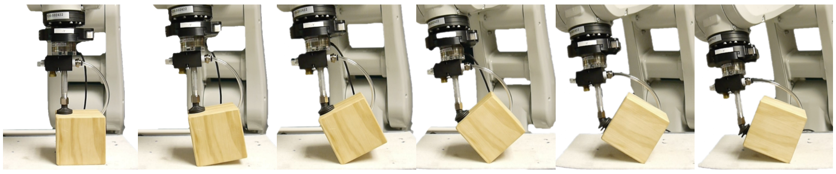

Manipulation with Suction Cups using External Contacts

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Abstract. Suction cups are the most common manipulation effectors in industry, but they are mostly only used for the purpose of pick-and-place. This paper proposes to use suction cups for a wider variety of tasks with the help of external contacts. A major hurdle in improving the dexterity of suction cups is the challenge of soft material modeling. Model error causes inaccurate contact location estimation as well as undesirable control performance. In this work, we propose a general framework for manipulation with suction cups under external contacts. The solution consists of a locally linear force-deformation model for suction cups with large deformation, and an estimation-control framework which utilizes contact constraints and feedback control to counter modeling errors. We verify the efficacy of our method experimentally by tilting a block on a table with a suction cup. Our method works reliably under modeling error even under large suction cup deformation (over 40 degree of bending). We also show the superiority of suction cups by performing tasks that are not possible with any normal fingertip[1].

Keywords: manipulation, suction cup, soft fingertip, extrinsic dexterity

1 Introduction

Suction cups are the most popular robot effectors in industry. As the universal picking tools, they dominate the market of picking and grasping in automation because they are flexible about the object shapes, materials and sizes. Suction cups are shown to be very effective in pick-and-place and maintaining grasps [1][2][3], but the applications of suction cups may go way beyond picking. For example, Shome *et al.* showed that a suction cup can topple boxes using a lateral motion [3]. Correa *et al.* used a point on the suction cup to topple objects to

[1] The video is available at: https://youtu.be/eK77vK8wkUE

obtain robust vacuum suction grasps [4]. In this paper, we further explore how to use suction cups in more dexterous manners.

If we treat suction cups as soft fingertips, we see these advantages over traditional high stiffness robot fingertips: (1) They can conform to the object shape, including wrapping around vertices and edges, which brings greater friction and stability; (2) The elastic material introduces passive compliance into the manipulation system, which is necessary for tasks with external contacts such as polishing, assembly and packaging. (3) suction cups' ability to pull as well as push enables maneuvering capabilities beyond a traditional soft fingertip. Essentially, manipulation with a suction cup is actually manipulation with a soft fingertip and a bilateral finger contact.

With these benefits in mind, why is the use of suction cups and soft fingers limited to grasping or picking? A major reason is that deformable elements sacrifice the precision in position control. The difficulty in accurate modeling of soft fingertips makes it hard to estimate the location of the actual contact point, especially when the deformation is large. A position error exists whenever the suction cup touches anything, adding to the difficulty of predicting and controlling the motion of the object being manipulated. As a consequence, researchers treat compliance as a shortcoming for manipulation control, limiting the usage of soft fingertips to applications where the deformation is small, or where the exact contact location doesn't matter.

In this work, we attempt to realize the true potential of suction cups with a state estimation and control framework. Both state estimation and control are formulated as optimization problems where the constraint from environment contacts must be satisfied. Feedback signals from robot pose and finger forces are used to initialize the optimization problems at every time step.

To enable online computation, we propose a locally linear elastic model for suction cups. Our model maps 6D deformations directly to 6D local wrenches and makes few assumptions about the mechanical structure of the fingertip (we only assume elastic materials), so it can be applied to soft fingertips in commonly-known concepts such as GelSight-like [5] fingertips/palms.

We test our method with a suction cup on the problem of tilting a block, as shown in the teaser figure. The object has an edge-to-face sticking contact with the table, so the compliance from the finger is necessary. In our experiments, the suction cup sometimes needs to bend more than 40 degree to satisfy constraints. Our method shows resilience against modeling errors from the inaccurate suction cup model as well as from purposely added parameter errors. We also demonstrate the advantages of a suction cup in several challenging block tilting problems that are impossible with a normal fingertip.

