

# Adaptive Control for Pivoting with Visual and Tactile Feedback

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**Abstract**—In this work we present an adaptive control approach for pivoting, which is an in-hand manipulation maneuver that consists of rotating a grasped object to a desired orientation relative to the robot's hand. We perform pivoting by means of gravity, allowing the object to rotate between the fingers of a one degree of freedom gripper and controlling the gripping force to ensure that the object follows a reference trajectory and arrives at the desired angular position. We use a visual pose estimation system to track the pose of the object and force measurements from tactile sensors to control the gripping force. The adaptive controller employs an update law that accommodates for errors in the friction coefficient, which is one of the most common sources of uncertainty in manipulation. Our experiments confirm that the proposed adaptive controller successfully pivots a grasped object in the presence of uncertainty in the object's friction parameters.

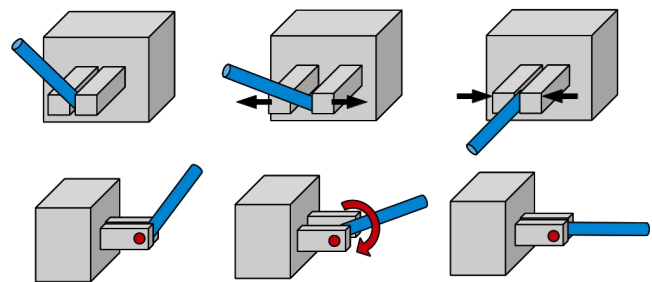
## I. INTRODUCTION

Humans are capable of in-hand manipulation, i.e., repositioning grasped objects in the hand, by sliding, rolling and/or pushing the objects through precisely coordinated motions of the fingers. This is possible among other reasons due to the high mechanical complexity of the human hand and because humans are able to simultaneously control the motion of the fingers with great precision. Replicating this *intrinsic dexterity* in robots is to some degree achievable by equipping robots with hands that are composed of multiple fingers and actuators. However, most robot platforms today have rather simple grippers with few degrees of freedom given that they are generally more robust, cost efficient, easy to control and also because they simplify grasp planning and execution. At first sight such grippers may not seem capable of performing regrasps by only actuating the fingers, raising the question of whether they are actually suitable for in-hand manipulation.

This apparent lack of dexterity can however be compensated by the use of *extrinsic dexterity*, i.e., by leveraging resources external to the robot such as external contacts, gravity and inertial forces that can enable the robot to perform meaningful manipulation tasks. Extrinsic dexterity essentially enables roboticists to trade off complexity in gripper hardware design and control with more clever and active use of the robot's environment through an effective combination of control, interactive perception and motion planning.

Numerous examples of how a robot can make effective use of extrinsic dexterity for in-hand manipulation have

been shown in the literature [1]–[4]. These can include e.g. pushing the grasped object against an external pusher to make the object slip in a controlled manner within the gripper. Other examples include accelerating the manipulator such that inertial forces drag the object to a specified location within the gripper, and allowing the object to slip within the robots hand due to the object's weight.



**Fig. 1** : Pivoting with gravity by controlling the gripping force exerted by a two finger pinch grasp. The top row shows how the robot opens and closes the gripper to control the object's rotational motion induced by gravity. The object rotates around a fixed axis of rotation connecting the two fingers as shown in the bottom row.

In this paper we address a specific regrasp action known as *pivoting*, in which the objective is to rotate a grasped object to a desired angular position relative to the robot's hand. We perform pivoting by using extrinsic dexterity as shown in Fig. 1, allowing the gravitational torque generated on the grasped object's center of mass to rotate the object, while using the gripping force of a 1 DOF parallel jaw gripper as a braking mechanism to control the object's trajectory.

One of the major challenges of pivoting as well as other in-hand manipulation actions is how to account for imperfect knowledge of the grasped object's friction parameters. This is a common situation given that a robot may for instance grasp novel objects and tools relevant for a task. Furthermore, it may be difficult in practice to accurately measure some of the friction parameters given their dependence on e.g. contact geometry and pressure distribution.

This motivates the main contribution of our work, which is performing pivoting with a closed loop adaptive controller that accounts for imprecise estimates of the torsional friction parameters. The control scheme uses visual tracking of the object and force measurements from tactile sensors at the fingertips. Comparing to our previous work on closed loop pivoting [5] we do not rely on assumptions such as saturation

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of the control input and achieve enhanced tracking control performance as a result of the following improvements:

- Improved torsional friction modeling using results from previous studies on soft finger mechanics.
- Incorporation of tactile sensing for control of the gripping force.
- Online adaptation of the torsional friction coefficient. This allows us to successfully pivot the object given errors in the initial estimate of this coefficient.

This paper is organized as follows: Section II contains the related work, Section III contains the contact and dynamics model of the system, in Section IV we formulate the adaptive control law and Section V shows our experimental results. Finally, we present our conclusions and planned future work in Section VI.

