Extrinsic in-hand manipulation with gravity

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Abstract*— Autonomous robots use tools for performing everyday tasks and they commonly require the tool to be placed in a certain pose with respect to the robot's hand in order for the grasp to be compatible with the task. Repositioning a tool within a robot's hand can be achieved via *intrinsic* in-hand manipulation, i.e., by coordinating the fingers' motion such that the tool moves to the desired configuration. If the robot has a limited number of DOF then it is more feasible to use *extrinsic* in-hand manipulation by using resources external to the robot. We propose a controller for extrinsic in-hand manipulation that repositions a tool in the robot's hand by using gravity. The tool is grasped via a pinch grasp so that we model the contact between the tool and the gripper as a passive joint, i.e. the grasp affords only rotational motions of the tool around a given axis of rotation. The robot modulates the grasping force in order to allow the tool to fall into the desired angular position following a specified trajectory. Given the nonlinearities and modeling uncertainties of the system we propose a sliding mode control law and show experimentally how the proposed controller achieves convergence while varying the inertial parameters of the tool.

I. Introduction

Robots often require tools to augment their capabilities and perform certain tasks. Before the robot performs the task, it must pick up and grasp the tool in a suitable manner that fulfills certain dynamic and/or kinematic requirements of the task. For example if the task, such as hammering, requires the robot to apply large forces with the tool in a given direction, then the robot must ensure that it applies enough grasping force and that the tool is correctly positioned in the robot's hand to avoid undesired displacements of the tool while executing the task. However, even if the robot plans correctly the grasp, once the robot picks the tool up from a table or a shelf the resulting grasp configuration will usually be different due to imprecise sensory feedback or uncertainties in the controllers. Moreover, the grasp configuration can change as the robot performs the task due to externally applied forces such as unplanned collisions with the environment.

The robot must then evaluate the state of the grasp. Either the grasp configuration is still acceptable for performing the task or the robot might need to readjust the grasping force or even reposition the tool with respect to the gripper. Repositioning the tool can be done e.g. by placing the tool or object on a fixed surface, releasing the tool and picking up the tool again from a different position [1]. On the other hand, if the robot's fingers have multiple degrees of freedom then it can coordinate the motion of the fingers such that the tool moves to the desired position, commonly referred to as *intrinsic* in-hand manipulation. On the other hand, if the robot hand has a rather simple kinematic structure, it is perhaps more feasible to employ an *extrinsic* in-hand manipulation strategy by using resources that are external to the robot embodiment [2]. The robot may for instance push the tool against an external object or it may loosen the grip so that the tool falls to a desired position due to gravity.

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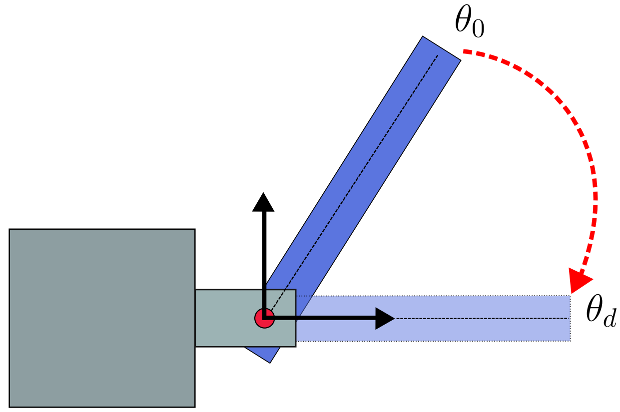

Fig. 1 : Extrinsic in-hand manipulation with gravity via a pinch grasp.

In this work we explore how a robot can control the grasping force it applies on a tool to perform extrinsic in-hand manipulation by means of gravity. We assume that the robot has already grasped the tool via a predefined pinch grasp, such that the motion of the object is constrained to one rotational degree of freedom as shown in Fig. 1. We thus model the contact between the robot gripper and the tool as a passive joint with friction and the control objective is to rotate the tool from an initial angular position to a desired angular position in the gripper reference frame by modulating the friction exerted at the contact, which we achieve by controlling the grasping force of the gripper. Due to the nonlinearities and modeling uncertainties of the system, we implement a sliding mode control law and show experimentally the robustness of the controller to parametric uncertainties.

II. Related Work

Early works on regrasping focused on pick-and-place operations where the robot would release an object on a surface and pick it up from a different position. For instance, Tournassoud *et al.* identified sets of stable grasps and placements of polyhedral objects on a table and combined these in a discrete sequence of pick and place actions, taking into account the kinematic constraints of the manipulator [1].