2 Related Work

2.1 Modeling of suction cups and soft fingertips

Modeling of nonlinear behavior in soft fingertips is well studied. Finite-Element-Analysis (FEA) is often used to obtain one dimensional force-compression models for soft fingertips [6,7,8]. Specifically, Xydas *et al.* verified that the elastic force obeyed a power law about the deformation by experiments [8]. Higher dimensional behavior of the soft fingertip was also analysed. Akella *et al.* derived a soft fingertip model from plasticity theory [9]. Inoue and Hirai modeled a hemi-sphere fingertip by infinite number of virtual springs, and distinguished the nonlinearity caused by shape and material. For planar motions relative to the fingertip, force-motion models were proposed to predict when slipping could happen, such as the limit surface [10,8] and its variations [11]. For planar pulling actions, an exact bound can be developed [12].

Modeling of suction cups is trickier due to its complicated shape. A variety of FEA methods can be used to simulate its behavior under deformation [13]. But such models are hard to estimate and use. Simpler spring-mass systems were also designed to approximate the elastic behavior of suction cups [14,15]. In order to describe the amount of external wrenches a suction cup can bear before breaking the seal, several analysis approximated suction cup with a ring of contacts [14,16] and gave linear constraints on the external wrenches.

2.2 Sensing with a soft fingertip

There is a long list of work where tactile information is used to estimate the object poses [17,18,19,20,21]. Koval [18] and Yu *et al.* [19,20] used tactile information as a sign of contact constraints, which filtered out pose candidates that are not on the contact manifold; Bauza *et al.* [21] directly estimated the pose of an object grasped by tactile sensing pads from the footprint of the deformation. We combine the idea from both line of work: the exact wrench from the fingertip is used to estimate the object pose, in the meantime we restrict the feasible object poses to satisfy all the contact constraints.

2.3 Manipulation with soft fingertips

In robotic manipulation, we are not aware of any work that use suction cups for non-picking tasks in a principled way. Looking at soft robotics in general, there is work on kinematic control of an actuated soft robot body [22,23], and dynamic control of flexible link robots [24]. When there is an object, solutions exist for regulating contact force on a soft fingertip using feedback control [9,25]. In the community of dexterous/multi-finger hands, grasping and finger gaiting using soft fingertips were also widely studied [6,26,17,27]. However, these work were not considering significant finger deformation, the contact location on the object was trivially known. Also none of these work tackled situations where the object has external contacts with the environment.

2.4 Manipulation with external contacts

Beside contacts with the robot, contacts with the environment can also be utilized to move an object. Methods are available for motion planning of manipulation through contacts [28,29], but it is challenging to execute such motion plans without crushing the object or break desired contact modes. Sometimes crushing can be avoided by setting the external contacts in such a way that the objects are not overly-constrained, such as in planar pushing [30] and prehensile pushing [31]. When too many contact constraints are inevitable from the environment, compliance in the robot side becomes necessary [32]. Hou and Mason [33] provided a principled way of controlling over-constrained system using hybrid force-velocity control; this work tries to solve the robust task execution problem using passive compliance instead.

3 Problem Formulation

3.1 Assumptions and symbols

Consider a system consisting of a robot, a free rigid object and a fixed rigid environment. The robot contacts the object with suction cups, while the object has rigid contacts with the environment. A contact between the object and the environment can be in one of the two modes: STICKING or SLIDING. For suction cups, we only consider using sticking contacts. Additionally, we make the following assumptions in our model:

- All motions are quasi-static, i.e. inertia forces are negligible.
- The suction cup is under a constant air pressure.
- The locations and normals of all the contacts are known (finger contacts and environment contacts). The object properties are known. But the known model parameters may not be accurate.
- Feedbacks of the applied wrenches of all the soft fingertips is available.

Denote x as the configuration of the whole system, which includes the robot and object degrees of freedom. We assume all the contacts on the object are known, so the suction cup deformation is determined by the robot and object poses. Denote v, λ as the generalized velocity and force, respectively. Usually v has fewer degrees of freedom than $\dot{x}$ if redundant representations such as quaternions are used, but they are linearly related: $\dot{x} = \Omega(x)v$.

3.2 Problem statement

Given a motion plan of the system, we would like to control the robot to achieve the motion plan robustly. Here the control robustness for manipulation is defined as in [34], which involves satisfying the following conditions under modeling uncertainties and force disturbances:

1. The system does not violates its velocity constraints;
2. Each contact stays in its contact mode as described in the motion plan.

