

Agile Trajectory Generation for Tensile Perching with Aerial Robots

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Abstract: This paper presents a novel agile trajectory generation method for tensile perching with aerial robots. The method is based on a deep reinforcement learning framework, which can learn the optimal trajectory for tensile perching in a high-dimensional state space. The method is evaluated on a series of simulations and experiments, showing that it can generate agile trajectories for tensile perching with aerial robots in a high-dimensional state space.

Keywords: agile trajectory generation, tensile perching, aerial robots, deep reinforcement learning

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Progress Update

- Demonstrations
 - Recorded all demonstrations
 - Integrated into the training
 - Results are strong (20%-40% improvement time to perch)

From Previously

- Issue around wrapping from different sides.
 - Starting position in state space
 - Previous n states
 - Discussion last time.
 - Take advantage of the symmetry in the environment.
 - More mathematical information on the Reward Function.

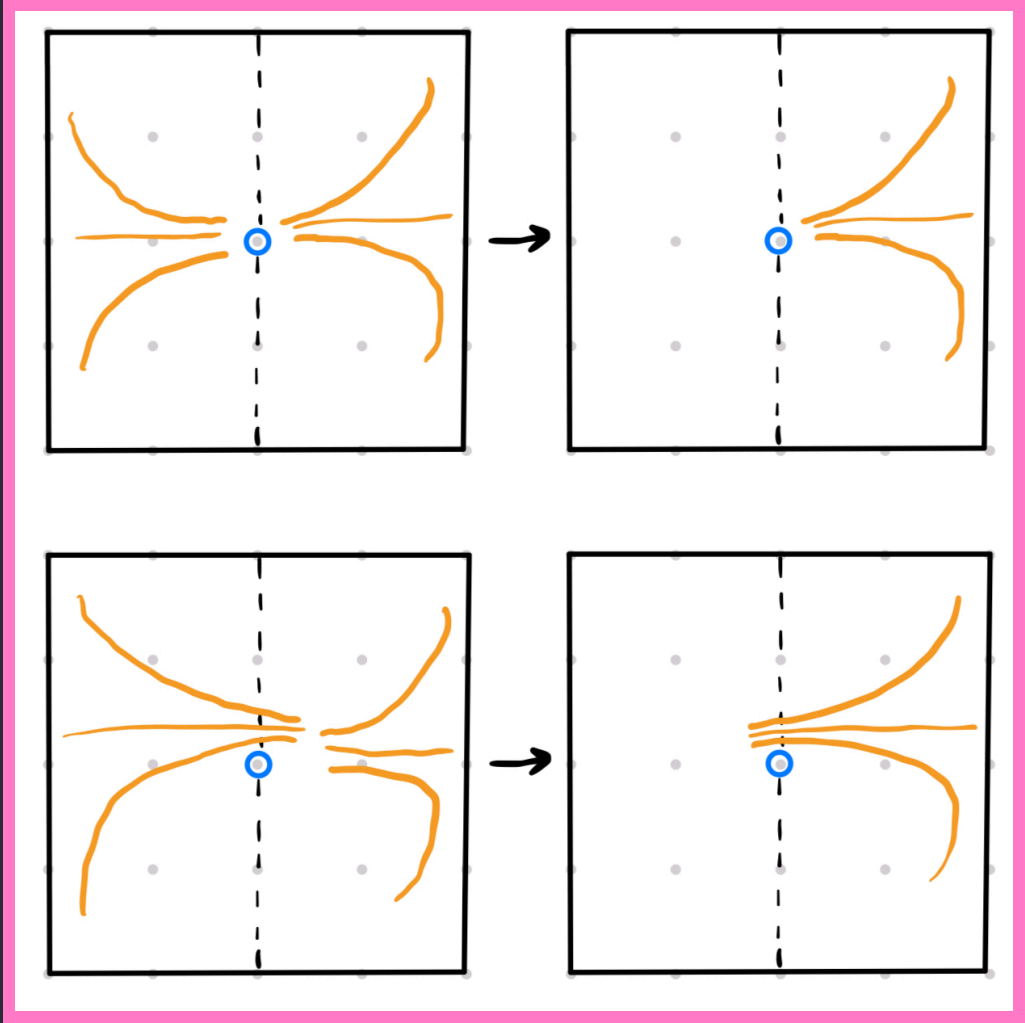
Symmetry

We can assume symmetry across the $x=0$ plane i.e. from either approaching side of the branch.

