Kinodynamic-RRT for Robotic Free-Flyers: Generating Feasible Trajectories for On-orbit Mobile Manipulation

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Abstract— **Increasingly complex robotic systems demand motion planning that can produce dynamically feasible trajectories while enforcing other difficult constraints. One particularly challenging example is microgravity robotic free-flyers, i.e., satellites with manipulator arms of non-negligible mass. These systems (when free-floating) are nonholonomic and often have high-dimensional state spaces. As such, trajectory optimization is a challenge: direct methods might fail to produce even a feasible solution. To account for the free-flyer dynamics we use a sampling-based method, kinodynamic-RRT, and explicitly forward propagate the satellite dynamics under actuator constraints. This approach is meant as a way to produce feasible reference trajectories in the face of "difficult" dynamics to hand off to solvers that desire a feasible initialization trajectory, and is a stepping-stone toward future development of efficient optimizing sampling-based planners that might tackle this problem; solving the requisite two-point boundary value problem for optimizing sampling-based planning remains an open research challenge, and is a desired target of future investigation.**

I. Introduction and Problem Formulation

The standard continuous-time trajectory optimization problem is summarized by Paden. [1] The dynamics must be satisfied as a constraint, $\dot{\mathbf{x}} = f(\mathbf{x}, \mathbf{u})$. Additional hard constraints such as collision avoidance, $\mathbf{x}(t) \in \mathcal{X}_{free}$, and actuator saturation, $\mathbf{u}(t) \in \mathcal{U}$, are often included. Free-flying robotic systems have highly nonlinear, high-dimensional dynamics. Trajectory planning for high-dimensional systems with highly nonlinear dynamics often suffers from an inability to obtain even feasible solutions. Such problems can be converted into nonlinear programs (NLPs) via direct methods (e.g. collocation, transcription, etc.), but these methods often benefit from a good initial guess for convergence. [2] Iterative methods including, for example, SQP and SCP, also require trajectory initializations. [3] As a first step in efficiently generating feasible trajectories for other solvers (and in looking toward optimizing sampling-based methods) we guarantee constraint satisfaction via explicit evaluation of the satellite dynamics through kino-RRT.

A. Free-flyers: Astrobee and SPHERES

Some robotic free-flyer testbeds exist today on-orbit. The SPHERES satellites onboard the International Space Station are the most prominent example, though they only exhibit rigid body dynamics. The soon-to-be operational Astrobee system [4] will include a 2-DOF robotic manipulator and will be the first microgravity testbed of its kind for free-flying manipulator dynamics. These systems are expected to become increasingly prevalent as groups look toward on-orbit servicing, assembly, and assistive tasks–effective motion planning will be crucial in controlling these difficult systems. [5]

B. Sampling-Based Planning

Sampling-based planners develop tree (e.g. RRT) or graph structures (e.g. PRM) in the configuration or state space to represent discretized plans tied together at the nodes. Optimizing variants exist [6], but for kinodynamic planning the solution of a two-point boundary value problem is required for implementation. For non-optimizing variants, some common functions are required–see the Approach section for further details on implementation. One of the key advantages of sampling-based kinodynamic planning is that these methods explicitly enforce constraints during evaluation of new nodes.

C. Free-flying Manipulator Dynamics

The state vector for a free-flying two-link manipulator, given in equation 1, consists of rigid body position $\mathbf{P_{base}}$, orientation $\mathbf{Q_{base}}$, linear velocity $\mathbf{V_{base}}$, and angular velocity $\omega_{\mathbf{base}}$, and arm angles $\theta_{\mathbf{arm}}$ and rates $\dot{\theta}_{\mathbf{arm}}$. Motion of the manipulator arm results in an overall attitude change of the system, which exhibits path-dependency.

$$\begin{aligned} \mathbf{P_{base}} &= \begin{bmatrix} p_x & p_y & p_z \end{bmatrix}^\top \\ \mathbf{Q_{base}} &= \begin{bmatrix} q_\theta & q_x & q_y & q_z \end{bmatrix}^\top \\ \mathbf{V_{base}} &= \begin{bmatrix} v_x & v_y & v_z \end{bmatrix}^\top \\ \omega_{\mathbf{base}} &= \begin{bmatrix} \omega_x & \omega_y & \omega_z \end{bmatrix}^\top \\ \theta_{\mathbf{arm}} &= \begin{bmatrix} \theta_1 & \theta_2 \end{bmatrix}^\top \\ \dot{\theta}_{\mathbf{arm}} &= \begin{bmatrix} \dot{\theta}_1 & \dot{\theta}_2 \end{bmatrix}^\top \end{aligned} \quad \mathbf{x} = \begin{bmatrix} \mathbf{P_{base}} \\ \mathbf{Q_{base}} \\ \mathbf{V_{base}} \\ \omega_{\mathbf{base}} \\ \theta_{\mathbf{arm}} \\ \dot{\theta}_{\mathbf{arm}} \end{bmatrix} \tag{1}$$

For brevity, the full dynamics, $\dot{\mathbf{x}} = f(\mathbf{x}, \mathbf{u})$, can be seen in some common references mainly due to Dubowsky and Longman in the 1990s, e.g. [7].

