Interception of moving objects with a robotic arm in a simulated environment

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Abstract— **The problem of catching a moving object can be divided into two sub problems. First, the object must be perceived and its path must be estimated in order for movements to be calculated that would result in successfully catching the object in the future. The second sub-problem is to find a catching configuration. This paper focuses primarily on the second problem of finding an acceptable configuration. Simple models that simulate sensor inaccuracy and randomness are used to closely simulate real environments, and regression models are used to estimate the object's path in these simulated real environments. Since multiple end configurations are acceptable as the goal, we introduce a new concept called a multi-goal RRT, a modified version of Rapidly-exploring Random Trees (RRTs), which grows towards multiple goals simultaneously. This approach was implemented in an attempt to have the RRT grow toward several predicted path nodes. The multi-goal RRT was compared against a regular RRT. The results show promise for the application of Multi-goal in a real-world setting.**

I. INTRODUCTION

A. Motivation

Robots will need to successfully intercept and catch moving objects as their abilities become more acquainted for daily human use. The applications of such ability range from military to assistive operations in the home. Robotic agents able to track and intercept moving objects constitute a valuable military asset, as they could provide protection and tactical superiority to ground troops through the stoppage of missiles, grenades and harmful projectiles. Flying-drones would enhance their current capabilities, as they would be able to automatically track objects of interest and intercept enemy projectiles aimed at larger vehicles with human personnel. Tracking and interception abilities also have an application in the Biology and Genetics fields as researchers could benefit from automated counting and transporting of live cells, essential operations in many cellular engineering applications such as cell sorting and fusion [3]. An ability to catch moving objects would also be beneficial in the field of Socially Assistive Robotics (SAR), as the main objective is to stimulate the rehabilitation and management of lifelong cognitive, social and physical disorders [9]. Robotic agents could motivate patients to lift objects as part of their training and rehabilitation, serving as playmate for ball throwing, object lifting and tool handling exercises. In addition, robots could monitor patient's progress in order to catch drop objects and avoid injuries.

We were specifically motivated to pursue this project by two ideas. One is a video that illustrates a robot capable of catching a piece of trash thrown using a vision system and limited path planning. The little trash robot seemed pretty interesting and useful, and initially the thought of expanding on the idea was toyed with. The other source of motivation came from a previous piece of work performed under Professor Mike Stilman at Georgia Institute of Technology. Tobias Kunz had worked on an algorithm that blocked known sword paths in a simulated environment [7]. The group had not explored the idea of predicting a sword swing given the current path of the sword.

B. Problem

Given the explained motivations, we defined the problem to be tackled as the interception of a moving object using a 7 DOF robotic arm in a noisy simulated environment with limited information on the objects path. The object in our case would be a moving sphere that is allowed to go through obstacles as it follows its calculated projectile path. The arm is not allowed to hit any obstacles as it tries to catch as many sequential spheres as possible, with an increasing amount of sensor and environment simulated noise.

C. Solution

The solution described in this paper utilizes an algorithm which tracks the object, predicts its future path, and then moves a virtual robot arm to intercept it. This is done by using two different prediction algorithms, a linear predictor, used for straight motions such as punching, and a quadratic predictor, used for projectile objects such as thrown trash or balls. After computing a predicted path, a Multi-goal RRT is used to move the robot arm to intercept the object while still avoiding obstacles in its environment.

II. RELATED WORK

The problem of tracking and intercepting moving objects with robotic agents has been a well-researched topic through the combination of Computer Vision, Planning and Machine Learning techniques. As there have been many previous efforts to intercept moving objects, we will list key results that provide insights into the challenges of such endeavor. Peter Allen et al. at the University of Columbia utilized optic-flow techniques to track a moving object in a circular track with a PUMA robotic arm. Most importantly, they separated the perceived coordinates into a XY plane and a Z-axis, modeled motion through derivations of velocity and curvature, and ran a developed filtering method to handle noise sources and estimate arc and bending characteristics [1]. Their results showcased a robust enough method able to repeatedly pick up an object moving in a planar surface and

