Cooperative Real-Time Inertial Parameter Estimation

Extended Abstract

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ABSTRACT

Cooperative cargo transport (e.g., two agents moving a table) is trivial for humans, but poses exceptional challenges to robots. One challenge is learning the dynamics properties of unknown cargo, which is critical for safe operations. We present an algorithm to estimate the inertial parameters of an object grasped by one or more robots in real-time. We model each robot's N sub-body system— considering external and joint actuation— using the Recursive Newton-Euler equations. A constrained Unscented Kalman Filter estimates the grasped object's mass, center of mass and moments of inertia. Our approach is validated through simulation using Astrobee, a free-flying robot.

KEYWORDS

free-flyer robots, inertial parameters, recursive Newton-Euler equations, constrained unscented Kalman filter

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1 INTRODUCTION

When a robot grasps any cargo, its dynamics change greatly depending on the cargo's inertial properties, affecting how the robot responds to actuation. Thus, explicit methods to estimate cargo inertial parameters are needed to ensure safe navigation. Supply delivery missions to the International Space Station (ISS) motivate our work on the cooperative cargo transport problem. Astrobee [2] robots could assist in unloading, saving valuable crew time.

We introduce a real-time estimator for the inertial parameters of an unknown firmly grasped object. Full actuation— including force, torque and arm joint commands— does not interfere with the estimation. To the best of our knowledge this is the first approach to estimate the inertial properties of a grasped object in real-time for multiple fully actuatable robots with n revolute arm joints.

2 RELATED WORK

For terrestrial applications and quadcopters, inertial parameter estimation has previously been explored in [1, 1, 6, 13], and on vision for on-orbit servicing missions [5, 10].

Estimation based on the Conservation of Momentum has the advantage that no acceleration estimation is needed [7, 8, 11]. However, it does not allow for simultaneous non-conservative actuation, excluding robots with propulsion. If Conservation of Momentum is considered, actuation must be conservative, where [14] takes advantage of the effect of the gravity gradient torque, and in [8], arm movements are considered.

The Newton-Euler Motion Equations have been used to solve this estimation problem, such as a single rigid body free-flyer [4] and a two-body system [8]. A modified formulation models an N sub-body system with direct arm joint torque sensing [11], which solves the problem offline. These methods are mostly solved using offline estimators, optimizing over all the data points [8, 11]. Moreover, the robots execute excitation trajectories, optimizing solely for the estimation task [12].

In this work, the estimation is in real-time, where non-conservative forces are considered and the excitation trajectory is not optimized.

3 ROBOT MODEL

The robot is modeled as N links connected through revolute joints with an unknown object U fixed to the last link. Each sub-body can be subjected to an external force, torque, and the revolute joints.

3.1 Free-Flyer Kinematics

To calculate the forces throughout the sub-body system, one needs to propagate the accelerations, given that only the base of the robot contains acceleration sensors. The Kinematic formulation is depicted in Fig. 1. The positions $\mathbf{p}$ and $\mathbf{r}$ are the position vectors of the reference frame origin, and the center of gravity of each sub-body respectively; a is the relative position from the sub-body reference frame to the center of gravity and b from the center of gravity to the next reference frame. $\dot{\omega}$ is the angular acceleration.

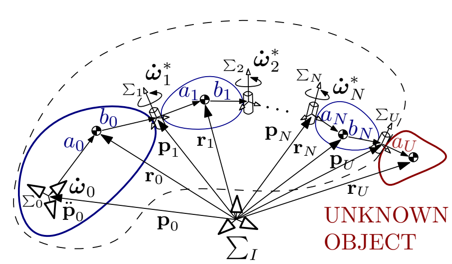

Figure 1: Kinematic variables can be propagated through the sub-body system by knowing the base and joint kinematics.

Given this, one can calculate the acceleration in each sub-body's center of mass recursively.

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Starting at the base reference frame where the sensors and actuation is projected, the acceleration at the center of mass can be obtain through subsequently differentiating the position and velocity, as

$$^0\ddot{\boldsymbol{r}}_0 = {}^0\ddot{\boldsymbol{p}}_0 + {}^0\dot{\boldsymbol{\omega}}_0 \times {}^0\boldsymbol{a}_0 + {}^0\boldsymbol{\omega}_0 \times \left({}^0\boldsymbol{\omega}_0 \times {}^0\boldsymbol{a}_0\right). \quad (1)$$

For the subsequent sub-bodies, each acceleration $^1\ddot{\boldsymbol{r}}_i$ in the reference frame $\sum_i$ can be propagated similarly as in [11], arriving to the last link, the unknown object as:

$$^U\ddot{\boldsymbol{p}}_U = {}^U\mathrm{R}_N\left[{}^N\ddot{\boldsymbol{p}}_N + {}^N\dot{\boldsymbol{\omega}}_N \times {}^N\boldsymbol{b}_N + {}^N\boldsymbol{\omega}_N \times \left({}^N\boldsymbol{\omega}_N \times {}^N\boldsymbol{b}_N\right)\right] \quad (2)$$

$$^U\dot{\boldsymbol{\omega}}_U = {}^U\mathrm{R}_N {}^N\dot{\boldsymbol{\omega}}_N \quad (3)$$

$$^U\ddot{\boldsymbol{r}}_U = {}^U\ddot{\boldsymbol{p}}_U + {}^U\dot{\boldsymbol{\omega}}_U \times {}^U\boldsymbol{a}_U + {}^U\boldsymbol{\omega}_U \times \left({}^U\boldsymbol{\omega}_U \times {}^U\boldsymbol{a}_U\right). \quad (4)$$