We assume the motion plan can be interpreted as an instantaneous goal at every time step, which are constraints on the generalized velocities v and generalized forces λ:

$$\begin{aligned} S_v v &= v_{goal} \\ S_\lambda \lambda &= \lambda_{goal}. \end{aligned} \tag{1}$$

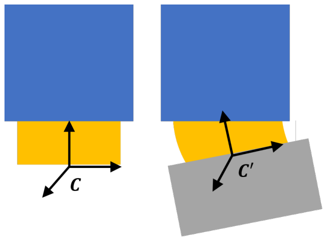


Fig. 1: Illustration of the soft fingertip deformation representation. The blue finger is installed with a soft fingertip (yellow). Left: when the fingertip is free of contact, the fingertip location is described by frame C. Right: when an object (grey) exerts force to the fingertip, the contact frame moves to C'. For simplification, the difference between C and C' determines the reaction force on the fingertip.

For example, if the motion plan is the trajectory of an object in 3D space, then S_v will be a selection matrix with six rows to select the entries of v that belongs to the object velocity, v_{goal} is the desired object velocity computed from the trajectory. S_λ has zero rows.

Our task is to compute the robot action at each time step to satisfy the goal as described in Equation 1 as well as the robustness conditions.

3.3 Method Overview

We address the proposed problem in Section 3.2 in three steps. In Section 4, we introduce a simple soft fingertip model that works for suction cups. Using this model, in Section 5 we provide a state estimation framework for estimating the object poses and the locations of the contact frames. Finally, with the estimated system states, we compute the robust robot control actions in Section 6.

4 A Locally Linear Soft fingertip Model for Suction Cups

We care about two things of a soft fingertip/suction cup in contact: the relation between its deformation and the reaction force, and the condition for breaking the sticking contact. Consider a soft fingertip as shown in Figure 1. In the most general case, the fingertip may deform in all six dimensional directions. The reaction forces are 6D wrenches.

4.1 Local Linearization Model

For a 6D spring under the small displacement assumption [35], its deformation-reaction force relationship can be modeled with a 6×6 stiffness matrix. But in more general situations, the deformation of suction cups can be large. The actual deformation-reaction force model is complicated [9,36], even in low dimensional cases [6,7,8]. Such models are usually nonlinear and are hard to use in control.

We find a trade-off between modeling simplicity and accuracy by using local linear models. Given a suction cup, we collect a dataset of deformation - reaction force pairs. During the online execution, we fit a linear model from the dataset around the current working point at each time step. So we have a linear model to use for control, while keeping the nonlinearity of the model with the dataset.

The local linear model has the following form:

$$\Delta W = K(X)\Delta X \tag{2}$$

where $K(X) : \mathbb{R}^6 \mapsto \mathbb{R}^6$ is a positive semi-definite matrix, $X = (x, y, z, \alpha, \gamma, \delta)$ are the linear and angular displacement of CC' in Fig. 1, ΔX describes the incremental change from the previous time step. $W = (F_x, F_y, F_z, T_x, T_y, T_z)$ is the corresponding external reactive wrench applied on the fingertip.

4.2 Online Model Fitting

Assume we have a deformation-reaction force dataset $\{X_{data}, W_{data}\}$ of N pairs of $\{X, W\}$. Given a new wrench measurement W', its k-nearest neighbors are firstly identified with weighted Euclidean distance from W_{data}, represented as a $6 \times k$ matrix W_k, together with the corresponding displacement matrix X_k. Locally, the linear relationship can be written as

$$K(X)(X_k - \overline{X_k}) = W_k - \overline{W_k}$$

where $\overline{X_k}$ and $\overline{W_k}$ are the means of X_k and W_k respectively.