## II. RELATED WORK

In-hand manipulation, i.e., repositioning an object in a robot's hand, has been a long standing research topic in robotics where several aspects of modeling, motion planning and control have been addressed. Early studies by Tournasoud et. al. showed how regrasping can be accomplished by repeatedly picking and placing an object on a surface from different grasping positions [6]. This procedure can however be time consuming and the number of possible regrasps is limited by the number of stable poses in which the object can be placed on the surface. Researchers thus quickly realized the need for more advanced dexterous manipulation skills. One proposed solution was to control the motion of the fingers of a robot hand to achieve a desired repositioning of a grasped object via e.g. rolling, sliding and finger gaiting [7], [8].

On the other hand, other studies promoted the idea of leveraging the robot's environment to facilitate in-hand manipulation. Brock et. al. were among the first to propose the idea of augmenting a robot's dexterity through controlled slip of a grasped object due to externally applied forces [9]. Daffle et. al. defined the concept of *extrinsic dexterity* and showed how a robot manipulator with a rather simple gripper can still perform meaningful in-hand manipulation by using a diverse set of primitive actions which take advantage of resources external to the robot such as gravity and contact with the environment [1]. This idea of leveraging the robot's environment has also been used e.g. in the context of grasping [10].

These works have highlighted the importance of contact and friction modeling as central components to dexterous manipulation. Goyal developed the concept of limit surfaces which describe both the bounds on the wrenches that can be applied on a grasped object slippage occurs and the sliding motion of the object once slippage takes place [11]. Howe et. al. further developed these ideas and proposed computationally tractable approximations of limit surfaces in the context of manipulation planning and control [12].

Friction modeling has also been studied for the design of friction identification and compensation schemes in mechanical systems [13], [14]. However, the control techniques

developed in these studies cannot be directly applied to our work since they consider friction as an additive disturbance, while in our case friction represents a control input. In this sense, our controller for pivoting holds some resemblance to antilock braking systems (ABS) in vehicles, however, the objective of these works is to maximize the traction force between the tire and the road [15].

Tactile sensing has also played an instrumental role in robotic manipulation, motivated in part by the essential role that it plays in even the most basic pick-and-place manipulation tasks carried out by humans [16]. Many studies have addressed the problem of slippage detection through tactile sensing, however, the main focus has been on grasp control for slippage prevention rather than controlled slip [17], [18]. Some works have also proposed online estimation of friction parameters [18], but have focused on friction forces rather than torsional friction as in our case.

Some more recent works have studied mechanical modeling and design as well as motion planning aspects of in-hand manipulation with extrinsic dexterity. Daffle et. al. studied the mechanics of prehensile pushing, analyzing the effect of pushers with different contact geometries on the slippage of a grasped object [2]. Daffle et. al. also designed fingertips which allow a robot to easily transition between a fixed grasp on an object and a pinch grasp in which the object can freely rotate [19].

Shi et. al. proposed a motion planning framework that determines the required manipulator accelerations that achieve a desired sliding motion of an object relative to the robot's hand [4]. This work addresses a scenario similar to ours, namely an object held by a two-finger pinch grasp, and has the advantage of reconfiguring 3 degrees of freedom of the object's pose. Although the simulations in the study validate the proposed approach, the experiments do not match the expected performance which the authors attribute in part to lack of feedback control and tactile sensing.

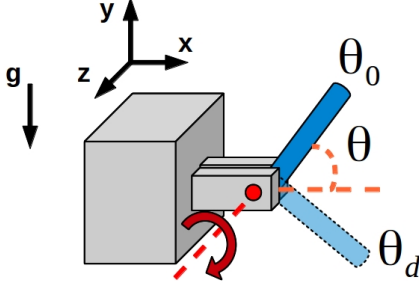
Also closely related to our work is the open-loop pivoting framework proposed by Holladay et. al. [3]. In this work the robot first plans a pinch grasp on an object resting on a surface and subsequently lifts it following a precomputed motion plan. The object can only be rotated between a discrete set of stable poses given that the pivoting is done open loop without online tracking of the object's pose and without control of the gripping force.

In contrast to these recent works [3], [4] which employ open-loop motion planning strategies we focus on using adaptive feedback control with online vision tracking and tactile sensing for controlling the gripping force.

## III. MODELING

In this section we specify the friction and dynamics models that describe the pivoting action. Let us denote with  $\theta$  the angular position of the object relative to the gripper as shown in Fig. 2. The objective of pivoting is to rotate a grasped object from an initial angular position  $\theta_0$  to a desired orientation  $\theta_d$ . We control the rotational motion of the object by varying the torsional friction  $\tau_f$  generated by

the fingertips, which we control with the gripping force. We assume that the gripper has one degree of freedom with two soft hemispherical fingertips and that the object rotates around a fixed axis of rotation connecting the fingertips.



**Fig. 2 :** Modeling of the pivoting task. The gravity vector is denoted by  $\mathbf{g}$ ,  $\theta$  is the relative orientation between the object and the gripper and  $\theta_0, \theta_d$  are the initial and desired angular positions respectively.