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grasp it. More recently, Jens Kober et al. at Disney Research developed tracking and prediction methods to allow a robot to play catch and juggle a ball [4]. In their approach, they utilized Hough-transforms to track the moving balls through an external camera system. For prediction, they modeled the balls motion as point masses (i.e. quadratic predictors) and implemented Kalman filters for handling noise and environment uncertainties. The results obtained showed a potential for having safe human-interactive robotic characters throughout theme parks, but much work was still needed in order to increase the robot's reachable area and degrees of freedom, both constrained during experimentation in order to facilitate the approach. To tackle catching objects with robots in real-time, Jan Peters et al. proposed in [7] the formulation of a non-linear constrained-optimization problem where the desired trajectories are encoded through parametric representation. The result of such optimization is then used through Nearest Neighbor, Support Vector Machines and Gaussian regression to allow a real-time execution. Their results showcases the trade-offs between computational time and accuracy for real-time operations, as accuracy in prediction must be satisfied in order for the robot to be able to catch the moving object. In this project, we wish to explore the initial feasibility of using RRTs variants for intercepting moving objects in a simulated environment. Although RRTs have been extensively used in the planning domains, no relevant previous work was found where such technique was specifically used for object interception.

III. METHODS

We'll cover the methods in the order they are used in a complete simulation. First, we must generate a projectile path, then distortion is applied. In order to know where it's possible to catch the object some path prediction is used. Then to actually get a series of possible robot stances, inverse kinematics is applied to get some corresponding joint configuration for each projectile position. Finally, and most highlighted part in this paper, we search for the easiest to reach joint space configuration. It should be noted that this whole process is done iteratively, as at fixed time steps we replan taking into account the most recent observation of the projectile.

A. Path Projection

We create a path by sampling positions from the formula for projectile motion:

$$\vec{x}(t) = \vec{x}_0 + \vec{v}t + \frac{\vec{a}t^2}{2}$$

Where the arrow notation denotes a variable being a vector in the workspace. This simple equation covers most of the motions in our application except for wind resistance. Note that by setting the acceleration to $\vec{0}$ the projectile will be a straight line resembling a straight punch. By setting $\vec{a} = -\vec{g}$ where $\vec{g}$ is a gravity constant we get a standard "shoot from canon" projectile motion. Wind is simulated by adding a random constant to the acceleration.

1) Deciding $\vec{x}$, $\vec{v}$ and $\vec{a}$: We just saw how changing the acceleration we'll get simple models of different behaviors that might be desired for our intended application. However, in all cases we must make sure that it will be possible at all to catch the thrown object, in other words, the trajectory must intersect the set of reachable points of the arm. To ensure that we introduce two new points, a *random start position*, that simply is $\vec{x}_0$ and a *random reachable position* which is a random point reachable by the robot arm. With these approach in mind one can solve for the velocity if we fix the acceleration. To simplify further and decrease the solution space we set that the velocity to have an angle of 45 degrees from the floor plane. For the wind to actually have a negative impact, we let the calculations of the velocity be oblivious of it.

2) Distortion: Since in later steps of the iteration the robot is going to predict the remaining path, we must add distortion to it to make it impossible to retrieve the whole original exact path again. It's hard to motivate any model besides simple randomness here.

$$\vec{x}_{observed}(t) = \vec{x}(t) + noise$$

Where for each discrete time step in our simulation the *noise* is a vector where each coordinate is a uniform distribution in $[-\mu, \mu]$

B. Path Prediction

Given some sample points, we work backwards from the equations in the model for path projection. We have two prediction models, one assumes straight motion and the other projectile motion. The equation

$$\vec{x}_{observed}(t) = \vec{x}_0 + \vec{v}t + \frac{\vec{a}t^2}{2}$$

will cover both cases, only that you set $a = 0$ in the linear version. However, only two and three data points are required to solve this system for the linear and quadratic version respectively, to fix that we simply only look at the most recent data points we require.

Note that this is of course not exact as it does not compensate for the unknown noise, to compensate for the noise, one can treat a chunk of points as one point by taking their average. Note that with this strategy we still need more points for the quadratic version. If the chunk sizes are to small, we won't defeat noise and if it's too small we won't be able to estimate the trajectory, as we must wait until we have enough points to create the chunks. Therefor a dynamic chunk size was chosen that grows with number of data points. A cap was set on the chunk size to avoid looking at too old and outdated data.