Constraining $K(X')$ to be a symmetric positive semi-definite matrix, we can solve it by[37]:

$$K(X') = U_P \Sigma_P^{-1} U_Q \Sigma_Q U_Q^T \Sigma_P^{-1} U_P^T$$

U_P, Σ_P, U_Q and Σ_Q are from the eigen decomposition of P and Q: we have $U_P \Sigma_P^2 U_P^T = P$ and $U_Q \Sigma_Q^2 U_Q^T = Q$, where

$$P = (X_k - \overline{X_k})(X_k - \overline{X_k})^T$$

$$Q = \Sigma_P U_P^T (W_k - \overline{W_k})(W_k - \overline{W_k})^T U_P \Sigma_P$$

After obtaining $K(X')$, we have the corresponding displacement:

$$X' = K^{-1}(X')(W_k - \overline{W_k}) + \overline{X_k}$$

4.3 Sticking condition

A grasp by a suction cup could break if the air seal breaks somewhere on the contact. To describe the condition of breaking contact, researchers modelled the suction cup with a ring of contact points and proposed linear constraints on the external wrench [14,16]. In our experiments, we find it enough to simply apply upper and lower bounds on the contact wrenches. However, the more delicate constraints [14,16] can also be used in our framework as long as they are linear.

5 State Estimation with Suction Cups

The state estimation computes the object poses given robot positions and force-torque feedback (the reaction force exerted on the suction cup). Theoretically, we can use the local model described in Section 4 to directly compute the suction cup deformation and then the object poses. However, we observed relatively large errors using this straightforward approach. There are two reasons:

1. The local model has notable error since we collected a sparse deformation-reaction force dataset to keep the sample complexity low. Densely sample the six dimensional wrench space is difficult in practice; 2. One suction cup tip displacement may generate multiple solutions of the reaction force. Each solution is a local minimizer of the soft material's potential energy [38].

To resolve the above issues, we make another assumption: during the task execution, the change of fingertip deformation is continuous, so that the deformation will not jump between two far away solutions. As a result, we can uniquely determine the deformation by requiring it to be close to the previous solution.

To minimize the influence of the aforementioned modeling error, we use knowledge of environmental contacts to filter out unlikely solutions. We formulate an optimization problem to solve for all the object poses as well as the contact locations such that the constraints from contacts are all satisfied.

5.1 Problem Description

The configuration of the system can be denoted as $x = \left[x_o, x_r\right]^T$. x_r denotes the configuration of the robot, and x_o denotes the configuration of finger contact and the object. The corresponding generalized velocity is denoted as $v = \left[v_o, v_r\right]^T$ At time step t, we can obtain:

- $W^{(t)}$: the applied contact wrench on the finger;
- $x_o^{(t-1)}$: estimated gripper-object configuration from the last time step;
- $x_r^{(t)}$, $x_r^{(t-1)}$: robot configuration from current and previous time step.

The goal of the state estimation is to find the best estimation of current gripper-object system $x_o^{(t)}$ which is realistic in the physical world. This means that the solution should: 1) never violates the contact constraints; 2) stay in force equilibrium.

5.2 Optimization Formulation

Variables Instead of solving $x_o^{(t)}$ directly, we solve for its generalized velocity v_o. This way we can write down linear constraints and quadratic cost function on velocity variable using local linearization, which speeds up the computation greatly and ensures optimal solution. Let $\Delta t = 1$, the relationship of $x^{(t)}$, $x^{(t-1)}$ and v is given by

$$x^{(t)} = \Omega(x^{(t-1)})v + x^{(t-1)} \tag{3}$$

Constraints In this system, we have two types of contact: finger contact and external contacts. Contact modes of both types of contact should be maintained during execution. For the any contact i, its contact mode can be generally represented as $\Phi_i(c_i(x)) = 0$, where $c_i(x)$ is the i^{th} contact configuration as a function of x. Putting all contacts together, we have the constraint $\Phi(c(x)) = 0$. As $\Phi(c(x))$ equals to zero all the time, its time derivative is also zero:

$$J_{\Phi(c(x))}\dot{x}_{wo} = J_{\Phi(c(x))}\Omega(x)\left[v_o, v_r\right]^T = 0 \tag{4}$$

where v_r can be computed from: $v_r = \Omega_r^{-1}(x^{(t-1)})(x_r^{(t)} - x_r^{(t-1)})$.