We model the torsional friction interaction in pivoting based on previous studies on mechanical modeling of soft fingers. These models allow us to establish a relationship between the torsional friction at the fingertips and their applied gripping force, which we will then use in the control design. Furthermore, we assume that the gripper is in a fixed position, such that the motion of the object is solely determined by the gravitational torque on its center and the torsional friction.

#### A. Soft finger contact model

Robotic fingertip contact models have been traditionally classified in three categories according to their friction properties as hard-finger contacts without friction, hard-finger contacts with friction and soft finger contacts [20], [21]. The soft finger contact model assumes that the finger can exert friction forces tangential to the contact surface as well as torsional friction around the direction normal to the contact surface. Furthermore, there is a nonlinear relationship between the maximum force and torque that can be exerted on an object held in a soft finger grasp until slippage of the object occurs [11], [12], [17]. This boundary is known as a limit surface and can be approximated by an ellipsoid [4]

$$\mathbf{f}^\top \mathbf{A} \mathbf{f} = 1 \quad (1)$$

where  $\mathbf{f} = [f_x, f_y, \tau_z]$  represents the friction wrench applied at the contact with  $(f_x, f_y)$  being the tangential friction force components and  $\tau_z$  the torsional friction around the normal. Assuming isotropic friction the matrix  $\mathbf{A} \in \mathbb{R}^{3 \times 3}$  becomes a diagonal matrix whose elements are the maximum friction force and moment

$$\mathbf{A} = \text{diag}(f_{t,max}^{-2}, f_{t,max}^{-2}, \tau_{z,max}^{-2}) \quad (2)$$

where the maximum tangential force  $f_{t,max}$  can be modeled as Coulomb friction

$$f_{t,max} = \mu f_n \quad (3)$$

where  $\mu$  is the friction coefficient and  $f_n$  the force applied in the normal direction of the contact. On the other hand, the maximum torsional friction  $\tau_{z,max}$  before a grasped object rotates exhibits a more complex behavior that depends on the geometry of the contact area and the pressure distribution. We assume that the grasped object has a locally smooth surface at the contact locations, such that the contact patches are circular. The maximum torsional friction thus assumes a Coulomb-like model [12], [22]

$$\tau_{z,max} = a\beta\mu f_n \quad (4)$$

where  $a$  is the radius of the contact surface and the constant  $\beta$  depends on the local pressure distribution. This parameter may be for example  $\beta = 0.589$  in the case of a hertzian pressure distribution or  $\beta = 0.667$  in the case of a uniform distribution [12].

When the external wrenches applied on an object are contained within the ellipsoid limit surface (i.e.  $\mathbf{f}_{ext}^\top \mathbf{A} \mathbf{f}_{ext} \leq 1$ ), the object remains static. Once the object starts sliding, the limit surface model assumes that the friction wrenches remain on the limit surface and that the sliding velocity is perpendicular to the ellipsoid. In our case we assume that the object is grasped sufficiently far from its center of mass so that the gravitational torque is large compared to the object's weight. Hence, the translational motion of the object is negligible with respect to its rotational motion and the torsional sliding friction  $\tau_f$  is approximately equal to  $\tau_{z,max}$  from Eq. (4)

$$\tau_f = a\beta\mu f_n \quad (5)$$

It is important to note that the limit surface model ignores potential velocity-dependent sliding friction phenomena such as the Stribeck effect and viscous friction. Despite this limitation, similar to the approach taken in previous works [4] we will assume in our controller design that the model described by Eq. (5) captures the most representative components of the torsional sliding friction during the pivoting task, namely the dependence on the applied gripping force.

In order to complete our model we also require a deformation model that relates the normal force  $f_n$  and contact radius  $a$ . Xydas et. al. have shown that hemispherical fingertips follow a power-law deformation model [22]

$$a = c f_n^\gamma \quad (6)$$

where  $c$  is a constant and the exponent  $\gamma$  has a value between 0 and 1/3 depending on the fingertip material. Substituting (6) in (5) we obtain the following torsional friction model

$$\tau_f = \mu_{tors} f_n^{1+\gamma} \quad (7)$$

where we denote  $\mu_{tors} = c\beta\mu$  as the torsional friction coefficient.

#### B. Pivoting dynamics

Given our assumption that the gripper is in a static position, the rotational dynamics of the object during slippage is determined by the gravitational torque and the torsional

friction of the fingers. The rotational dynamics of the object around the  $z$  axis shown in Fig. 2 is given by

$$I\ddot{\theta} = \tau_g + \tau_{f_1} + \tau_{f_2} \quad (8)$$

where  $I$  is the moment of inertia of the object around the axis of rotation at the fingertips,  $\ddot{\theta}$  the angular acceleration of the object,  $\tau_g$  the gravitational torque exerted on the object's center of mass and  $\tau_{f_i}$  with  $i \in [1, 2]$  the torsional friction generated at the contacts between the grasped object and each of the fingertips.