We found both the working backwards from the equations prediction and the idea of chunking the data to be the simplest to implement and choose that over more sophisticated regression.

C. Inverse kinematics

Knowing the trajectory, one can use inverse kinematics to find a corresponding joint space configuration. We do use the pseudo inverse Jacobian method. That is to simply iterate

$$\Delta q = \mathbf{J}^{+}\Delta x$$

until convergence where $\mathbf{J}^{+} = \mathbf{J}^{T}(\mathbf{J}\mathbf{J}^{T})^{-1}$.

D. Planning

Either one of the two algorithms are used for planning, the regular RRT [8] and the multi-goal RRT that is introduced in this paper. Their final selection depends on the parameters set before a simulation is started.

The multi goal RRT is working very much like the traditional one with the exception that there are multiple goals and reaching any one of them is considered a success. One might think of two different strategies for the multi goal RRT. The first being that you return the first path that leads to any of the goals and the second strategy is to make sure you've got a path for each goal and then return the shortest. The first one is always faster because it don't need to grow the tree until each goal has been reached. Since it also was simpler to implement we went with a multi goal RRT using the first strategy.

What differs between a regular RRT and any of the two multi goal RRTs kinds is only the termination condition. The single RRT continues to grow until the goal has been reached, the first strategy of the multi goal keeps growing until *any* goal has been reached while the other strategy keeps growing the tree until *all* goals have been reached.

As for the concepts of greedy, connect and bidirectional, only greedy and the connect strategy is applicable to the multi goal RRT. The original greedy strategy takes the goal and grows towards it[6], [2]. In our case we take any of the goals randomly and grow towards it. As for connect one would imagine growing towards a random configuration and then keep growing to the same configuration until one collides, just like the original connect algorithm does[5]. We will, however, only use the greedy goal biasing in both our regular RRT implementation and multi-goal RRT. The reason for this was to make the behavior easier to reason about than it would be if multiple features could cause unexpected results.

E. Replanning, Discretization and Arm Speed

Before one iteration is done and we start replanning with the most recently observed data we move the arm. For the simulation to be realistic, the maximum distance the arm can move must be limited for each time step. The question is how distance is measured, or rather in which norm. Most realistically for our application might have been the infinity norm, which means that all joints are allowed to rotate a fixed amount of degrees independent of each other. Regardless of that we used regular euclidean distance, the two norm. The reason is that we set the step size parameter to the RRT and interpret the second position in its returned path as the next position for the arm.

With the joints configured to their new angles, we increase the simulation time by the fixed Δt and keep iterating and replan as we allow our path predictor is fed with more points in the observed trajectory.