Optimization Criteria A stable mechanical system is at its local potential energy minimal point. For simplicity, we write down the energy for only one object and one suction cup. The optimization minimize the potential energy of the suction cup-object system:

$$\begin{aligned} E(x^{(t)}) &= E_{object}(x^{(t)}) + E_{elastic}(x^{(t)}) \\ &= G_o h(x^{(t)}) + \int_C W(l)\mathrm{d}l \end{aligned} \tag{5}$$

where G_o is the object weight; $h(x^{(t)})$ is the object height. The suction cup has the elastic energy in the form of a path integral of the elastic wrench $W(l)$ in the direction of displacement l along its curve of deformation C. The end point of C is the suction cup contact frame displacement $X = X(x)$. We have $\Delta X = J_X(x)v$. The change in potential energy, $\Delta E(v) = E(x^{(t)}) - E(x^{(t-1)})$, can be written with local linearization:

$$\begin{aligned} \Delta E(v) &= \Delta E_{object}(v) + \Delta E_{elastic}(v) \\ &= -mg\Delta h(v) + \frac{1}{2}\Delta X^T K(X)\Delta X + {W^{(t)}}^T \Delta X \\ &= -(mgJ_h\Omega(x))v + \frac{1}{2}v^T(J_X^T K(X)J_X)v + ({W^{(t)}}^T J_X)v \end{aligned} \tag{6}$$

Adding a regularization term, the final cost function is

$$C_{est}(x, v_r, v_o) = \Delta E(x, \left[v_r, v_o\right]) + \left[v_r, v_o\right] Q_v \left[v_r, v_o\right]^T \tag{7}$$

where Q_v is a diagonal matrix with small regularization coefficients.

To conclude, the whole state estimation problem at time step t is to optimize for v_o with the quadratic energy cost (equation (7)), under the linear contacts constraints (equation (4)). This is a Quadratic Programming (QP) problem, so the computation can be very efficient.

6 Robust Control with Soft Fingertips

With estimated state, now we are ready to solve the task described in Section 3. Here we give a more concrete problem formulation. Since there are preferences we want to enforce, we again formulate an optimization problem. At time step t, we need to compute the robot action $x_r^{(t)}$ such that: 1) the control goal (1) is satisfied; 2) avoid crushing; 3) all contact modes are maintained. We use the generalized velocity v and force λ as variables instead of $x_r^{(t)}$ so as to use linearized constraints.

For clarity, we omit the known argument $x^{(t-1)}$ for symbols in this section. For instance, $J_{\Phi(c(x^{(t-1)}))}\Omega(x^{(t-1)})v = 0$ is written as $J_\Phi \Omega v = 0$.

6.1 Constraints

The constraints in this optimization problem are as follows:
a) Control Goal Satisfaction: As stated in Section 3, the desired motion plan can be described by affine constraints on the generalized variables. Rewrite (1) here:

$$S_v v = v_{goal}$$
$$S_\lambda \lambda = \lambda_{goal}.$$

v_{goal} and λ_{goal} are computed from the motion plan and the estimated state.
b) Avoid crushing: The robot action should not create conflicting velocity constraints on the object [33], which would cause infinite internal force. Because of the compliance in the suction cup, the robot can not effectively do velocity control on the object. So we don't need to explicitly enforce constraints to avoid crushing. In practice, we find it enough to add a penalty term on the magnitude of generalized force in the cost function.
c) Maintaining contact modes: Conditions for maintaining contact modes can be represented as or approximated by linear constraints:

$$A(x)\lambda \leq b \tag{8}$$

For example, for point to face STICKING contacts, Coulomb friction model says the contact force f_c must be within the friction cone, which can be approximated with octagonal polyhedron [39]:

$$\mu f_c^{[z]} > d_k^T \begin{pmatrix} f_c^{(x)} \\ f_c^{(y)} \end{pmatrix}, d_k = [sin(\frac{k\pi}{4}), cos(\frac{k\pi}{4})], k = 1, 2, \ldots, 8. \tag{9}$$

The normal forces must be greater than some threshold to maintain contacts:

$$f_{c_i}^{[z]} > \text{thr}. \tag{10}$$

For the suction cups, we ensure they are STICKING by applying upper and lower bounds on the contact forces λ_c: $\lambda_{lb} < \lambda_c < \lambda_{ub}$ (Section 4). However, more complicated linear constraints [14] can also be used.