We assume that the grasp is symmetric such that the normal forces  $f_{n_i}$  exerted by each finger on the object are equal and that both fingertips have the same deformation and friction parameters such that  $\tau_{f_1} = \tau_{f_2}$ . If gravity is aligned with the  $y$  axis as shown in Fig. 2, i.e.  $\mathbf{g} = g\mathbf{y}$ , and by using the torsional friction model (7) we then obtain the following nonlinear rotational dynamics

$$I\ddot{\theta} = -mgl_{cm} \cos \theta + 2\mu_{tors} f_n^{1+\gamma} \quad (9)$$

where  $m$  is the object's mass,  $g$  gravity and  $l_{cm}$  the distance between the axis of rotation and the object's center of mass.

#### IV. CONTROL DESIGN

Our control design is guided by the following observations and assumptions

- 1) The inertial parameters ( $I, m, l_{cm}$ ) of the object are known but we allow some uncertainty in the torsional friction coefficient  $\mu_{tors}$ . The inertial parameters can be obtained by using e.g. wrist-mounted force-torque sensors prior to the pivoting task [23]. The torsional friction coefficient  $\mu_{tors}$  is however more difficult to measure in practice given its dependence on contact geometry and pressure distribution. This justifies the use of an adaptive controller with adaptation on  $\mu_{tors}$ .
- 2) The visual model of the object is known and the angular position  $\theta$  of the object is tracked by a vision system.
- 3) The normal forces  $f_n$  exerted by the fingers are measured via tactile sensors.
- 4) The gripper is oriented such that the gravitational torque can rotate object towards the desired reference, i.e.  $\text{sgn}(\tau_g) = \text{sgn}(\theta_d - \theta_0)$ .
- 5) The exponent  $\gamma$  from the soft finger deformation model (6) is known. This parameter depends on the fingertip material and can be estimated offline by using either (6) or (7).
- 6) The angular position  $\theta$  of the object must not overshoot past the reference angle  $\theta_d$  since we perform passive pivoting. The manipulator would otherwise have to rotate the gripper to perform passive pivoting again, or we would need to generate angular momentum on the object by accelerating the manipulator.
- 7) The object is initially at rest and in a secure grasp.

Following assumptions 2) and 3) we decompose our controller in two subcontrollers as shown in the diagram in Fig. 3. First, an adaptive controller takes as input the

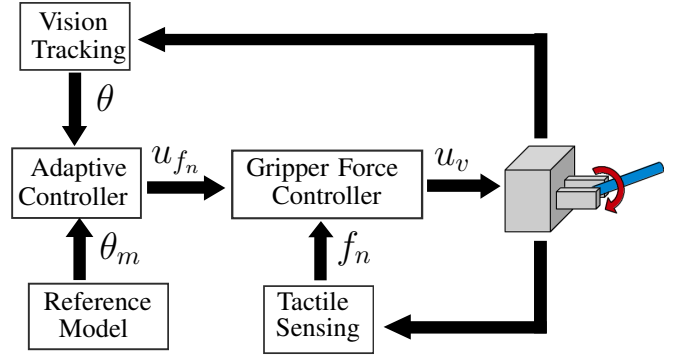


Fig. 3 : Overview of our proposed control scheme for pivoting.

angular position  $\theta$  measured by the vision system and the desired angular position  $\theta_m$  given by the reference model and computes a reference normal force  $u_{f_n}$  to control the trajectory of the object. This reference force  $u_{f_n}$  is then used together with tactile measurements of the normal force  $f_n$  by a PI controller to adjust the velocity of the fingers, minimizing the error between the measured and reference normal force.

##### A. Adaptive controller

We choose model reference adaptive control given that we aim to perform the pivoting task given errors in the torsional friction coefficient  $\mu_{tors}$ , which represents a parametric uncertainty in the nonlinear model (9).

Adaptive control performs tracking control by driving the system's state  $\mathbf{x}(t) = [\theta(t), \dot{\theta}(t)]^T$  along a state trajectory  $\mathbf{x}_m(t) = [\theta_m(t), \dot{\theta}_m(t)]^T$  defined by a reference model. This reference model is designed by the user and describes the ideal response that the system should follow, satisfying the control requirements and constraints of the task. In our case the angular position response should not overshoot, thus, we design the reference model as a critically damped second order system with unit DC gain with the following transfer function

$$H_m(p) = \frac{\theta_m}{\theta_{in}} = \frac{\lambda_0^2}{(p + \lambda_0)^2} \quad (10)$$

where the reference input  $\theta_{in}$  follows a trapezoidal velocity profile.

To formulate our controller, we rewrite the model from Eq. (8) considering the normal force as a control input  $u_{f_n}$

$$h\ddot{\theta} + b\tau_g = u_{f_n}^{1+\gamma} \quad (11)$$

where  $h = 0.5I\mu_{tors}^{-1}$  and  $b = 0.5\mu_{tors}^{-1}$ . We then define the following tracking control error  $s$

$$s = \dot{\tilde{\theta}} + \lambda\tilde{\theta} \quad (12)$$

where  $\tilde{\theta} = \theta - \theta_m$  and  $\dot{\tilde{\theta}} = \dot{\theta} - \dot{\theta}_m$  are the angular position and velocity errors respectively and  $\lambda$  is a constant.

