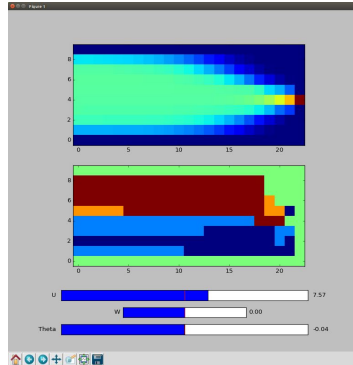
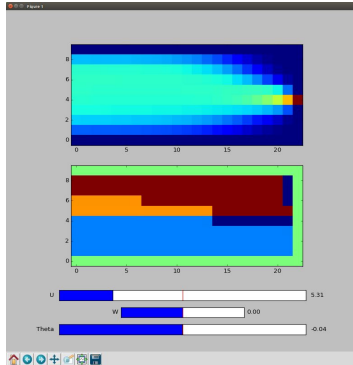
Computational speedups

- Pre-compute transition probabilities
 - Over 1 million transition probability function calls per iteration
- Position-invariant transition probability

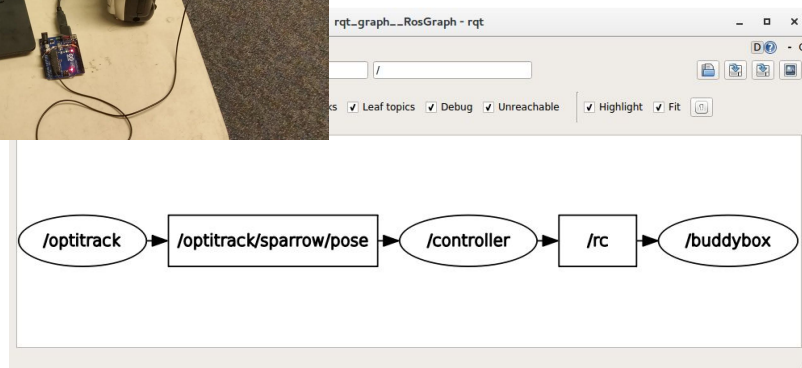
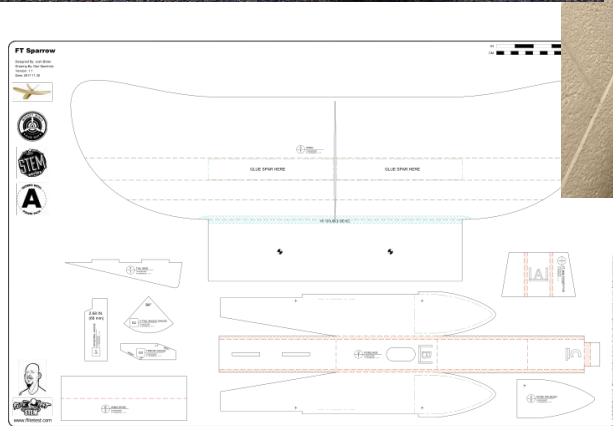
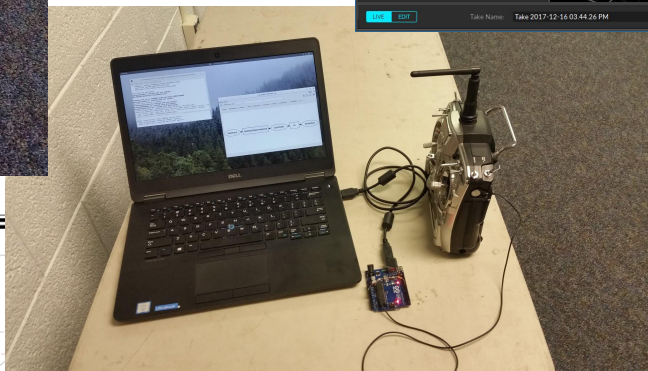
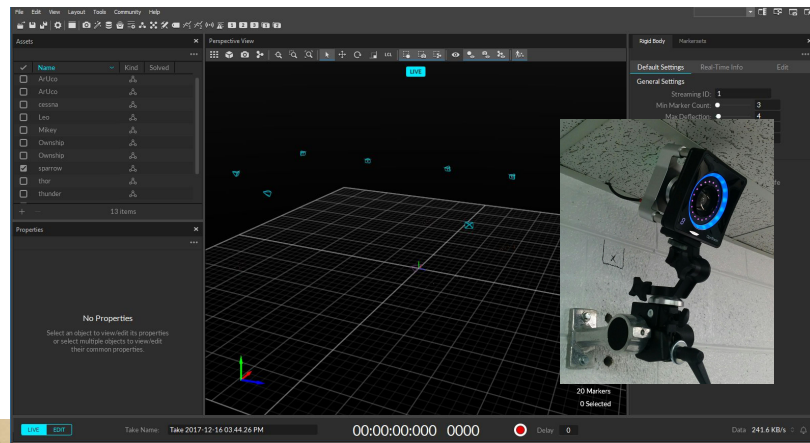
$$p \left(\left[\begin{array}{c} x' \\ z' \\ u' \\ w' \\ \theta' \\ q' \end{array} \right] \middle| \left[\begin{array}{c} x \\ z \\ u \\ w \\ \theta \\ q \end{array} \right], \delta_e \right) = p \left(\left[\begin{array}{c} x' - x \\ z' - z \\ u' \\ w' \\ \theta' \\ q' \end{array} \right] \middle| \left[\begin{array}{c} 0 \\ 0 \\ u \\ w \\ \theta \\ q \end{array} \right], \delta_e \right)$$