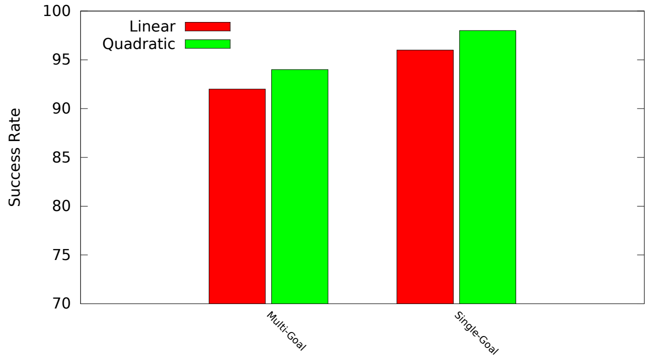
IV. EXPERIMENTS

The experimentation and accompanied development were targeted towards (1) determining the robustness of the approaches presented to noise sources and (2) selecting the best combination of predictors and RRT-variants for use in a future non-simulated setting. The overall approach presented in the previous sections was tested in the DART/GRIP environment through a developed interface that allowed for the specification of different amounts of noise, number of simulations, predictor type, among other parameters. In order to visualize the implementation's behavior, additional markers were added as shown in Figure 4c to show the arm's perceived location of the ball, the predicted location of the ball and the current-best prediction to be used for final interception. The results were analyzed according to the following criteria: (i) success rate given an amount of noise, (ii) success rate vs. increasing amounts of noise for different combinations of RRT-variants and predictors, (iii) completion time given an amount of noise. Success rate was defined as the amount of times the arm was able to intercept the moving sphere divided by the total number of simulations (i.e. a percentage). The workspace distance d between the arm's end-effector and the moving sphere was repeatedly calculated in order to determine whether an interception had occurred. If d was less than a given threshold t, then the arm successfully intercepted the moving sphere. In this case, t was set to the radius of the sphere (i.e. 0.12). The graphs shown below summarize the results of the experiments undertaken. Their connotations and insights will be analyzed in the following section.

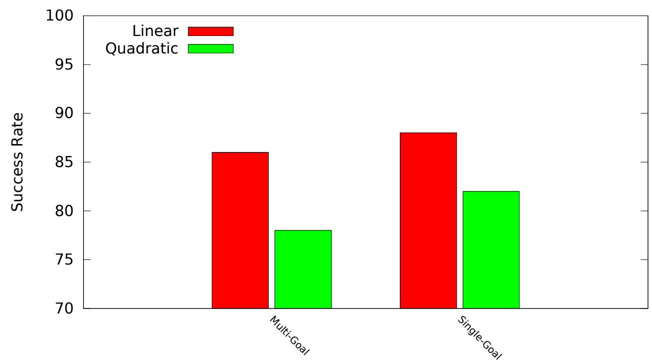
V. ANALYSIS

Figure 1a shows the success rates for combinations of Multi-goal and Single-goal with Linear and Quadratic predictors after 100 simulations with a noise of 0.05. In both cases, the Single-goal approach achieves a higher success rate than the Multi-goal approach. The difference in such success, an average of 3 percent units, is not enough to conclude the dominance of one method over the other for this given noise amount. In addition, the quadratic predictor seems to yield higher success rates when used by both approaches with this noise amount, indicating the better representation of the projectile path by our predicting equations.

Figure 1b , in contrast, showcases a much more interesting scenario. With a noise amount of 0.09, the Multi-goal and Single-goal approaches achieve similar success rates (about 87 percent) when employing the Linear predictor. When the approaches utilize the Quadratic predictors their success rates drop by a combined average of 8 percent units. In this case, the Multi-goal approach achieves a noticeably lower success



(a) $\mu = 0.05$



(b) $\mu = 0.09$

Fig. 1: Success rates for combinations of Multi-Goal RRT, Single-RRT, Linear and Quadratic predictors after 100 simulations having varying noise μ

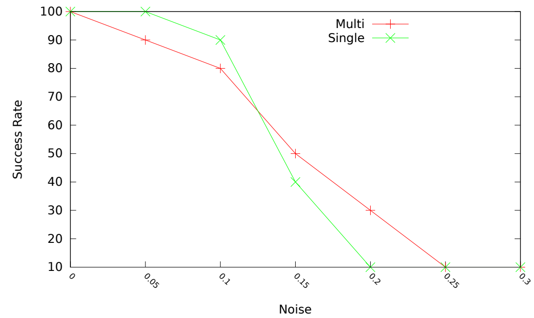


Fig. 2: Average RRT success rates versus increasing noise with Linear Predictor; 10 simulations for each increase in 0.05 the noise μ