We can then formulate the following standard adaptive control law [24]

$$u_{f_n}^{1+\gamma} = \hat{h}\ddot{\theta}_r - k_s s + \hat{b}\tau_g \quad (13)$$

The control law is composed of a velocity error and feedforward acceleration term  $\hat{h}\ddot{\theta}_r$ , a tracking error term  $k_s s$ , and a nonlinear gravity compensation term  $\hat{b}\tau_g$ . The reference angular acceleration  $\ddot{\theta}_r$  is given by  $\ddot{\theta}_r = \ddot{\theta}_m - \lambda\dot{\theta}$ ,  $k_s$  is a positive tracking control gain and  $\hat{h}, \hat{b}$  are adaptive estimates of  $h$  and  $b$  given by

$$\dot{\hat{h}} = -\alpha_h s \ddot{\theta}_r \quad (14a)$$

$$\dot{\hat{b}} = -\alpha_b s \tau_g \quad (14b)$$

where  $\alpha_h, \alpha_b$  are positive adaptation gains. It is important to note that the online estimates (14a), (14b) are not guaranteed to converge to the correct values unless persistent excitation conditions are met. We do not consider this a major limitation since the scope of our work is to perform the pivoting task and not accurate estimation of the friction parameters. The control scheme does however guarantee convergence of the tracking error  $s$  which implies that the object pivots to the desired orientation.

### B. Gripper force controller

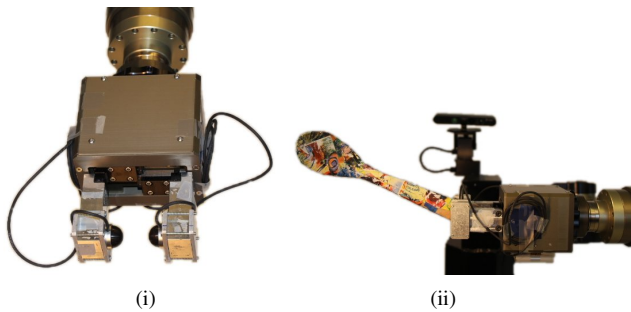
We regulate the normal force  $f_n$  by opening and closing the fingers with a PI controller

$$u_v = k_p \tilde{f}_n + k_i \int_0^t \tilde{f}_n dt \quad (15)$$

where  $u_v$  is the velocity set point commanded to the gripper,  $k_p, k_i$  are the controller gains and  $\tilde{f}_n = f_n - u_{f_n}$  is the error between the measured normal force  $f_n$  and the normal force set point  $u_{f_n}$  from the adaptive control law of Eq. (13). The controller is tuned such that  $f_n \rightarrow u_{f_n}$ .

## V. EXPERIMENTAL EVALUATION

We evaluated our proposed adaptive controller on a robot platform equipped with a 1 DOF 2-finger parallel gripper with Optoforce<sup>1</sup> tactile sensors and an RGBD camera as shown in Fig. 4. We track the object's pose throughout the experiments using *Simtrack*, a model-based vision tracking system that generates realtime pose estimates at 30 Hz [25]. The control loop operates also at 30 Hz.



**Fig. 4** : Robot platform with parallel gripper and Optoforce tactile sensors at the fingertips used in our experimental evaluation.

<sup>1</sup>www.optoforce.com

The Optoforce tactile sensors provide 3-axis force measurements at 100 Hz, and we chose them for these experiments given their low cost, robustness and suitability for force control. The sensors operate based on an optical principle providing high resolution force measurements of 0.03N with noise levels of approximately 0.01N, which are not commonly available from other types of tactile sensors.

In our experiments we grasp an object whose inertial and frictional parameters are given in Table I. Furthermore, Table II shows the controller gains and parameters used in the adaptive control law (13) and the PI gripper force controller (15). We kept the control gains fixed throughout the experiments.

$I[\text{kg} * \text{cm}^2]$	10.64
$m [\text{g}]$	48.5
$l_{cm} [\text{cm}]$	12.22
$\mu$	0.47
$\mu_{tors}$	$0.643 \times 10^{-3}$

**TABLE I** : Inertial and frictional parameters of the grasped object.

$k_s$	23.0
$\lambda$	10.0
$\gamma$	0.1849
$k_p$	$5.0 \times 10^{-4}$
$k_i$	$2.0 \times 10^{-5}$

**TABLE II** : Controller gains and parameters used throughout the experiments.

We obtained the torsional friction coefficient  $\mu_{tors}$  and the power-law exponent  $\gamma$  using Eq. (5) through measurements of the torsional friction  $\tau_f$  provided by the force/torque sensor in our manipulator's wrist and tactile measurements of the normal force  $f_n$ . However, the hardware limitations of our system made it difficult to accurately estimate these parameters: the torsional friction measurements from the force/torque sensor had a low signal to noise ratio and were also affected by gravity compensation errors, which generated significant errors in the estimated  $\mu_{tors}$ . We tuned this parameter by running the controller with different values of the friction coefficient as will be explained further on.