Apart from the above three constraints that describe the control goal, we additionally have a few physical constraints:
d) Velocity constraint from contacts: Same as the equation (4), each contact exerts constraint on the generalized velocity:

$$J_\Phi \Omega v = 0 \tag{11}$$

e) Robot Velocity Bound: the linearization we used assumes small robot motion within each time step. So v_r should be bounded:

$$|v_r| < v_{bound} \tag{12}$$

f) Force Equilibrium on Object: through the quasi-static assumption, there is a balance among the object gravity and contact forces:

$$T_o \lambda + G^o = 0 \tag{13}$$

where T_o transform contact forces to the object frame, G^o is the object weight.
g) Force Equilibrium on Finger: there is also a force balance on each soft fingertip, which relates forces and velocities:

$$\begin{aligned} \lambda_c &= K \Delta X + T_c W^{(t)} \\ &= K J_X v + T_c W^{(t)} \end{aligned} \tag{14}$$

where $\Delta X = J_X v$ is the displacement change of finger contact, and K is the locally linearized stiffness matrix; λ_c is the finger contact force as part of λ; $W^{(t)}$ is the current force feedback, T_c transforms the force feedback to the contact frame.

6.2 Optimization Criteria

When we solve for states in force-equilibrium, we must avoid unstable balance. We can again do so by minimizing the potential energy in the system. So ΔE from equation (6) is the first term in our cost function.

Users can add more terms to the cost function to express their specific preferences. For example, we can force the robot not to protrude its elbow by penalizing the rotation of the end-effector:

$$C_{rot} = (R v_r - \omega_r)^T Q_\omega (R v_r - \omega_r) \tag{15}$$

where $R(x) v_r$ is the robot rotational velocity, ω_r is the expected rotational velocity towards robot initial orientation. We can also minimize the change of contact force for more stable behavior:

$$C_{ct} = (\lambda - \lambda^{(t-1)})^T Q_{d\lambda} (\lambda - \lambda^{(t-1)}). \tag{16}$$

The final cost function looks like this:

$$C_{ctrl}(v, \lambda, x^{(t)}) = \Delta E(v) + C_{rot}(v, x^{(t)}) + C_{ct}(\lambda, x^{(t)}) + v^T Q_{vc} v + \lambda^T Q_\lambda \lambda \tag{17}$$

where the last two terms are the regularization terms.

To conclude, the whole control problem at time step t is to solve for v and λ to minimize the cost (17), under the constraints (1)(8)(11)(12)(13)(14). The problem is again a QP.

7 Experiments

7.1 Hardware Setup

We use an ABB IRB 120 industrial robot with an ATI mini-40 force-torque sensor mounted on the robot wrist. The end effector is a Buna-N rubber vacuum cup with multiple bellows (cup diameter: 0.98 inch; cup height: 1.32 inches). The vacuum suction force is about 12 N. We only consider the 5D compliance for this suction cup (the compliance on the rotational z-axis can be ignored).

Our method is implemented in python. We use the python package CVX-OPT [40] to solve our quadratic programming problems. At each time step, solving state estimation and control together requires about 10ms on a 2.2GHz CPU. This means that our algorithm can work with fast robot motion. In our experiments, the robot motion is slow because of low level communication delays which can be removed by better engineering.

7.2 Self-Supervised Data Collection

We design the suction cup data collection to be in a self-supervised manner to reduce human effort. We let the suction cup stick to a calibrated point on the table. The robot is commanded to go to positions corresponding to uniformly sampled contact frame displacements. Wrench data is measure by the force torque sensor. To prevent the suction cup from slipping, we check the wrenches in a neutral position (only non-zero displacement on z-axis) before and after the motion. If the difference exceeds an empirically selected threshold, we consider there is a slip of the suction contact. Then the suction cup is reset by re-engaging the suction contact.

7.3 Example: the Block Tilting Problem

We test our algorithm with the block tilting task. The robot rotate an object about one of its edges on the table. The edge-to-face contact is sticking and approximated by two point contacts.

7.4 Results

We test the block tilting task with different object weights and sizes. Our method shows robustness under modeling uncertainty and the capability of executing tasks impossible for other kind of fingers. The video of our experiments is provided as a multimedia attachment.

Method Evaluation We evaluate our method with the object position control. The task of tilting a block to 60 degree is performed with a light wooden block (about 108g) and a heavy metal block (about 1kg) for multiple times.