3.2 Free-Flyer Dynamics

Forces: The expected actuation force can be obtained, considering that $^i\hat{\boldsymbol{f}}_i = m_i {}^i\ddot{\boldsymbol{r}}_i$, as the sum of the reaction forces from all the sub-bodies, where the term $\hat{\boldsymbol{f}}_U$ incorporates inertial parameters as

$$^I\boldsymbol{f}_{Act} = \sum_{i=0}^{N} {}^I\mathrm{R}_i {}^i\hat{\boldsymbol{f}}_i + {}^I\mathrm{R}_U {}^U\hat{\boldsymbol{f}}_U. \quad (5)$$

Torque Using the cross-product distributive property in whi $a \times c + b \times c = (a + b) \times c$, and using the geometrical definition which the cross product is invariant under proper rotations, we c obtain the actuated torque as

$$^A\boldsymbol{n}_A = \sum_{i=0}^{N} {}^A\mathrm{R}_i {}^i\hat{\boldsymbol{n}}_i + {}^A\mathrm{R}_U {}^U\hat{\boldsymbol{n}}_U + \sum_{i=1}^{N}({}^I\boldsymbol{r}_i - {}^I\boldsymbol{p}_0) \times ({}^I\mathrm{R}_i {}^i\hat{\boldsymbol{f}}_i) + ({}^I\boldsymbol{r}_U - {}^I\boldsymbol{p}_0) \times ({}^I\mathrm{R}_U {}^U\hat{\boldsymbol{f}}_U), \quad (6)$$

where the term $^U\hat{\boldsymbol{n}}_U$ incorporates the inertial parameters $^U\mathbf{I}_U$, and $\hat{\boldsymbol{f}}_U$ incorporates the terms $\mathbf{a}_u$ and m_U.

4 UNSCENTED KALMAN FILTER

The Unscented Kalman Filter (UKF) samples several points(sigma points) around the current state estimate, based onthe covariance, propagating them through the nonlinear map.

This estimation implies that the robot's geometry, $^B\mathbf{p}_B$, $^B\dot{\boldsymbol{\omega}}_B$, $^B\mathbf{p}_B$, $^B\boldsymbol{\omega}_B$, $\ddot{\theta}_i$, $\dot{\theta}_i$, θ_i, where $i = 1, ..., N$, is calculated or estimated from measurements beforehand. The states of the filter are the inertial parameters, the prediction model considers that the states are a constant, and the measurement model is defined by the dynamic equations in 3.2.

5 MULTI-ROBOT ESTIMATION

To estimate inertial parameters with multiple robots, a tree structure with the cargo as the origin node is considered. Each branch is comprised of one robot interacting only with the cargo. Each robot considers that all the grasping forces and torques performed by other robots are external forces on the on the cargo, considered in the update step of the UKF and communicated.

6 RESULTS

The described algorithms were tested using Astrobee, a free-flying robotic system currently on the International Space Station.

Astrobee uses electric fans as a propulsion system that allows free flight through the microgravity environment of the station and localizes itself by using visual landmarks [2], [3]. Astrobee can incorporate different payloads, one of them being a perching arm, which we use to grasp into cargo [9]. The robot and arm system is comprised of three sub-bodies, the robot base, the proximal arm link and the distal arm link. Experiments can be seen at https://youtu.be/iY_nuyLe26E.

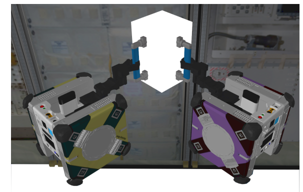

Figure 2: Multiple Astrobee carrying a cargo in the ISS simulation

The testbed consists of one or two Astrobees grasping a cargo containing a handrail Fig. 2 in the ISS simulation. To test the algorithms proposed, we execute a figure-eight trajectory for position, yaw ramp for attitude and pan ramp for arm. The estimation for the trajectory is depicted in Fig. 3, where convergence occurs towards the end. It can be seen that when the robot turns suddenly in yaw ($40s$), the estimation convergence is faster.

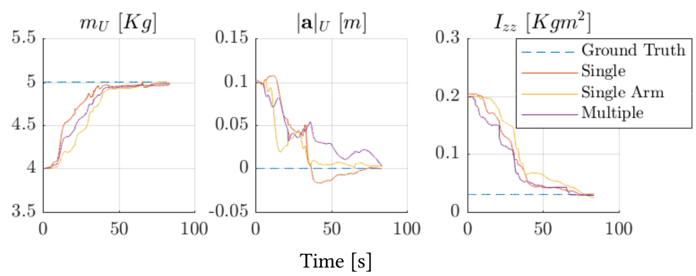

Figure 3: Estimation of the inertial parameters of the grasped cargo.

Comparing all scenarios, the convergence rate is comparable when using the same filter parameters, this shows that arm movement and multiple robots grasping does not deteriorate the estimation due to added actuation, sensor noise and synchronization.

Estimation in all the scenarios tested was successful, obtaining the correct parameters. As expected, in all cases, the mass, as the most consequential inertial parameter, converges faster and more accurately than the remaining inertial parameters. The estimation converges quicker when there is more actuation present, e.g. change of direction.

7 CONCLUSIONS

This paper proposes a solution for the estimation of the inertia parameters for a cargo grasped by fully actuated free-flying robots. It was proven that inertial parameter estimation is successful for single and multiple robot grasp, even under sensor noise and uncertainty.

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