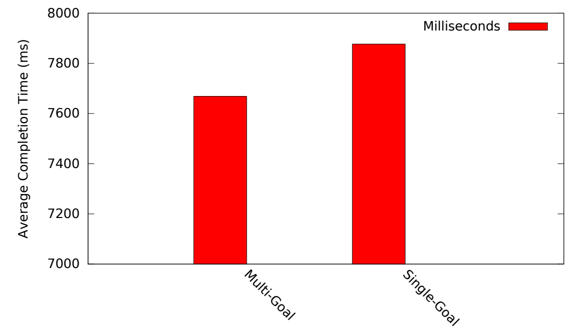


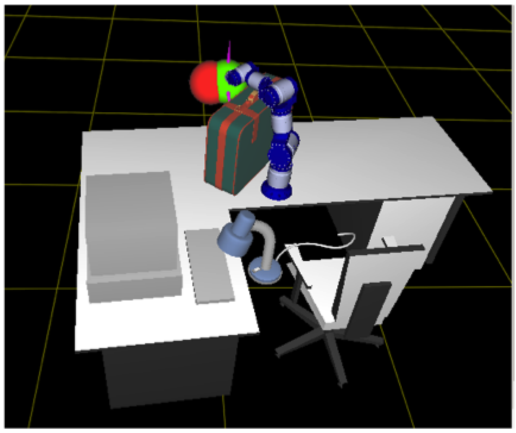
Fig. 3: Average times for Single-goal and Multi-goal RRTs after 100 simulations with both Linear and Quadratic predictors where $\mu = 0.05$

rate. With a significant increase in sensor noise, the robotic arm's perceived sphere path does not longer follow projectile motion characteristics as the sphere bounces around. In this case, the Quadratic predictor in a way over fits the model as it uses 3 averaging points to predict a curved motion. The Linear predictor only predicts line trajectories that with a clutter of perceived points yield higher accuracy rates.

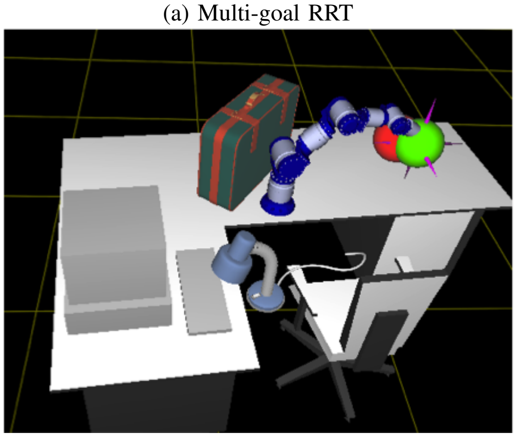
Figure 2 depict the performance of both the Single-goal and Multi-goal RRT approaches as the noise amount increases. A Linear predictor was utilized in both cases as previous analysis demonstrated its robustness to sensor noise. For each noise case, the average success rate of 10 simulations was computed. Both approaches rates steadily drop as the amount of noise increases, with the Single-goal RRT staying above 90% for noise sources between 0 and 0.1 while the Multi-goal RRT only for value between 0 and 0.05. The similar behavior of both approaches regarding an increase in noise showcases the need to implement better prediction techniques, as the current ones are only naive approaches to tackle such noise and uncertainty scenarios. A more thorough analysis of these approaches response in noisy situations would be achieved through known regression and estimation techniques. Time constraints forced these topics to be considered for future work.

At last, Figure 3 presents the average execution times during 100 simulations of Single-goal and Multi-goal RRTs with Linear predictors. Multi-goal RRTs achieve faster execution times (i.e. 200ms difference) than Single-goal RRTs as the tree growth is biased by all reachable points of the sphere trajectories. When any goal is reached, reaching the rest is not computationally expensive as these points are expected to be mostly close in space and time. Single-goal RRTs in contrast, constantly expands the tree towards the closest point in terms of joint space distance, thus taking longer to get there.

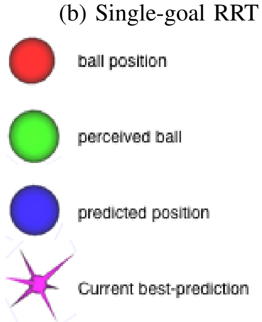
Additionally, projectile paths passing through reachable areas surrounded with obstacles were examined to determine further differences between the RRT kinds. Figure 4 shows two resulting configurations for Multi-goal and Single-goal RRTs given the same projectile path. Above 80% of the time, the Multi-goal RRT choose to catch the object before it collided with the object, while Single-goal RRT usually waited for the object in the later parts of the motion. We believe such behavior is due to the fact that the Single-goal RRT picks the closest point in terms of joint space distance and in this case, such point is located in the space after the sphere passes through the obstacle. In a sense, Single-goal RRT is a lazy approach, as it will try to intercept the moving



(a) Multi-goal RRT



(b) Single-goal RRT



(c) Legend

Fig. 4: Comparison of intercepting locations for the two RRTs.

sphere with the minimum joint effort possible. On the other hand, Multi-goal RRT considers all points in the reachable object trajectory, and when any of them is reached, it returns a path to follow. This implementation generally tries to catch objects at earlier times as this allows for some leniency in terms of replanning if the arm is not able to catch the moving sphere.