First, the series of photos for two experiments are shown in Figure 2. In the last three pictures for both blocks, the robot allowed for a large suction cup

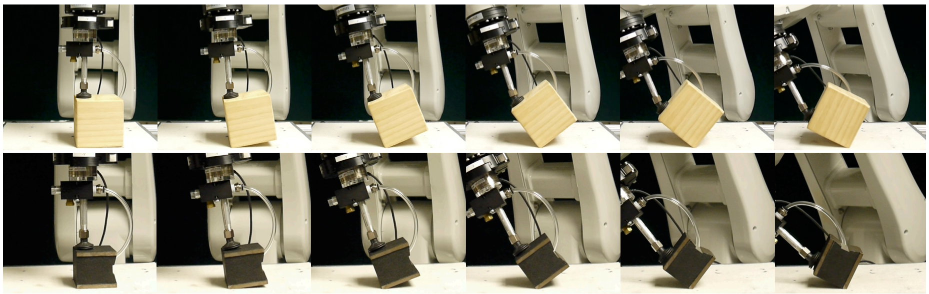
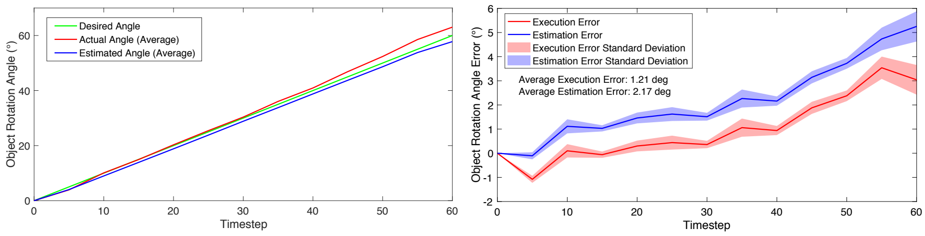


Fig. 2: The series of photos for the robot tilting a wooden block (the first row) and a metal block (the second row)



(a) (b)

Fig. 3: Angle measurement data of state estimation and control for the wooden block in 5 runs. (a) The average of actual angles, the state estimated angles and desired angles at each time step. (b) The average error of actual angles to the state estimated angles (estimation error) and to desired angles (execution error) at each time step

deformation to provide torsional torque to balance the object while minimizing robot motion. Moreover, since the metal block is heavy and short, it requires a very large force to tilt the object by pressing. To reduce contact forces, the robot leverages the suction force: instead of 'pressing', the suction cup deforms to provide torsional torque towards the desired rotational direction, as shown in the second picture for the metal block in Figure 2. The suction cup cannot pick up the heavy block due to vacuum force limitation, but with our approach, reorientation of the object can be achieved with support from external contacts.

Next, to evaluate our state estimation and control accuracy, we measured the actual tilting angles. The actual final angles has an average of 62.19° and a standard deviation of 2.11°, for metal block tilting in 10 runs. With the wooden block, the actual angle values were measured every 5 time steps in 5 runs. The trajectories of the angles and their errors are plotted in Figure 3. As the estimate in the previous time step is an input to the next, errors accumulate but still stay within an acceptable range. We also notice that the actual angles are almost always larger than estimated angles. We speculate this be a systematic error from inaccurate soft finger modeling at large rotation angles ($> 30°$), where collecting non-slipping data is hard. We believe that the performance can be improved with more accurate modeling.

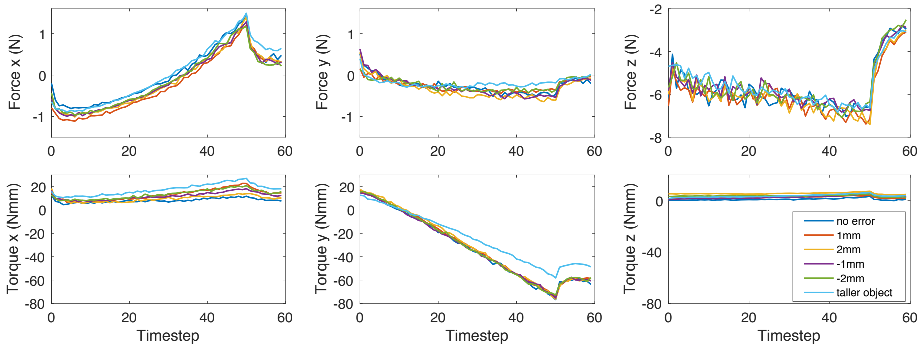


Fig. 4: Finger contact wrenches during block tilting under uncertainty. Each subplot shows the trajectories on one wrench axis. Legend on the lower-right corner applies for all subplots. '1mm' - '-2mm' stand for the environment calibration error on z-axis

