Project Pre-proposal

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Motivation

Humans manage to throw and catch objects with relative ease; it's often the fastest and most energy-efficient way to move an object from point A to point B. However, catching flying and free-falling objects is a pretty big challenge; the objects may only be in the air for a few hundred milliseconds, leaving very little time to continuously track their trajectories and plan/re-plan catching motions. This challenge in evident in the real world, where almost all robotic manipulators are in constant contact with objects they're manipulating. Therefore, the motivation for this project is to tackle the challenge of dynamic object handling for robotic manipulators using mainly just the techniques we have learned in class.

This project is also in part inspired by Shane Wighton's Moving Basketball Hoop on YouTube [5] and Mark Rober's Viral Moving Dartboard [3].

Project

Baseline Deliverable

We propose a project of a robot catching objects in flight based on the feedback from RGBD cameras observing the scene. Our initial goal will be to catch spherical objects thrown at the robot with random trajectories from any direction. To achieve this, we devised the below method with 2 parts:

- **Trajectory prediction** - in its simplest form, this part will consist of a 2 stage pipeline. First our algorithm will use the Iterative Closest Point method learned in class to find the object's position at a certain keyframe from noisy point clouds. Then, the algorithm will perform some sort of heuristic (most likely the weighted average RANSAC learned in class and extended in [4]) to extract the ballistic trajectory of the moving object.

- **Catching** - in this section we find the best way to catch the object given the predicted trajectory. To do this, we will use the optimization-based Inverse Kinematics method learned in class. This will allow the robot to plan a trajectory and move from the default position to match the object's spatial pose and velocity, and to therefore grab the object with minimal force and deceleration.

Extensions

It is likely that the base deliverable will be achieved by us before the deadline for the project. For this reason, we define extensions to the project that can make the setup match the real world closer:

- Improving the catching optimization algorithm [6] (see Related Works section for details) by doing a lower-dimensional optimization or performing a hybrid sampling and optimization technique. We may also explore additional paramaterizations of the trajectory beyond B-splines, which is the primary method we learned in class.

- Modelling camera noise [1] and probabilistic trajectory prediction [4]

- Placing/dropping objects in a bin after they are caught.

- Catching objects that have a more complex geometry (e.g. YCB objects) by searching for optimal antipodal grasps.

- Catching objects that are rotating (potentially very quickly) mid-air.

Related Work

There have been previous works on dynamical object handling. The method in [2] utilizes a 7 DoF arm and Allegro gripper also to catch objects, and uses learning-based methods and probabilistic models to simultaneously predict object trajectory and control the robot's position, which presents a fairly different approach than our primarily optimization-focused method. In [7], a reinforcement learning with residual physics is used to achieve dynamic tossing movements, which presents yet another different approach.

We also investigated a number of related works that present methods that are similar or build upon the concepts we learned in class. Previous work discusses techniques for improving both speed and performance of trajectory-planning [6]. Firstly, they sample multiple initial predictions for the optimizer to better performance on local minimums. They also use a repeated method of lower-dimensional optimization and interpolation into higher dimensions to decrease the time taken by the optimization while improving the size of the search space (according to the paper). Both are possible extensions for our project, although we hypothesize that the random sampling may not help much because the constraints on the trajectory optimization are relatively simple to begin with.

There has also been previous work related to modelling noise in certain kinds of depth cameras. This is necessary for us to model, since the default depth camera output in Drake is perfect and does not allow us to simulate uncertainty. In [1], the authors consider modelling the noise in structured light depth cameras. They identify that the most notable source of noise in such cameras is quantization noise, the ways to model that noise, as well as methods of dealing with this issue by denoising.

Some work also considers dealing with uncertain object positions and constructing trajectories around that, which is also necessary for the probabilistic trajectory prediction extension. In [4] the authors consider a modification to the classical RANSAC algorithm that is able to deal with pose uncertainties. However, the method only considers the first-order Taylor Series approximation of object's movement, so some work will be required to extrapolate that into ballistic trajectories.

Timeline

Deadline	**Minimum deliverables**
First check-in (15th Nov)	Environment ready and running with cameras generating point clouds
Second check-in (29th Nov)	The base method implemented and successfully catches simple objects/throws.
Final deliverable (12th Dec)	One or two of the extensions implemented.

References

[1] Avishek Chatterjee and Venu Madhav Govindu. Noise in Structured-Light Stereo Depth Cameras: Modeling and its Applications, May 2015. arXiv:1505.01936 [cs].

[2] Seungsu Kim, Ashwini Shukla, and Aude Billard. Catching Objects in Flight. *IEEE Transactions on Robotics*, 30(5):1049–1065, October 2014. Conference Name: IEEE Transactions on Robotics.

[3] Mark Rober. Automatic Bullseye, MOVING Dartboard, March 2017.

[4] Tal Nir and Orit Eden. Video motion detection algorithm using probabilistic time integrated RANSAC. In *2011 18th IEEE International Conference on Image Processing*, pages 2349–2352, September 2011. ISSN: 2381-8549.

[5] Stuff Made Here. Moving hoop won't let you miss, 2020.

[6] Alessandro Tringali and Silvio Cocuzza. Globally Optimal Inverse Kinematics Method for a Redundant Robot Manipulator with Linear and Nonlinear Constraints. *Robotics*, 9(3):61, September 2020. Number: 3 Publisher: Multidisciplinary Digital Publishing Institute.

[7] Andy Zeng, Shuran Song, Johnny Lee, Alberto Rodriguez, and Thomas Funkhouser. TossingBot: Learning to Throw Arbitrary Objects With Residual Physics. *IEEE Transactions on Robotics*, 36(4):1307–1319, August 2020. Conference Name: IEEE Transactions on Robotics.