VI. DISCUSSION

It would be interesting to test the algorithms in an environment where there are more objects that the arm can't touch. Such experiments might lift the potential from multi goal RRTs, if a multi goal RRT should prove useful against the single goal RRT aimed at the closest goal, it must expand a towards a more distant goal which in fact is closer with respect to there being objects in the way for reaching the close goal. While there might be many factors for the results for figure 3, one might guess that the approximately equal run times was due to that they reached their goal in the same amount of steps and that is because the closest goal without respect to object was the same goal with respect to objects. On the other hand then one might expect their performance over all be quite similar which it appears not to be from figure 1 and 2, maybe it's decrease in performance was simply due to it usually founds the same closest object but occasionally in between the iterations detours to another goal making it somewhat more clumsy.

Another idea stemming from the discussion above is to not actually do replanning, since the nature of randomness in the RRT makes it non optimal and it would be better to committing to trying to reach one particular stance rather than reevaluating the situation all the time and go for occasional detours. A great future work would be to actually analyze if the multi goal RRT does take detours or not.

We mentioned an alternative strategy for the Multi-goal RRT. The strategy basically was to not stop once it reaches it's first goal, instead expanding until it hits all goals and then pick the one with the shortest path. The idea is that this should not be computationally expensive at all because

As an extra benefit to both RRT planners, path shortening could be applied. Here one can also try to use some sort of lazy path shortening, utilizing the fact that since replanning occurs so often you only need to know the beginning of a plan.

It must also be said that the most obvious step for actually having a good moving object interceptor would be to improve upon the path prediction, using standard tools like linear/quadratic regression or Kalman filters.

REFERENCES

[1] Peter K. Allen, Aleksandar Timcenko, Billibon Yoshimi, and Paul Michelman. Automated tracking and grasping of a moving object with a robotic hand-eye system. *IEEE Transactions on Robotics and Automation*, 9:152–165, 1991.

[2] Dave Ferguson, Nidhi Kalra, and Anthony Stentz. Replanning with rrts. In *ICRA*, pages 1243–1248, 2006.

[3] Tao Ju, Shuang Liu, Jie Yang, and Dong Sun. Apply rrt-based path planning to robotic manipulation of biological cells with optical tweezer. In *Mechatronics and Automation (ICMA), 2011 International Conference on*, pages 221 –226, aug. 2011.

[4] J. Kober, M. Glisson, and M. Mistry. Playing catch and juggling with a humanoid robot.

[5] J.J. Kuffner Jr and S.M. LaValle. Rrt-connect: An efficient approach to single-query path planning. In *Robotics and Automation, 2000. Proceedings. ICRA'00. IEEE International Conference on*, volume 2, pages 995–1001. IEEE, 2000.

[6] B. Sujith Kumar, Pratik Agarwal, P. Abhimanyu, Prem Bhargav, and Dr. K. Madhava Krishna5. Robocup ssl team description, irl rc. 2010.

[7] R. Lampariello, D. Nguyen-Tuong, C. Castellini, G. Hirzinger, and J. Peters. Trajectory planning for optimal robot catching in real-time. In *Robotics and Automation (ICRA), 2011 IEEE International Conference on*, pages 3719–3726. IEEE, 2011.

[8] S.M. LaValle and J.J. Kuffner. Randomized kinodynamic planning. *The International Journal of Robotics Research*, 20(5):378–400, 2001.

[9] A.M. Okamura, M.J. Mataric and, and H.I. Christensen. Medical and health-care robotics. *Robotics Automation Magazine, IEEE*, 17(3):26 –37, sept. 2010.