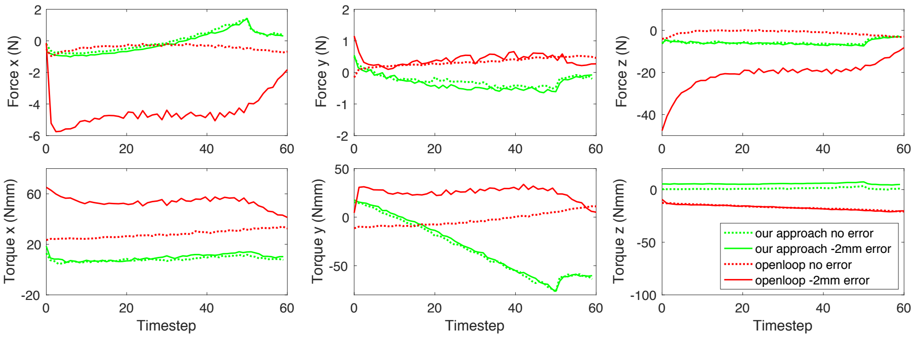


Fig. 5: Contact wrench trajectories of our approach and an open loop optimized trajectory execution. Legend on the lower-right corner applies for all subplots

Then, the robustness of our approach is tested with calibration errors: environment errors (+2 to -2mm offset on the z-axis of the world frame origin) and object uncertainty (an 8mm thick foam pad glued on the block). Figure 4 shows that the actual contact wrenches do not vary a lot among errors. This advantage is more obvious when compared with optimized open-loop trajectory execution in Section 7.4. The final angles for all error added tests have an average of 63.36°, and a standard deviation of 0.86°.

Our approach also allows for various finger contact locations at shown in the video. As a comparison, through mechanical analysis a point finger without suction cannot perform counter-clockwise block tilting with the finger contact location on the right half of the object. Readers may notice some sliding external contacts. This can be fixed by increasing external contact normal force threshold.

Comparison with open loop trajectory optimization At last, we compare our approach with an offline open-loop trajectory optimization method.

We developed the open loop trajectory optimization method with soft fingers as a baseline. Given a desired object trajectory, the baseline method computes wrench trajectories for all contacts to optimize the robustness criteria developed in [34]. From the wrench trajectories, robot motion trajectory is computed using soft finger stiffness model. The robot executes offline computed motion trajectory in open loop. The offline computation time is about 1min in MATLAB. As comparison, our approach requires no offline computation but about 10ms online computation in python at each timestep.

For robustness, we test two methods with environment calibration errors: z-axis offset for the world frame origin. As shown in the video, for +1mm error, the object was lifted up in open loop execution. Given desired angle as 60°, the final object angles with our approach and with the open loop execution are 63° and 40° respectively. The contact wrenches with -2mm error are plotted in Figure 5. As shown in Figure 5, our approach is almost not influenced by the error, while the open loop execution experienced very large contact force with small error. Moreover, our method can plan for larger y-axis torques to provide the y-axis rotational motions of the object. But it is hard for the baseline method to come out such plans.

8 Conclusion

In this paper, we propose a state estimation and control framework that enables vacuum suction cups to perform manipulation tasks with external contacts. We formulate the state estimation and control both as optimization problems, where external contacts are considered as constraints. External contacts help to reduce estimation errors and to generate object motions. Our experiments show that this approach opens up new possibilities of using suction cups. For example, by using rotational compliance, the robot can perform tasks in a more confined workspace. Moreover, the robot can now use suction cups to reorient things it cannot pick up by combining compliance, vacuum force and external contacts. Our algorithm can also be extended to soft fingers.

For future work, we would like to explore the following aspects:

1) Add different finger contact models and contact modes. Our method allows for different finger contact models and modes using general linear constraints. Potential contact models to test includes patch contacts, soft finger contacts, etc. For soft finger contact modes, we can try rolling or sliding contacts.

2) Model soft fingers using vision or bend sensors. Possible solutions for more accurate soft finger modeling includes: a) Attach the suction cup to an object with a marker. Use vision to identify movable contact frames during calibration. b) Add a bend sensor on the suction cup, which reflects deformation directly.

3) Extend control modes to hybrid force velocity control. Using the hybrid force velocity control algorithm as an outer loop, our method might be able to tolerate larger uncertainty with properly chosen velocity controlled directions, and perform more robustly with specified force directions and magnitudes.

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