Symmetrical Wrapper

- Takes in the positions and actions and converts the positions to be +ve with respect to the starting position.
- Making the problem easier to solve by only needing to learn from one side.
- Implemented as a Gym Wrapper so that it is easy to add/remove to compare the learning effects.

Symmetry Diagram



Reward Function

Reward is currently calculated in levels:

- Approaching: $r_1 = -dist(x_{state}; a_{target})$
- Wrapping: $r_2 = num_wraps(x)$
- Hanging: $r_3 = max(1 \text{ if } within(x_{state}; h_{box} \text{ else } 0), -dist(x_{state}; h_{target}))$
- Overall:
 - If $num_wraps > 1$:
 - $r = scale(r_3; -1, 0)$
 - Otherwise:
 - $r = scale(r_2 + r_1; -3, 0)$ otherwise

Further Mathematics

- Distance: $dist(x, target) = norm_{L2}(x, target)$
- Number of Wraps: Algorithm on next slide - based around the position of the two ends of the tether - tracking through different timesteps to calculate rotation.
- Scale: $scale(x; min_x, max_x, a, b) = ((x - min_x) / (max_x - min_x) \times (b - a))$

Num Wraps

```
def compute_total_rotation(self):
    pos, _ = p.getBasePositionAndOrientation(self.segments[-1])
    last_x = pos[0]
    last_y = pos[2]
    delta_x = last_x - 0
    delta_y = 2.7 - last_y

    # Compute the angle using arctan2, which considers quadrant location
    angle_radians = np.arctan2(delta_x, delta_y) # swapped x and y to align with the vertical
    angle_degrees = np.degrees(angle_radians)

    if self.prev_angle is not None:
        # Calculate angle change considering the wrap around at 180/-180
        angle_change = angle_degrees - self.prev_angle
        if angle_change > 180:
            angle_change -= 360
        elif angle_change < -180:
            angle_change += 360

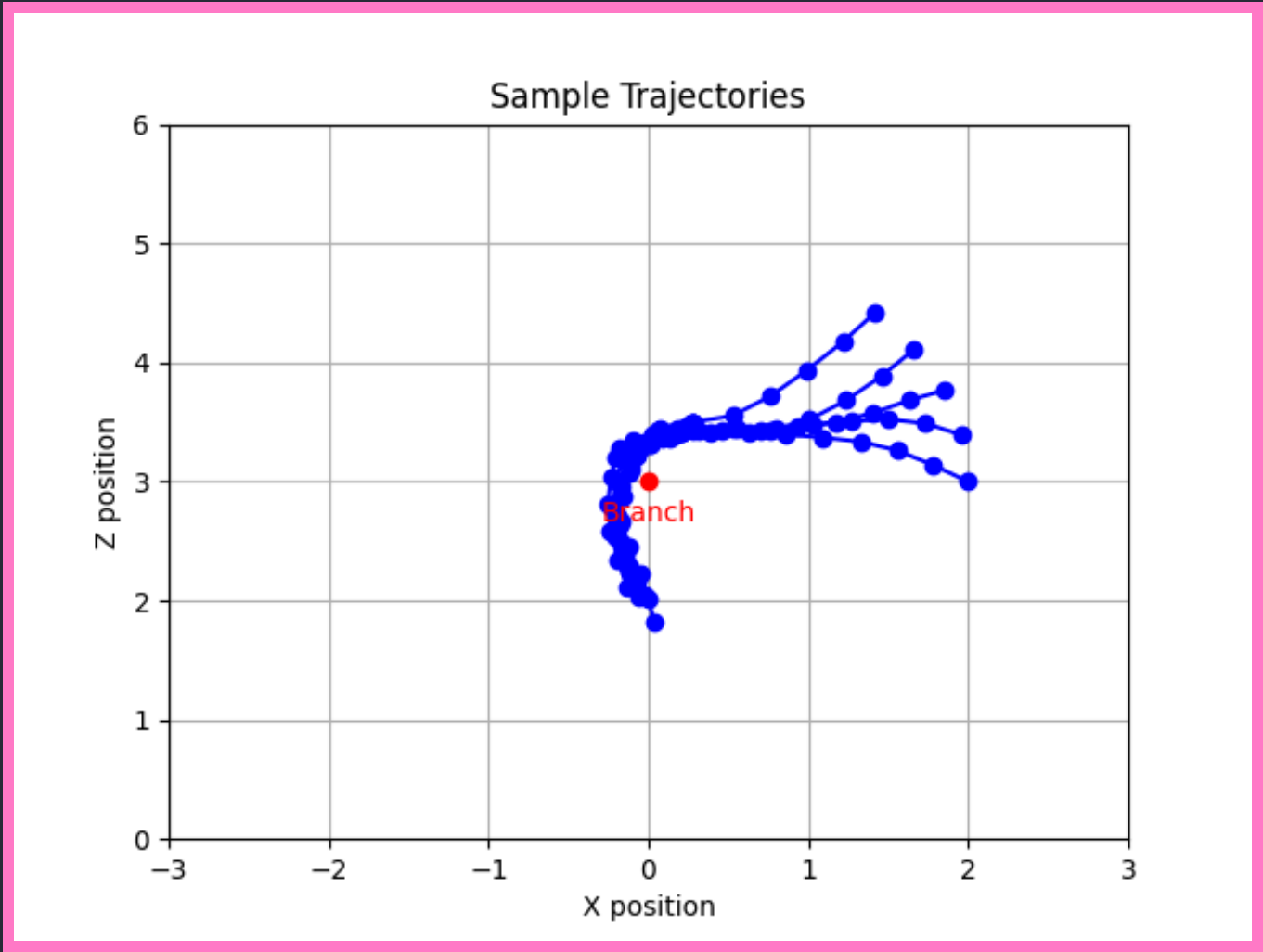
        # Update cumulative angle change
        self.cumulative_angle_change += angle_change

        # Update wraps as a float
        self.wraps = self.cumulative_angle_change / 360.0

    # Update the previous angle for the next call
    self.prev_angle = angle_degrees

    return abs(self.wraps)
```


