Optimization-Based Control and Estimation in Compliant Robotic Systems

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Abstract.
This project is centered on carrying out robotic manipulation tasks using a robot end-effector that is compliant in six dimensions. The compliance in the robot end-effector leads to a coupling between forces and the configuration of the system comprising the object and the end-effector, which presents challenges in control and state estimation. The approach of this project is to frame the control and state estimation of the compliant end-effector as constrained optimization issues. The effectiveness of our approach is demonstrated through a block tilting task, achieving a closed-loop control frequency of up to 50 Hz.

1 Introduction

Many robotic end-effectors possess varying degrees of compliance, including soft robots, 6-axis compliant Stewart platforms, vacuum suction cups, and rigid grippers with compliant mechanisms. This passive compliance enhances the end-effectors' tolerance to positional inaccuracies but at the cost of reduced control precision. The primary challenge arises from the coupling between the forces within the system and its configuration, meaning that forces and positions cannot be independently controlled due to compliance. This complexity adds to the difficulty of executing manipulation tasks with compliant end-effectors.

We introduce a framework that allows a 6-axis compliant end-effector to execute manipulation tasks involving multiple external contacts, utilizing only a 6-axis force torque sensor. This framework is structured into three segments: identification of the compliant system, state estimation, and control, with the focus of this project being on the latter two segments. These are addressed through the application of constrained optimization techniques for both state estimation and control.

Our methodology was validated through a block tilting experiment using a 6-axis compliant vacuum suction cup. The computation time required for both state estimation and control at each timestep was under 20ms, enabling a control frequency of up to 50 Hz.

The remainder of this report is organized as follows: Section 2 provides a brief overview of our preliminary work on compliant system identification. Sections 3 and 4 detail the algorithms developed for state estimation and control, respectively. In Section 5, we discuss the experimental setup and results from the block tilting experiment utilizing a vacuum suction cup.

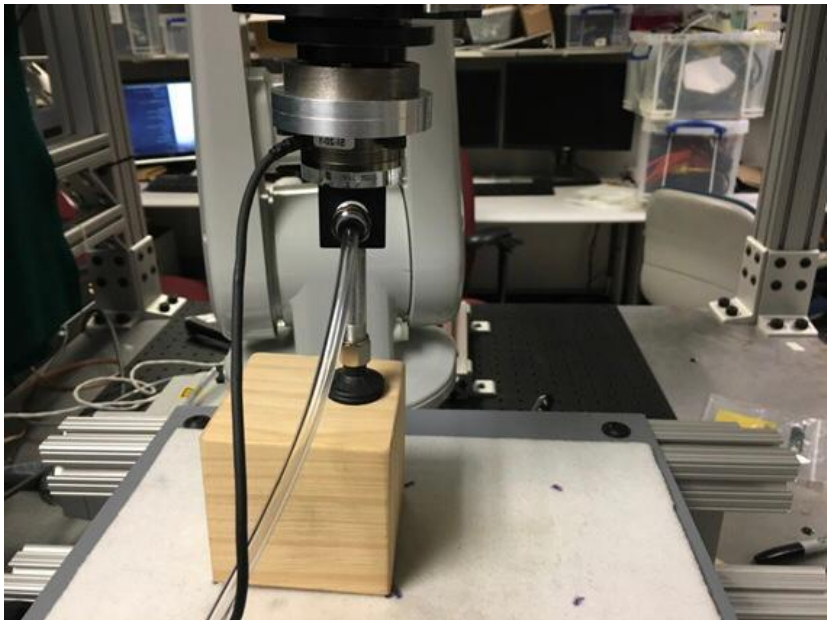

Fig. 1. Our robot system for block titing with a vacuum suction cup.

2 System Identification

Starting with the readings from the force torque sensor, our initial task is to determine the configuration of the compliant end-effector. This section outlines the creation of a simplified six-dimensional static model for compliant end-effectors and introduces a self-supervised procedure for data gathering to calibrate this model.

2.1 Static/Stiffness Model for Compliant End-effectors

For a compact and non-motorized compliant end-effector, it can be effectively modeled as a six-degree-of-freedom nonlinear spring. The displacement compliance S and the applied external forces and torques W at one end are denoted by:

$$X = (x, y, z, \alpha, \gamma, \delta)$$

$$W = (F_x, F_y, F_z, T_x, T_y, T_z)$$

Here, (x, y, z, α, β, δ) represent the translational and rotational displacements at one end of the compliant component, while W signifies the corresponding forces and torques exerted on this end. The local linear approximation of this spring mechanism is expressed as:

$$K(X) : \mathrm{R}^6 \mapsto \mathrm{R}^6, \Delta W = K\Delta X$$

In this relation, K stands for the local stiffness matrix, which should be positive semi-definite.

2.2 Data Collection

To gather force-torque data and the associated configuration data for a vacuum suction cup, we have developed an autonomous data collection method that eliminates the need for additional sensors to measure displacement and does not require human oversight. The setup of the robotic system is depicted in Figure 1. The sole sensor incorporated into our system is an ATI-mini force torque sensor attached to the end of the gripper. To ascertain the gripper's configuration, the open end of the suction cup is securely attached to a pre-determined point on the table using vacuum suction, making the configuration equivalent to the difference between the robot's end position and this fixed point. The steps for data collection are as follows:

1. Move to a neutral position where there is minimal displacement in the z-axis, and capture the initial force-torque sensor readings, denoted as D_{f0}.
2. Select a configuration at random from within an approximately estimated boundary.
3. Navigate to the robot position that corresponds to the configuration chosen in step 2 and document the force-torque sensor data as D_f.
4. Return to the neutral position and contrast the present force-torque data with Df0. If it surpasses a predefined limit, it indicates that the fixed contact has slipped; in this case, disregard all data and re-establish the suction cup (by moving to a specific height that interrupts the contact, then returning to the neutral position). If the threshold is not exceeded, log the sampled configuration along with the force-torque data D_f.