To obtain the control gains we first tuned the gripper force controller gains ( $k_p, k_i$ ) following standard practice for PI controller tuning. We then tuned the tracking control gain  $k_s$  by first deactivating the estimators, i.e. setting  $\alpha_h = \alpha_b = 0$  in Eq. (14) and using the ground truth values of the object's inertial and friction parameters in the controller. An excessive tracking gain  $k_s$  caused the object to stop repeatedly along the trajectory given that it would enter the stiction regime. On the other hand, a low  $k_s$  tended to generate large overshoots in the angular position  $\theta$  of the object with respect to the reference trajectory. We chose  $\lambda = 10.0$  for the tracking control error (12) in order to give a higher relative weight to



position tracking errors rather than velocity tracking errors given the higher quality of pose estimates provided by our vision tracker with respect to the angular velocity estimates. We designed the reference trajectory slow enough to avoid motion blur that would deteriorate the vision tracker's performance, yet fast enough to avoid stiction effects.

We evaluated our controller both under errors in the initial estimate of the torsional friction coefficient  $\mu_{tors}$  and when modifying the frictional properties of the material in contact with the fingertips. We thus performed the following set of experiments:

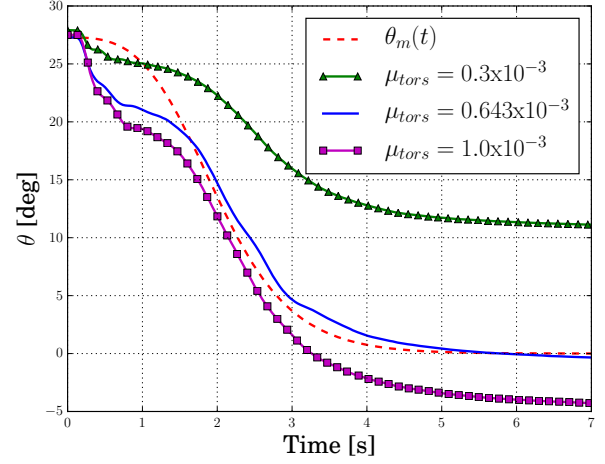
- **Effect of initial estimate of  $\mu_{tors}$  without adaptation.** We deactivate the adaptive estimators from Eq. (14), essentially transforming our controller in a feedback linearizing controller. We then show the controller's behavior assuming different values of the torsional friction coefficient  $\mu_{tors}$  in the control law (13).
- **Effect of initial estimate of  $\mu_{tors}$  with adaptation.** We repeat the previous set of experiments and show how adaptation is critical to accomplish the pivoting task despite errors in the initial estimate of  $\mu_{tors}$ .
- **Change of object frictional properties.** We further examine the adaptive controller's performance by using the same test object as in the previous experiments but changing the material at the point of contact with the fingertips, modifying thus the friction coefficient. We show that although there is an evident reduction in tracking control performance, the object still pivots to the desired position.

#### A. Effect of initial estimate of $\mu_{tors}$ without adaptation

In this set of experiments we deactivated the estimators by setting  $\alpha_h = \alpha_b = 0.0$  in the adaptation law (14) and executed the controller with 3 different values of the torsional friction coefficient  $\mu_{tors}$  in the control law (13). The reference trajectory  $\theta_m(t)$  from the reference model and the angular position  $\theta(t)$  of the object relative to the gripper for each case are shown in Fig. 5.

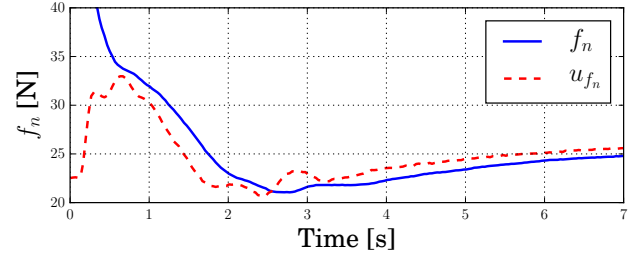
As mentioned previously, this experiment allowed us to adjust the approximate torsional friction coefficient we obtained using the wrist-mounted force-torque sensor. In our experimental trials the controller achieved the best tracking performance with  $\mu_{tors} = 0.643 \times 10^{-3}$ . Furthermore, the object stopped prematurely before reaching the goal angular position when the coefficient was below this optimal value, for example with  $\mu_{tors} = 0.3 \times 10^{-3}$  as shown in Fig. 5. This happens because a lower  $\mu_{tors}$  magnifies the nonlinear gravity compensation term  $b\tau_g$  in the control law (13), causing the controller to exert excessive gripping force. Analogously, an overestimated torsional friction coefficient, such as  $\mu_{tors} = 1.0 \times 10^{-3}$ , reduces the gravity compensation term and causes the object to slip past the desired angular position. This experiment clearly illustrates how errors in  $\mu_{tors}$  affect the control performance and justifies the use of adaptive control in our approach.

