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Optimal manipulation patterns can drive the estimation of object mechanical properties

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***Abstract*— The problem of grasping objects with robotic hands has a long history in literature, yet many issues are still open, especially when dealing with the perception of the touched object, and its manipulation. These two problems are usually analyzed separately; however, since the sense of touch is intrinsically an active sense, i.e. motion and perception are two sides of the same coin, it could be useful to deal with these two aspects in an integrated fashion. Indeed, as we can borrow from the active sensing literature applied to vehicles locomotion, the motion itself could be valuable source of information on the system's state. In this work, we propose a first step in this direction, targeting the development of a novel optimization framework for the estimation of the inertial parameters of a grasped rigid body. In a nutshell, the goal is to identify the optimal manipulation actions that a robot should exert on a generic object to maximize the accuracy and minimize the uncertainty for the estimation of unknown mechanical properties of the manipulated item, such as its center of mass and inertia tensor.**

***Index Terms*— Active sensing, rigid body dynamics, grasping, optimization**

I. INTRODUCTION

Having intelligent machines embedded in our society in the next years will come with a number of significant benefits, since this will provide significant improvements in the productive process and will increase the quality of life of workers and citizens. However, to reach this goal, we will need to teach robots how to interact with an unstructured and unknown environment. While a lot has been done in the field of robotic grasping and manipulation, from data-driven to model-based methods, as well as the haptic exploration of objects [1], [2], these efforts are not currently matched with the sensing – and then perception – of the grasped object. This represents an important prerequisite for an effective and natural interaction, which must be also guaranteed through a precise planning and control of the robotic end-effector.

Focusing on that, we took inspiration from [3], in which the authors discussed the problem of constructing an online trajectory that minimizes the maximum state estimate uncertainty offered by the used observer in the context of planning for information maximization. In other words, the goal is to determine which trajectories convey the most information about the internal state of the considered system. Building on this idea, we found the most informative trajectories that a generic robot should excert on a rigid object in order to collect the maximum information on its inertial parameters. Extensive simulations were performed, comparing 50 random movements, chosen as initial-guess for the optimization routine, to the correspondent 50 optimal movements.

II. METHODS

As reported in [3], the Constructability Gramian (CG) is directly linked to the state error covariance matrix P of the Extended Kalman Filter (EKF) by the relation $G_C(-\infty, t) = P^{-1}(t)$. While the expression of the CG is generally non-trivial, in certain circumstances it can be written in closed-form, for example when the state of the system is constant over time, i.e. $\dot{x} = 0$. In this case, given an output equation $y = h(x) + w$, where w is the measurement noise (gaussian, with noise covariance matrix R), with a corresponding linearized output matrix $H = \frac{dh(x)}{dx}$, the CG results:

$$G_C(t_0, t_f) = \int_{t_0}^{t_f} H^T(t) R^{-1} H(t) dt. \tag{1}$$

Since the CG for non linear systems depends on the input vector u of the system (through the matrix H), the goal is to find the optimal input u^* which maximize a particular norm of the Gramian. In particular, maximizing its lowest eigenvalue $\lambda_{min}(G_C)$ is equivalent to the minimization of the maximum estimation uncertainty of the estimated state [3]. So, u^* can be found solving the following problem:

$$u^*(t) = \arg\max_{u(t)} \lambda_{min}(G_C(t_0, t_f)) \tag{2}$$

Choosing as outputs the external wrench w_{ext} acting on the object, expressed in body frame, it is possible to obtain the Gramian expression from the Lagrangian form [4]:

$$w_{ext} = M(\pi)\dot{\nu} + C(\nu, \pi)\nu + G(r, \pi), \tag{3}$$

where π includes the 10 rigid body inertial parameters, constant with respect to each frame $\{b\}$ fixed to the object (the mass m, the center of mass ${}^b c \in \mathbb{R}^3$, and the six independent components ${}^b i \in \mathbb{R}^6$ of the inertia tensor ${}^b I$). ν, instead, includes the object linear and angular velocities, expressed also in body frame, while the quaternion r encodes