Works in the intrinsic in-hand manipulation literature have studied planning and control aspects when coordinating multiple degrees of freedom of multifingered hands to move the manipulated object along a specified trajectory. Cole *et al.* designed a control scheme which coordinates sliding motions of two planar fingers over an object assuming Coulomb sliding friction at the contacts [3]. Han *et al.* proposed an in-hand manipulation framework that combines finger rolling [4] and gaiting [5]. Hertkorn *et al.* formulated a planning framewok which also takes into consideration kinematic and dynamic constraints of the task [6]. Okamura *et al.* formulated a survey of different dexterous manipulation techniques that have been proposed in the literature, as well as a summary of the main kinematic, contact and dynamic models used in those techniques [7].

On the other hand, the work of Brock provides one of the earliest analysis of controlled slip and how it can be useful for dexterous extrinsic manipulation [8]. The author studied how to determine the possible directions of motion of a grasped object and the effect of grasping forces and externally applied forces on the motion of the object. This knowledge is then used by the robot to reposition a grasped object by controlling the slippage when it comes in contact with other objects in the environment.

Dafle *et al.* presented a strong case for the benefits of extrinsic in-hand manipulation [2]. Even though the robot used in the study is equipped with a rather simple gripper, the authors demonstrated that it is still physically possible to reposition the object in the hand of the robot by taking advantage of resources external to the robot's hand such as gravity, use of external objects for support and inertial forces due to the manipulator's acceleration. The authors show this by implementing a discrete set of preprogrammed manipulation actions and combining them via a graph. In contrast with [2], our work focuses on one specific manipulation scenario but instead of using discrete preprogrammed actions we design a continuous closed loop control law to move the tool to the target position.

Senoo *et al.* used high speed manipulators and vision systems to manipulate objects within the robot's hand [9], [10]. The authors demonstrated that the high speed feedback and control allow them to perform fine intrinsic and extrinsic in-hand manipulation. In [10] the authors also proposed in-hand manipulation via a passive joint. However, these approaches are custom tailored for specialized high-speed hardware while in our case we use standard commercially available hardware.

Kappler *et al.* developed a high level representation framework of pregrasping manipulation actions that enable a robot to slide objects on a tabletop to positions which are suitable for generating more robust grasps [11].

Given that our in-hand manipulation control scheme uses friction as the main source of actuation it is worth mentioning some of the works in the field of friction modeling and control. This topic has been extensively studied in the control community given the widespread presence of friction in different kinds of mechanical systems. Olsson *et al.* provide a detailed survey of friction models and friction compensation schemes [12]. De Wit *et al.* proposed the LuGre friction model and designed friction compensation control schemes for this model [13].

One of the main challenges when compensating friction in mechanical systems is to estimate the friction parameters that describe the friction model. To this end Feemster *et al.* proposed a couple of adaptive controllers for estimating the parameters [14]. Xie proposed an adaptive controller with sliding mode observer to estimate the friction parameters of a servo motor and perform position control with an unknown load [15].

One of the main differences between our work and the previous work on friction control comes from the fact that those previous studies were used mainly for friction compensation in servo motors or translation of objects on a surface. Working with robotic in-hand manipulation raises a number of challenges that we can enumerate as follows

1) The friction parameters of the servo motor or object are normally considered to be unknown but fixed. In the case of in-hand manipulation the friction and deformation properties of the tool can vary depending on e.g. the tool's material and the grasp position.
2) The friction control literature mainly deals with friction *compensation*. The general approach is to estimate the friction parameters and add a friction compensation term in the control signal while in our case we use the friction as *actuation* for our system, i.e. as a control input.
3) Manipulating objects in the robot's hand imposes some constraints on the control inputs of the system. In our case the fingers of the gripper can operate within a certain operating region, otherwise the object can fall out of the grasp.

The contribution of our work is the design of an extrinsic in-hand manipulation sliding control law for reorienting a tool by regulating the friction at the grasp. We show experimentally how the proposed sliding mode control law achieves convergence to the desired angular trajectory of the tool with robustness to changes in the inertial parameters of the system.

III. MODELING

A. System description and assumptions

In our in-hand manipulation controller we assume a 1 DOF parallel gripper with soft fingertips that generates a given pinch grasp on a tool as shown in Fig. 1 that affords only rotational motions around a fixed axis of rotation, which we assume is known a priori. The position of the tool in the robot's hand can thus be described by the angle $\theta(t)$ with respect to the horizontal axis. In our controller we also assume that the robot has already executed the initial pinch grasp on the tool.