Fig. 6 shows the normal force input  $u_{f_n}$  of the adaptive controller, as well as the normal force measured by the

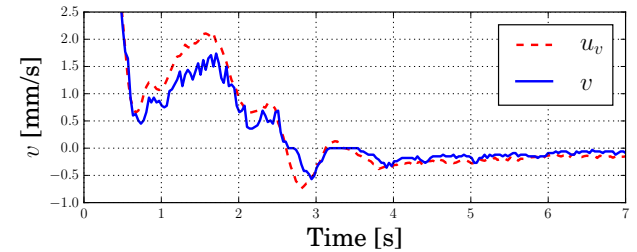


**Fig. 5 :** Reference angular position  $\theta_m$  and angular position  $\theta$  of the object under different values of  $\mu_{tors}$  in the control law without adaptation.

tactile sensor  $f_n$  when  $\mu_{tors} = 0.643 \times 10^{-3}$ . The figure shows that there is a force control error, which can be explained in part by the tracking errors in the gripper's internal velocity controller as evidenced in Fig. 7 which shows differences between the commanded gripper velocity  $u_v$  and the gripper's velocity  $v$  measured by encoder feedback. This occurs in practice because the internal controller's tracking performance degrades at low velocities. We could reduce part of the force control errors by using a more aggressive PI force controller, but in practice this caused the object to enter the stiction regime and lag behind the reference trajectory.



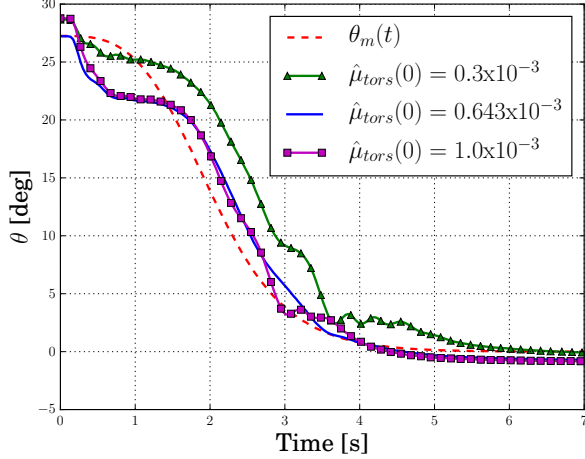
**Fig. 6 :** Gripping force control input  $u_{f_n}$  and measured normal force  $f_n$  with  $\mu_{tors} = 0.643 \times 10^{-3}$ .



**Fig. 7 :** Gripper velocity set point  $u_v$  and gripper velocity  $v$  with  $\mu_{tors} = 0.643 \times 10^{-3}$ .

### B. Effect of initial estimate of $\mu_{tors}$ with adaptation

We tuned the adaptation gains from (14a) and (14b) to  $\alpha_h = 1.5$  and  $\alpha_b = 7.5 \times 10^3$  respectively and repeated the previous set of experiments to analyze the controller's performance when using the proposed update laws. Fig. 8 shows the object's angular position with different initial estimates of  $\mu_{tors}$ , while keeping the controller and adaptation gains fixed.



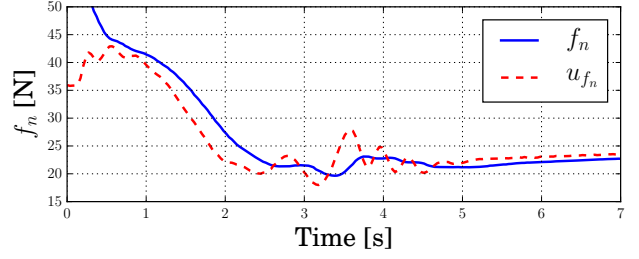
**Fig. 8 :** Reference angular position  $\theta_m$  and angular position  $\theta$  of the object under different initial estimates of  $\mu_{tors}$  when using the adaptive estimators.

We observe that the adaptive controller achieves the best performance when starting with the correct torsional friction coefficient estimate  $\hat{\mu}_{tors}(0) = 0.643 \times 10^{-3}$ . Furthermore, in contrast to the previous set of experiments, the controller manages to converge to the desired angular position  $\theta_d$  with both an underestimated ( $\hat{\mu}_{tors}(0) = 0.3 \times 10^{-3}$ ) and an overestimated ( $\hat{\mu}_{tors}(0) = 1.0 \times 10^{-3}$ ) coefficient. In all cases the steady state error was less than 1 degree.