Trajectory



Gazebo Integration

- Built a controller than can follow the waypoints

Todo:

- Integrate the Spline portion.
- Fix a bug with the plotting.

Show Demo

Report Plan

- Main Contributions
 - PyBullet Simulation to model simulation dynamics.
 - Learning from Demonstrations Integrations.

Report Plan

- Intro - Background
- Methodology
 - Environmental Modelling
 - Initial Environment
 - Pybullet Environment
 - Tether Modelling
 - Wrappers and Effects
 - Dimension
 - Symmetry
 - Memory
 - Timestep
 - Training
 - Reward Function Design
 - Algorithms
 - Demonstrations - Comparison of different training techniques.

- Results
 - Trajectory Experiments
 - Speed
- Conclusion

Report Content

- Setup seperate git repository for report.
- Added in an outline.
- Gathered the ideas and have created tickets for each section with a better description of what I want to show and how I'm going to show it.
- Linked to Overleaf for external viewing.

Overleaf: <https://tinyurl.com/TommyMengThesis>
(Will send in email)

TODO

- Gazebo
 - Integrate with Spline curves to match waypoint navigation in pybullet.
 - Fix bug in plotting diagram code for "true trajectory"
- Training
 - Hyper-parameter tuning
 - Produce final set of trajectories
- Experiment - To discuss
- Report

Overall Plan

- Report Deadline 17th June (2.5 weeks)
 - Week 27th May - 3rd June ----- Gazebo, Hyper-parameters, Final Trajectories
 - Week 3rd - 10th June ----- Evaluation, Experiments, Report
 - Week 10th - 17th June ----- Report