The control objective is to change the angular position of the tool to a desired set point $\theta_d(t_f)$ following a specified trajectory $\theta_d(t)$. We assume that the manipulator is static and we only actuate the separation d of the fingers of the parallel gripper to control the grasping force applied on the tool, and hence the magnitude of the friction torque. We assume that the state of the tool $\mathbf{x}(t) = [\theta(t), \dot{\theta}(t)]^\top$ is observable via sensor measurements.

Furthermore, we assume that we operate the gripper in such a way that the tool only rotates and doesn't fall out of the robot's hand. For a given pinch grasp as one increases the separation d of the fingers the object will first experience rotational slippage and then a combination of rotational and translational slippage until it falls out of the robot's hand as depicted in Fig. 2.

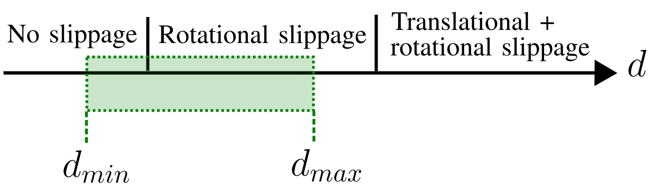

Fig. 2 : Slippage of an object grasped via a pinch grasp according to the separation d between the fingers of the parallel gripper. The interval $[d_{min}, d_{max}]$ denotes the desired region of operation for execution of in-hand manipulation with only rotational motion.

We assume that the bounds $[d_{min}, d_{max}]$ are given beforehand, where d_{min} is a lower bound designed to avoid damages to the tool and/or gripper and to ensure that the friction torque is large enough to stop the object at the desired position $\theta_d(t_f)$, and d_{max} is set small enough to allow some safety margin and avoid translational motions of the tool but large enough to ensure that the gravitational torque can overcome the stiction force.

B. Sliding friction model

Our proposed control scheme uses the sliding friction torque at the contact between the tool and the gripper to control the rotational motion of the tool.

We model the friction at the axis of rotation τ_f as Coulomb and viscous friction:

$$\tau_f(f_n, \dot{\theta}) = -\mu \operatorname{sgn}(\dot{\theta}) f_n - \sigma\dot{\theta} \tag{1}$$

where μ is the Coulomb sliding friction coefficient, f_n the normal force applied by the fingers of the gripper, $\dot{\theta}$ the angular velocity of the tool, $\operatorname{sgn}(\cdot)$ is the sign function and σ the viscous friction coefficient. From Eq. (1) we obtain a linear relation between the applied normal force and the resulting friction torque.

C. Deformation model

In principle the robot can control the friction torque described in Eq. (1) if measurements of the normal force f_n are available e.g. via tactile sensors.

However, we assume that such hardware capabilities are not available in our system and we control the normal force instead via the separation of the fingers assuming a linear deformation model

$$f_n(x) = k(x - x_0) \tag{2}$$

where k is the stiffness of the fingers, x_0 is the position of zero deformation at which the fingers initiate contact with the tool and x is the position of the fingers. Replacing $x = -d$ and $-kx_0 = f_0$, the deformation model (2) can be rewritten as a function of the finger separation d

$$f_n(d) = f_0 - kd \tag{3}$$

D. Dynamic model

Since we assume that the tool moves along one rotational degree of freedom, it suffices to analyze the rotational dynamics of the system which is given by

$$I\ddot{\theta} = \tau_f + \tau_g \tag{4}$$

where I is the tool's moment of inertia with respect to the rotation axis, $\dot{\theta}$ is the tool's angular acceleration, τ_f the torsional friction generated at the contact between the tool and the gripper and τ_g is the torque generated by gravitational pull on the tool's center of mass.

Substituting the friction and deformation models (1)-(3) into (4) and adding the expression for the gravity induced torque we obtain the following dynamic model

$$I\ddot{\theta} = -mgl\cos\theta - \mu \operatorname{sgn}(\dot{\theta})(f_0 - kd) - \sigma\dot{\theta} \tag{5}$$

where m is the tool's mass, l the distance from the axis of rotation to the tool's center of mass and g the gravity.