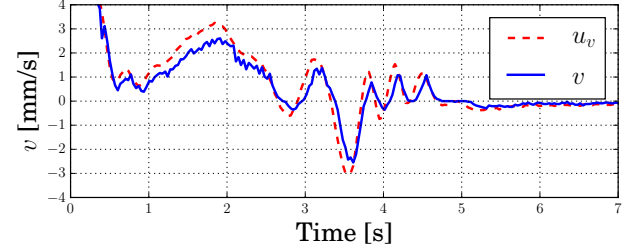
Fig. 9 and 10 show the control inputs to the system when  $\hat{\mu}_{tors}(0) = 0.3 \times 10^{-3}$ . Once again, there are force control errors. As previously mentioned, the adaptive estimates are not guaranteed to converge to the true values, and Fig. 11 confirms this. This figure shows the torsional friction coefficient estimate  $\hat{\mu}_{tors} = 0.5\hat{b}^{-1}$  which does not reach the ground truth value.

### C. Change of object frictional properties

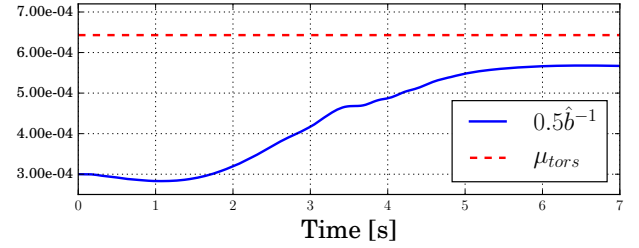
In this last set of experiments we substituted the manipulated object's material ( $\mu = 0.47$ ) with a lower friction material  $\mu = 0.37$  and a material with higher friction coefficient  $\mu = 1.08$ . Once again, we kept the controller and adaptation gains fixed. The experimental results are shown in Fig. 12 and Fig. 13. Although the adaptive controller shows inferior tracking performance when compared to the previous experiments, it still converges to the desired object orientation within acceptable steady state errors of 1.64 and 0.5 degrees respectively.



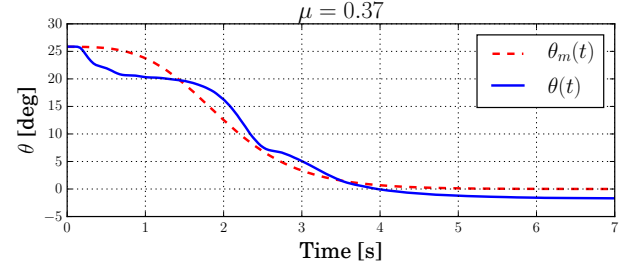
**Fig. 9 :** Gripping force control input  $u_{f_n}$  and measured normal force  $f_n$  when using adaptation and  $\hat{\mu}_{tors}(0) = 0.3 \times 10^{-3}$ .



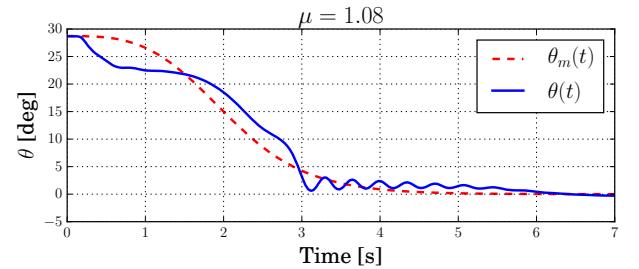
**Fig. 10 :** Gripper velocity set point  $u_v$  and gripper velocity  $v$  when using adaptation and  $\hat{\mu}_{tors}(0) = 0.3 \times 10^{-3}$ .



**Fig. 11 :** Adaptive estimate of the torsional friction coefficient  $\hat{\mu}_{tors} = 0.5\hat{b}^{-1}$ .



**Fig. 12 :** Angular position  $\theta$  of the object when using a new material with  $\mu = 0.37$ .



**Fig. 13 :** Angular position  $\theta$  of the object when using a new material with  $\mu = 1.08$ .

## VI. CONCLUSIONS AND FUTURE WORK

We have presented an adaptive control approach for pivoting with extrinsic dexterity by means of gravity and controlled slip. Given that wrongly estimated friction coefficients are a common source of error for in-hand manipulation, we designed an adaptive controller that accounts for errors in the torsional friction coefficient. In our controller we use visual tracking of the object's angular position and force measurements from high resolution and low noise tactile sensors. Our experimental results show how an incorrect torsional friction coefficient can have a negative impact in the performance of a feedback linearizing controller for pivoting, yet the proposed adaptation law compensates for this parametric error and manages to pivot the object successfully. Our approach complements recent works on in-hand manipulation with extrinsic dexterity since we make use of closed loop feedback control and tactile sensing.

One of the limitations of our work is that we perform passive pivoting by keeping the gripper static, which limits the range of possible regrasp unless we first rotate the gripper to reconfigure its alignment with gravity. We can extend the approach by accelerating the manipulator, reformulating the proposed adaptive controller to cope with disturbances generated by the inertial forces. We can also extend our approach to include prehensile pushing against external contacts, which opens the possibility to generate also translational displacements of the grasped object in the robot's hand.

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