II. Approach

Kinodynamic-RRT [8] is applied to the problem, resulting in explicit evaluation of the forward dynamics and hard enforcement of constraints. Leveraging these advantages,

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feasible solutions are guaranteed. However, there is no sense of optimality in this formulation–this is the subject of on-going and future work. In addition, the current sampling strategy is wasteful: many $\mathbf{x_{new}}$ fail to satisfy constraints. Nonetheless, this leads to a relatively fast exploration of the state space. The method is detailed in Figure 1.

Some of these routines are common among sampling-based planners, but must be tailored to use for the desired dynamics. Karaman provides a good summary in [6]. Notably, `SteerFF` guides the expansion from $\mathbf{x_{nearest}}$ toward $\mathbf{x_{new}}$, explicitly evaluating dynamics within actuator constraints. Since a quaternion is used, `Nearest` and `SampleFree` must be modified in a future iteration as a Euclidean metric does not suffice.

procedure KINO-RRT($\mathbf{x_0}, X_{goal}$)
  $V \leftarrow \mathbf{x_0}; E \leftarrow \emptyset; \mathbf{x_{new}} \leftarrow \mathbf{x_0}$
  while $\mathbf{x_{new}} \notin X_{goal}$ **do**
    $\mathbf{x_{rand}} \leftarrow$ `SampleFree`
    $\mathbf{x_{nearest}} \leftarrow$ `Nearest`$(G = (V, E), \mathbf{x_{rand}})$
    $\mathbf{x_{new}} \leftarrow$ `SteerFF`$(\mathbf{x_{nearest}}, \mathbf{x_{rand}})$
    if `ObstacleFree`$(\mathbf{x_{nearest}}, \mathbf{x_{new}})$ **then**
      $V \leftarrow V \cup \mathbf{x_{new}}; E \leftarrow E \cup (\mathbf{x_{nearest}}, \mathbf{x_{new}})$;
    end if
  end while
  return $G = (V, E)$;
end procedure

Fig. 1. **Kinodynamic-RRT, applied to the free-flying robot problem.**

III. Preliminary Results and Future Work

Figure 2 shows a visualization of a sample system using the full free-flying dynamics that were developed in simulation. `SteerFF` handles forward evaluation, currently for the rigid body dynamics. A kino-RRT implementation for the rigid body dynamics only has been implemented, with a sample search of the state space shown in Figure 3. Integration of the full manipulator dynamics will be performed shortly.

The work so far has demonstrated the use of sampling-based planning for an interesting class of robot dynamics.

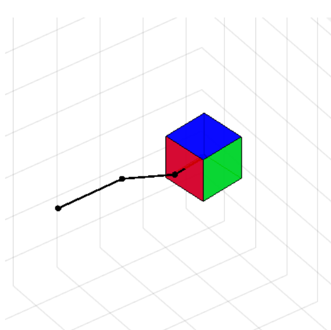

Fig. 2. **A free-flying satellite with a 2-link manipulator, with state space given by equation 2. The dynamics are forward propagated in kino-RRT's search. [9]**

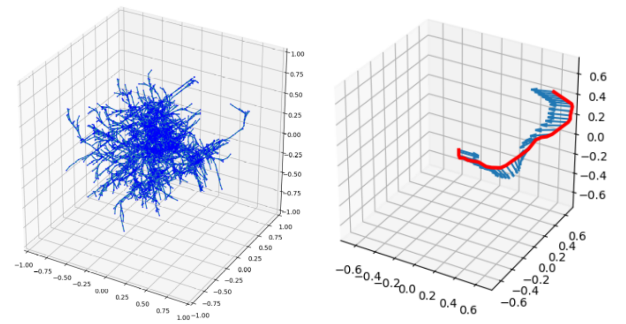

Fig. 3. **RRT nodes for the rigid body dynamics (left) and a feasible solution (right).**

The application of kino-RRT to free-flying robots specifically offers a path to developing feasible trajectories which can potentially serve to warm-start other optimizing solvers. The wider question of how to find optimal trajectories for high-dimensional dynamical systems, especially under challenging constraints, remains open. Future extensions aim to look at optimal control-inspired methods of guiding optimizing sampling-based planners (e.g. see LQR-RRT*, kino-RRT* [10] [11]), and in applying some of the exciting advances of fast iterative NLP methods.

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