IV. Sliding mode control design

To design a sliding model control law we rewrite the dynamic model described by Eq. (5) as

$$\ddot{\theta} = f(\theta, \dot{\theta}) + b(\dot{\theta})u_d \tag{6}$$

where we denote u_d the gripper position control signal, i.e., the separation between the fingers of the gripper commanded by the controller. $f(\theta, \dot{\theta})$, $b(\dot{\theta})$ are given by

$$f(\theta, \dot{\theta}) = -\frac{mgl\cos(\theta)}{I} - \frac{\sigma\dot{\theta}}{I} - \frac{\mu f_0 \operatorname{sgn}(\dot{\theta})}{I} \tag{7a}$$

$$b(\dot{\theta}) = \frac{\mu \operatorname{sgn}(\dot{\theta})k}{I} \tag{7b}$$

The robot can determine the value of $\operatorname{sgn}(\dot{\theta})$ given the initial orientation of the tool with respect to gravity so that Eq. (7a) and (7b) become continuous functions of the state $\mathbf{x}(t) = [\theta(t), \dot{\theta}(t)]^\top$.

It is important to note the modeling uncertainties in Eq. (6). Even though the mass and center of mass can be estimated online by the robot just before running the controller by using a force-torque sensor, this estimate is subject to measurement errors arising from e.g. sensor noise. The moment of inertia and the friction and deformation model parameters are in general more difficult to estimate and require some form of pre-manipulation of the tool. Furthermore, in our formulation we have used a simplified sliding friction model which ignores phenomena such as stiction, the Stribeck effect, hysteresis and stick-slip motion [13]. These observations make sliding mode control a natural choice since it is a robust control law when confronted with modeling imprecisions [16].

For the control law we define the first order sliding surface $s(t)$

$$s(t) = \dot{\tilde{\theta}}(t) + \lambda\tilde{\theta}(t) \tag{8}$$

where $\tilde{\theta}(t) = \theta(t) - \theta_d(t)$ and $\dot{\tilde{\theta}}(t) = \dot{\theta}(t) - \dot{\theta}_d(t)$ are the angle and angular velocity errors respectively with respect to a desired state trajectory and the control bandwidth λ is a positive constant. We design the reference trajectory $\mathbf{x}_d(t) = [\theta_d(t), \dot{\theta}_d(t)]^\top$ as the output of a second order critically damped system with unit DC gain with a trapezoidal angular velocity profile as input.

We can then formulate a standard sliding mode control law for the gripper position can then be formulated as follows [16]

$$u_d(t) = \hat{b}^{-1}\left(\hat{u}_d(t) - k_s \mathrm{sat}\left(\frac{s(t)}{\phi}\right)\right) \tag{9}$$

where $\hat{b}$ is an estimate of b in Eq. (7b) given the best available knowledge of the parameters, k_s is a positive switching control gain, ϕ is a constant parameter describing the boundary layer of the control signal whose purpose is to smoothen the switching behavior of the control signal given by the saturation function

$$\mathrm{sat}(z) = \begin{cases} z & \text{if } |z| \leq 1 \\ \mathrm{sgn}(z) & \text{otherwise} \end{cases} \tag{10}$$

The nominal control signal $\hat{u}_d(t)$ is designed such that the dynamics of the sliding surface becomes $\dot{s} = 0$ assuming perfect knowledge of the system parameters. This yields

$$\hat{u}_d = -\hat{f} + \ddot{\theta}_d - \lambda\dot{\tilde{\theta}} \tag{11}$$

where we have dropped the time argument (t) for notational convenience. In this expression $\hat{f}$ is an approximation of f given approximate estimates of the inertial, friction and deformation parameters in Eq. (7a).

In order to implement the position based control law (9 in our system we couple an additional proportional velocity control law for the gripper

$$u_v = -k_v\tilde{d} \tag{12}$$

where $\tilde{d} = d - u_d$ is the gripper position error, k_v a positive proportional control gain and u_v is the velocity that we command to the gripper.

V. Experimental evaluation

We implement the sliding controller proposed in section IV on the 2-finger parallel gripper shown in Fig. 3. The gripper is equipped with semispherical rubber fingertips which allows us to execute pinch grasps on the tool and control the grasping force due to the deformation of the rubber.

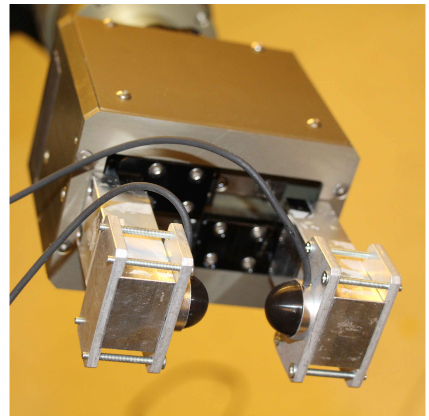

Fig. 3 : Parallel gripper with soft semispherical fingertips used in the experiments.