Value iteration results

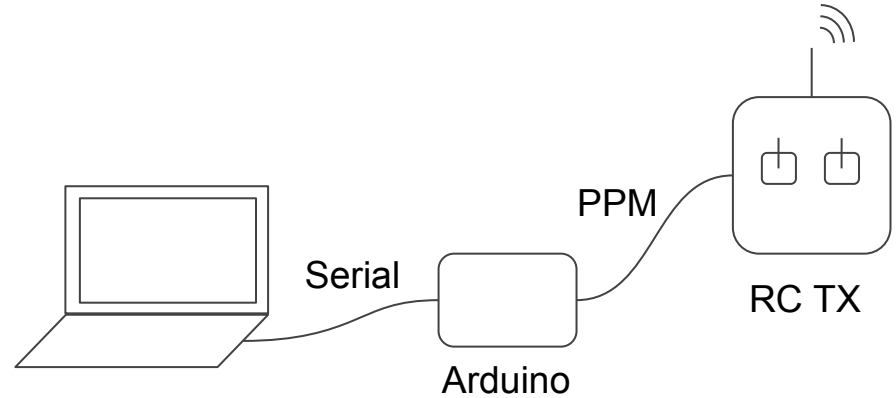


Hardware overview

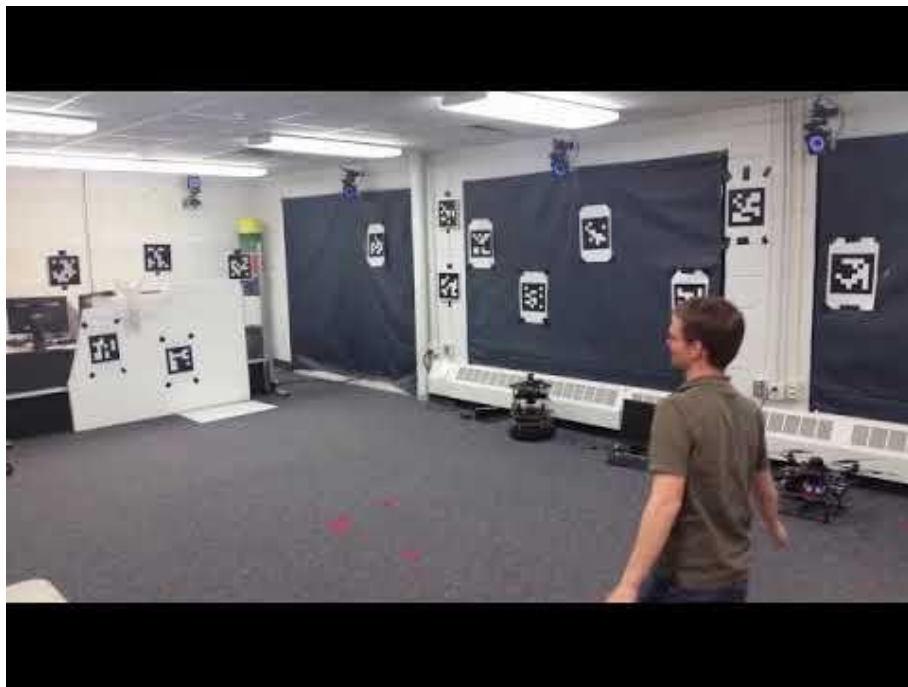


Hardware challenges

- RC buddybox delay
- Servo delay
- Airplane (weight)
- Size of the room



Hardware results





Conclusions

What did we learn?

- Computational tricks are important for non-trivial problems
- Accurate modeling is key

Why was it useful?

- Learning
- Developed buddybox system

What else would we try if we had more time?

- Model the actuator delay
- Policy iteration, other variants
- Continuous-time MDPs
- Continuous state space