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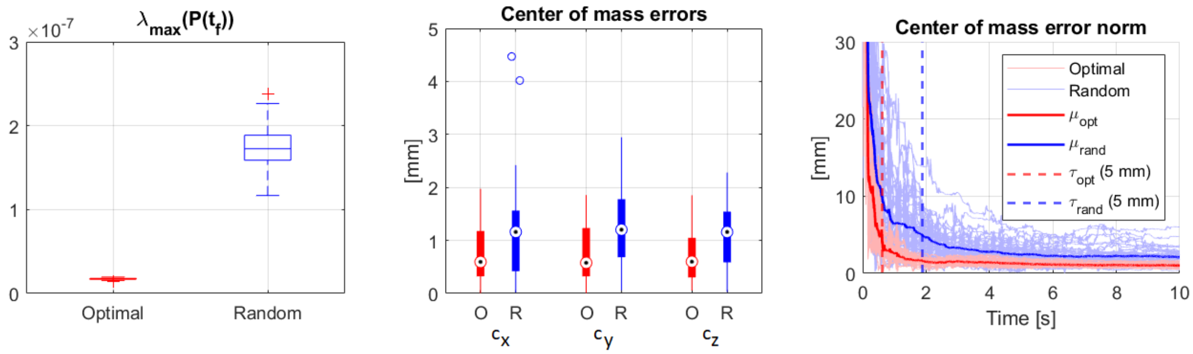

Fig. 1: Comparison of random vs. optimal movements: on the left, the maximum eigenvalue of the matrix P (mean $\pm$ interquartile range); in the middle, the estimation error along the three directions defined by the body frame (mean $\pm$ interquartile range); on the right, the convergence of optimal and random estimation errors, considered as distance from the effective center of mass (dotted lines correspond to convergence time at an error norm of 5 mm).

the rotation between the global frame $\{g\}$ and the body frame $\{b\}$.

Indeed, the output matrix consists in the form:

$$H = \frac{dh(\pi)}{d\pi} = \begin{bmatrix} \frac{\partial h_1}{\partial c} & \frac{\partial h_1}{\partial i} \\ \frac{\partial h_2}{\partial c} & \frac{\partial h_2}{\partial i} \end{bmatrix} = \begin{bmatrix} H_c & 0 \\ * & H_i \end{bmatrix},$$

where the inertia tensor terms do not affect how the center of mass and external forces interact. As a result, it is reasonable to proceed with a two-phase estimation procedure: first, we can identify the center of mass exploiting only the external force measures and the optimal movement founded through the Gramian $G_{COM} = \int_{t_0}^{t_f} H_c^T R^{-1} H_c dt$; then, the inertia tensor terms using the external torque information (supposing to already know the center of mass position), exploiting the Gramian $G_{IN} = \int_{t_0}^{t_f} H_i^T R^{-1} H_i dt$. Furthermore, the matrices H_c and H_i depend exclusively on the angular velocity ω and angular acceleration $\dot{\omega}$ of the rigid body. So, it is possible to choose a particular parametrization of the angular velocities (e.g. sinusoidal segments) that depends from a limited set of control points, and perform the optimization on those ones.

III. Results

Here we report some preliminary results obtained through extensive simulations, where 50 random movements were used as initial guess for the optimization on the estimation of the center of mass; the 50 optimal movements obtained through the algorithm were compared to the random ones, as reported in Figure 1. The robot Franka Emika Panda was considered as manipulating device, with the rigid object rigidly grasped by a gripper in a form closure situation. Similar results were obtained for the inertia tensor, and they are omitted here for sake of space. The control points of the optimization were bounded inside a window of ± 1 rad/s, while the time of simulation was fixed to 10 seconds. The maximum eigenvalue of the matrix P results smaller for the optimized movements, as the optimization tackles the reduction of this metric; as a consequence, the estimation error results way lower for the optimal movements, and also the time of convergence to a certain value of the error is faster for the optimal movements.

IV. Conclusions

We presented an optimization framework to find the optimal trajectories which allow to identify a rigid-body inertial parameters while being grasped. This optimization yields on the Constructability Gramian, which is an observability metric directly linked to the state error covariance matrix of an Extended Kalman Filter. The optimization is flexible to the introduction of constraints related to the robot's limits or for the accomplishment of lower-priority tasks, or even granting force closure on the object while manipulating it. This procedure could be applied to different generalized gripping tools, ranging from multi-fingered hands to fleets of drones or cooperating ground vehicles. This work could open interesting perspectives toward important improvements for robotic manipulation linked to the tactile exploration and manipulation of objects, thanks to a full exploitation of the connection between sensory acquisitions and control actions. The technology that will be developed could have a significant impact on industrial settings and also on other issues, where having a robot capable of performing tasks independently can dramatically improve the efficiency of human-robot interaction. Future works will focus on testing the framework in a real scenario, with particular attention on force closure with different grippers and simultaneous perception and manipulation.

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