We use a model-based visual tracking system to track the angular position $\theta(t)$ of the tool together with a standard 30fps RGB-D camera [17]. We then feed this signal to a Kalman filter to obtain estimates of the angular velocity $\dot{\theta}(t)$.

We saturate the gripper velocity command $u_v(t)$ in order to stay within the position bounds $[d_{min}, d_{max}]$ mentioned in section III-A to avoid damage to the gripper and tool and to avoid translational slippage.

Experiment	I[kg $*$ cm^2]	m [g]
1	10.64	52.83
2	14.27	68.50
3	17.90	84.17

TABLE I : Inertial parameters (moment of inertia and mass) of the tool used in experiments.

I[kg $*$ cm^2]	30
m [g]	100
l [cm]	12
μ	0.05
σ	0.2
f_0 [N]	175.0
k [N/m]	3871.0
k_s	600.0
k_v	4.0

TABLE II : Sliding mode controller parameters and gains.

We executed three experiments where we varied the inertial characteristics of the tool as shown in Table I with the controller parameters shown in Table II. We kept the controller parameters fixed throughout the experiments. We have conservatively overestimated the moment of inertia and mass of the tool to account for errors in the friction and deformation modeling.

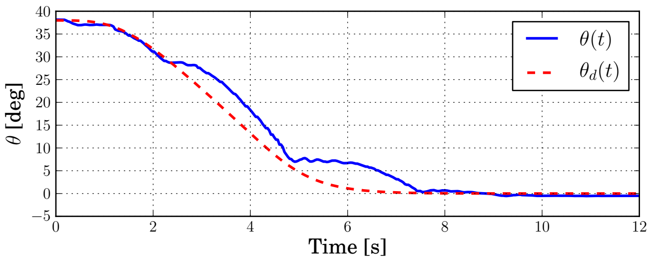

Fig. 4 : Experiment 1 angular position $\theta(t)$ of the tool and reference angular position $\theta_d(t)$.

Fig. 4 shows the angular position $\theta(t)$ of the tool in the first experiment. In this experiment the robot grasped a 52.83g tool and controlled the gripper position to allow the object to fall to the zero degree position following the reference trajectory $\theta_d(t)$. Despite the modeling uncertainties, the sliding controller managed to move the tool to the desired angular position with a final error of approximately 0.5 degrees. However, we also see that the controller had difficulty in achieving tracking convergence around $t = 2.2$s and $t = 5$s. This is due to unmodeled friction phenomena such as the Stribeck effect, which makes the friction coefficient increase as the sliding velocity decreases. The tool abruptly stopped and continued to move once the separation between the fingers was increased again.

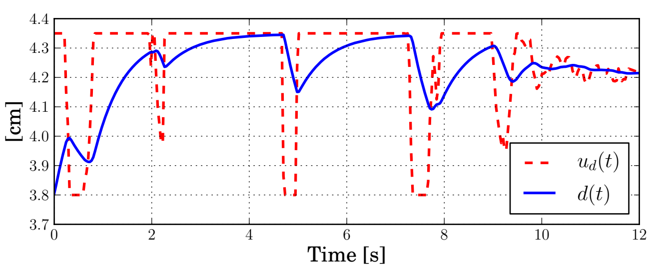

Fig. 5 : Experiment 1 sliding mode position control signal $u_d(t)$ and gripper position $d(t)$.

Fig. 5 shows the switching control signal $u_d(t)$ in the first experiment. The figure also shows the resulting separation of the fingers $d(t)$ measured from the gripper encoders after feeding the position control signal to the gripper velocity controller of Eq. (12). This figure highlights some of the difficulties when using friction as a control input for in-hand manipulation. First, even though we use soft fingertips which can deform accordingly, we have a limited range of operation ($d_{max} - d_{min} = 5.5$mm) before the gripper almost drops the tool. Secondly, comparing with Fig. 4 we notice that e.g. between $t = 2.2$s and $t = 5$s the tool can abruptly transition between zero velocity and a large angular velocity in a small range of motion of the gripper fingers of approximately 1mm.