2.3 Model Identification

Employing the outlined data collection method, we amassed 1637 data points for a single suction cup. When presented with a new sample of force-torque data, we can employ a locally linear regression model, denoted as W = K(X – X0) + W0, which utilizes the nearest neighbors based on a weighted Euclidean distance to forecast the associated configuration. The assumption of local linearity aids in simplifying the constraints within the optimization problems discussed in Sections 3 and 4

3 State Estimation

This section tackles the challenge of deducing the positions of objects and the configuration of compliant end-effectors using force-torque data alongside known robot positions. While Section 2 provides a relationship from force-torque readings to the compliant end-effector's configuration, this mapping is not perfectly precise and could lead to inferred object positions that breach external contact limitations. Therefore, it is necessary to adjust the initial estimation to comply with environmental constraints and ensure system stability. We approach this by formulating a constrained optimization problem that seeks to determine the object's position, xo, and the compliant gripper's configuration, xc, while adhering to the following constraints:

1. robot position consistency: the robot position kinematically computed by x_o and x_c should be consistent with the actual robot position, which can be written as $\Phi_{robot}(x_o, x_c) = x_{robot}$,
2. contact mode constraints: the object position should satisfy the natural constraints enforced by the task contact mode, which can be written as $\Phi_{env}(x_o) = 0$.

The cost function is the potential energy of the object-gripper system $E(x_o, x_c) = E_{object}(x_o) + E_{elastic}(x_c)$, since a stable configuration of a system is always at its local minima of energy under constraints. Thus, the state estimation problem can be written as:

$$\begin{aligned} \min_{x_o, x_c} \quad & E(x_o, x_c) \\ \text{s.t.} \quad & \Phi_{robot}(x_o, x_c) = x_{robot} \\ & \Phi_{env}(x_o, x_c) = 0 \end{aligned} \tag{1}$$

To speed up computation and ensure optimal solution, we can further turn this problem into quadratic programming using local linearization. If we solve for the change of x_o and x_c in the form of body twist represented as Δx_o and Δx_c, we can easily obtain a quadratic cost function as

$$\Delta E = mg\Delta x_{\{oz\}} + \backslash frac\{1\}\{2\}\Delta x_{\{c\}_{\{c\}}}^{\{T\}K(x_{\{c\}})\Delta x} + W_{\{c\}}^{\{T\}\Delta x}$$

The robot position consistency constraints can be represented as

$$J_{\Phi_{robot}}(x_o, x_c)\Omega(x_o, x_c)\begin{pmatrix}\Delta x_o \\ \Delta x_c\end{pmatrix} = \Delta x_{robot}$$

The contact constraints can be represented as

$$J_{\Phi_{env}}(x_o)\Omega(x_o)\Delta x_o = 0$$

4 Control

The goal of control varies. It could be position/velocity control of the object, the force control on compliant contact, or even hybrid force velocity control of the whole system. But eventually we achieve these goals by commanding the robot position or velocity. Thus we can formulate the control problem as to find the control action (robot velocity) optimal to certain criteria under the task and environment constraints. The variables are robot body velocity v^b_{robot}, object body velocity v^b_{obj}, gripper contact force f_c and external contact force f_{env}. The following constraints should be satisfied:

1. task goal: enforce the controlled variable to satisfy the task goal, as $S_v v^b_{obj} = v_{goal}$ and $S_f f_c = f_{goal}$.

2. contact constraints: maintain desired contact mode, written as $J_{\Phi_{env}}(x_o)\Omega(x_o)v^b_{obj} = 0$
3. quasi-static equilibrium (force balance on the object): $G_o + f^o_c + f^o_{env} = 0$
4. guard conditions: satisfy the requirement of for each contact, like normal force greater a threshold and contact force within its friction cone, which can be written as $f^n_{env} > f^n_{min}$ and $\mu f^n_{env} - f^t_{env} > 0$. The friction cone constraint can be turned into linear constraints by approximating the cone with octagonal polyhedron:
$\mu f^z_{env} = d_i^T \begin{pmatrix} f^x_{env} \\ f^y_{env} \end{pmatrix}, i = 1, 2, \ldots, 8$, where $d_i = [sin(\frac{i\pi}{4}), cos(\frac{i\pi}{4})]$.
5. compliant force relationship:

The cost function can be written as:

$$C(v^b_{robot}, v^b_{obj}, f_c, f_{env}) = v^{b\,T}_{robot} v^b_{robot} + v^{b\,T}_{obj} v^b_{obj} + f^T_c f_c + f^T_{env} f_{env}$$

This optimization problem can be easily solved with quadratic programming.

5 Experiments

Our approach was validated through an experiment where a vacuum suction cup was utilized to execute a block tilting task that was position-controlled, with only the reference trajectory of the object's position provided. The setup of the robotic system is depicted in Figure 1, and a snapshot of the block tilting in action is shown in Figure 2. An ABB 120 robot equipped with Cartesian control was used for the experiment. A total of 1647 samples for system identification were gathered following the methodology outlined in Section 2. The processing time for each timestep did not exceed 20ms. Videos of these experiments are available in the 'video' folder at the following link: https://github.com/Srecharan/Optimization-Based-Control-and-Estimation-in-Compliant-Robotic-Systems-.

Fig. 2. During the block tilting