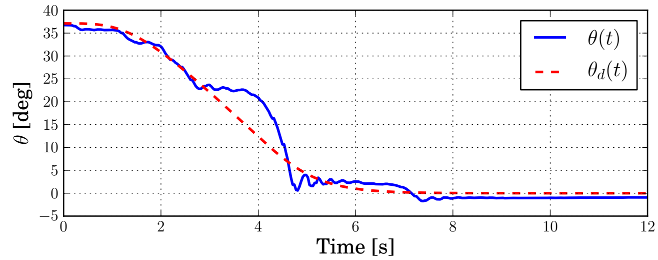

Fig. 6 : Experiment 2 angular position $\theta(t)$ of the tool and reference angular trajectory $\theta_d(t)$.

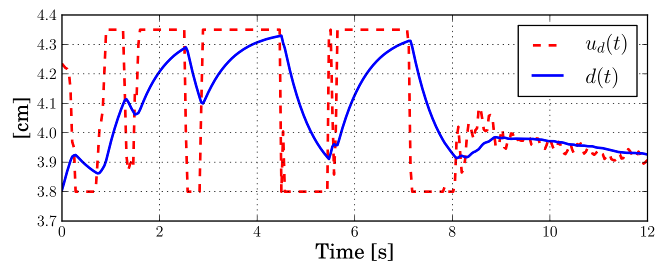

Fig. 7 : Experiment 2 sliding control position signal $u_d(t)$ and gripper position $d(t)$.

For the second experiment we attached a 15.67g mass to the tool at a 15 cm distance from the center of rotation, representing a 30% increase in the mass and roughly a 34% increase in the moment of inertia of the tool. Fig. 6 shows the angular position of the tool for this second experiment while Fig. 7 shows the respective control signals.

Once again, the controller converges to the desired position, albeit with a larger steady state error of 1 degree. Furthermore, one can notice the larger control effort when compared to the previous experiment.

We then performed the third experiment by attaching two 15.67g masses to the tool 15cm away from the center of rotation. This raised the mass by 60% and the moment of inertia by roughly 68% (see Table I).

The results of the experiment are shown in Fig. 8 and 9.

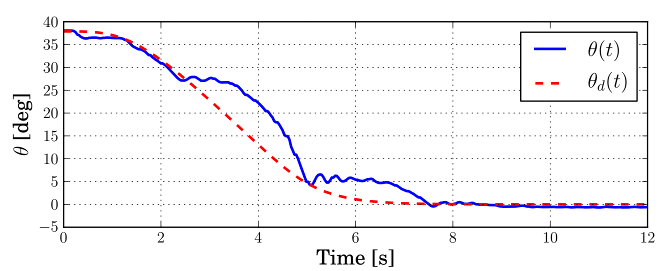

Fig. 8 : Experiment 3 angular position $\theta(t)$ of the tool and reference angular trajectory $\theta_d(t)$.

As shown in Fig. 9 we reduced the maximum finger separation d_{max} by 0.5mm with respect to the previous

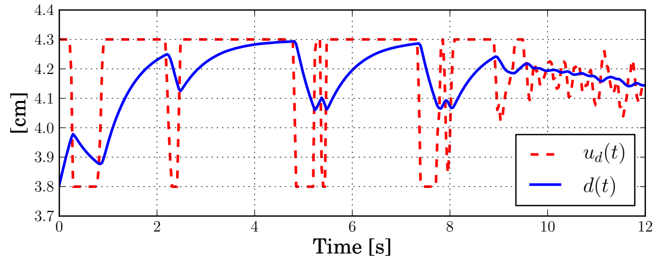

Fig. 9 : Experiment 3 sliding control position signal $u_d(t)$ and gripper position $d(t)$.

experiments in order to avoid loosing grip of the tool. We observe that this change in d_{max} is critical in the controller performance since the steady state error in this case is 0.5 degrees, outperforming the second experiment. Furthermore, Fig. 9 shows that the control signal converges to a larger finger separation d than the previous experiment, given that by lowering d_{max} we induce higher friction through the controller, resulting in lower angular accelerations of the tool.

VI. Conclusions and Future Work

We have proposed a sliding mode controller for extrinsic in-hand manipulation which uses gravity and friction to reorient a tool in the robot's hand. In our derivation of the control law we assume a pinch grasp on the object such that we can model the motion of the tool with a passive revolute joint with a fixed axis of rotation, constraining the problem to one rotational degree of freedom. In the experiments the controller converges to the reference position despite the modeling uncertainties in the friction and deformation.

As future work we plan to use more accurate dynamic friction models such as the Lugre-like model mentioned in [18] to gain more insights into the friction characteristics of the problem and propose more robust control schemes that could potentially improve the tracking performance. We also plan to incorporate tactile sensing to measure and control more directly the grasping forces, which could improve the results presented here and open the possibility to .

Acknowledgment

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