Overlooked Variables in Compliant Grasping and Manipulation

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***Abstract*— Reliable grasping and manipulation for deformable objects require accurate contact modeling and grasp stability estimation. One key component in contact modeling and stability estimation is the coefficient of friction, which is typically estimated as a standard single value from the literature, even though its actual values are variable and depend on many factors, such as compliance and contact velocity, especially for deformable objects. These factors are often overlooked in the applications of analytical grasp models as well as machine learning methods. Here we compare the coefficient of friction of objects with different compliance but identical materials (thicker/multi-layered vs. thinner/single-layered) at varying contact velocity, using a highly instrumented robot hand and vision-based tracking on both the robot hand and the object. The results show that compliance, as well as contact velocity, affect the coefficient of friction and stability estimation using grasp analysis. These findings suggest that reliable grasping and manipulation, whether from analytical grasp models or machine learning methods, require the ability to sense friction. This also implies that machine learning methods will require inputs from friction sensing. Without friction sensing capabilities, robotic grasping and manipulation are constrained to a much narrower range of objects.**

I. INTRODUCTION

Reliability is a central challenge for grasping in unstructured environments. A key example is kitchens, where dropped objects can cause expensive food waste and difficult cleanup tasks. The challenge is compounded with conformable objects, which entail deformation due to contact and gravity, difficult estimation of the object state, and modeling limitations due to unknown mechanical properties.

Reliable grasping requires the ability to predict grasp stability. Grasp analysis (e.g. [1]) can determine stability, but requires an accurate estimate of the coefficient of friction at contact. When the estimate is too conservative, it results in excess force and potential damage to the object; when it's too relaxed, it will result in unstable grasps. Incorrect estimates also lead to failures of in-hand sliding manipulation. Typically, the coefficient of friction is estimated as a standard value from the literature. Actual values, however, are variable and depend on many factors such as the materials in contact, pressure or load, temperature, and contact velocity [2].

Recently, much research has focused on machine learning methods in grasping and manipulation, particularly to handle the nonlinear behavior of compliant interaction [3], [4], [5], [6], [7], [8], [9]. It is important to provide the necessary inputs for machine learning methods to successfully distinguish the nuanced differences in such contact-rich environment.

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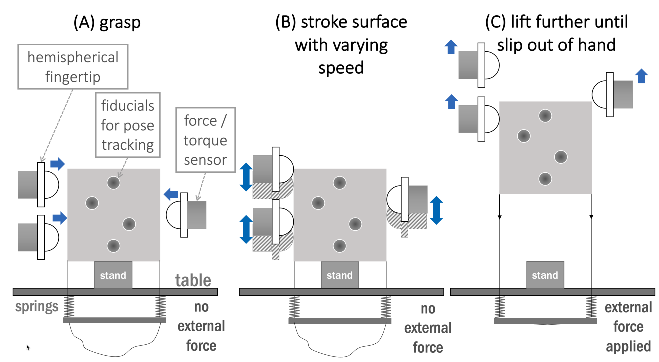

Fig. 1. (A) Components of the system. (B) The stroking experiment: each finger touches the object, sliding up and down in a repeated motion. (C) The grasp-lift-slip experiment: the object is grasped then slowly lifted until external force is applied via a string looped under the table, causing the object to slowly slip out of the robot hand.

This work identifies some of these key inputs that tend to be overlooked. Using a highly-instrumented robot hand, objects with different compliance but identical materials (thicker/multi-layered vs. thinner/single-layered) are grasped and lifted, then pulled from the grasp. The results demonstrate that compliance as well as contact velocity affect the coefficient of friction as well as stability estimation using grasp analysis.

II. METHODS

The experiments use a modified tendon-driven three-fingered robot hand (Reflex Hand, RightHand Robotics). The custom-designed fingers have joint encoders on both proximal and distal joints. Each fingertip is equipped with a high precision force/torque sensor (ATI Nano17. Resolution: 1/160 N, 1/32 Nmm). The hand is mounted on a robot arm (Universal Robot UR-5) and a high precision optical tracking system (Atracsys Fusion Track 500, Resolution: 0.090 mm RMS) measures the pose of each fingertip as well as the base of the hand and the grasped object.

The base object is a cube with mounting sites that allow different materials to be attached to the sides. Here we consider two materials: a very soft silicone rubber (Smooth-on Ecoflex 00-10) and natural cotton canvas. Each material has two configurations: stiff and soft. For rubber, the stiff sample is spin-coated in a thin layer on a rigid plate and the soft sample is molded into a 13 mm thick pad. For canvas, the stiff sample is a single layer sewed onto rigid plastic plate, and the soft sample is multiple layers directly rolled onto the object and lightly tied by cotton yarn.

A. *Experimental Setup*

For each object, we conduct two experiments. The first is a stroking experiment to study the coefficient of friction with respect to contact velocity. We lightly close the robot hand and repeatedly slide the fingers along the side of the object without lifting it at varying speeds. The second is a grasp-slide-drop experiment to examine the estimation of grasp stability using grasp analysis. A string is attached to the bottom of the object and looped under the table top (Figure 1). The object is slowly lifted until the string goes taut, then the object slides between the fingers until it is pulled out of the hand.

III. Results

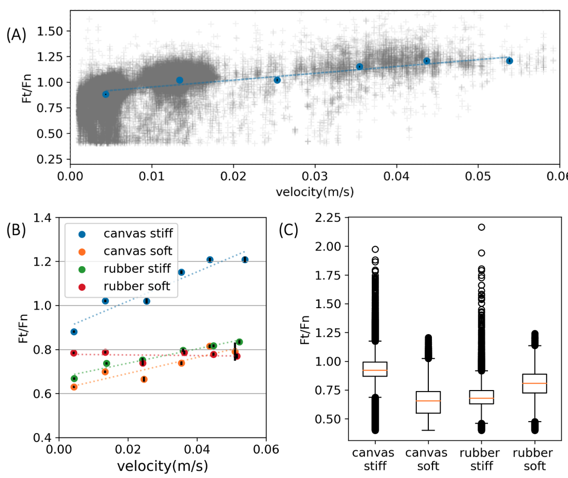

Fig. 2. (A) Typical distribution of coefficient of friction (ratio of tangential to normal force during sliding) versus sliding velocity (canvas stiff case). (B) Trends of coefficient of friction with respect to contact velocity for the four object cases. (C) Soft cases have far fewer outliers and a wider distribution.

A. *Coefficient of friction varies with contact velocity*

The results demonstrate that the coefficient of friction is often, although not always, a function of contact velocity. Figure 2(A) shows a typical stroking experiment. Each instance in time is plotted as a grey point. Here we divided the data points into bins of 0.01 m/s. In each bin, we calculate the mean values and standard errors for contact velocity and coefficient of friction and the results are shown in blue, together with a linear fit. Figure 2(B) shows that for cotton canvas both cases and rubber stiff case, the coefficient of friction increases as contact velocity goes up, while it remains roughly constant for the rubber soft case.

B. *Softer leads to cleaner signals and better slip estimates*

Figure 2(C) shows the distribution of the coefficient of friction across all velocities for all four cases. For both materials, the soft and stiff cases have different means and distribution widths, with the higher mean value for the stiff case with canvas and the soft case for rubber. Although the inter-quartile range is somewhat larger for both soft cases, soft has far fewer outliers and they span a much smaller range than for the stiff cases.

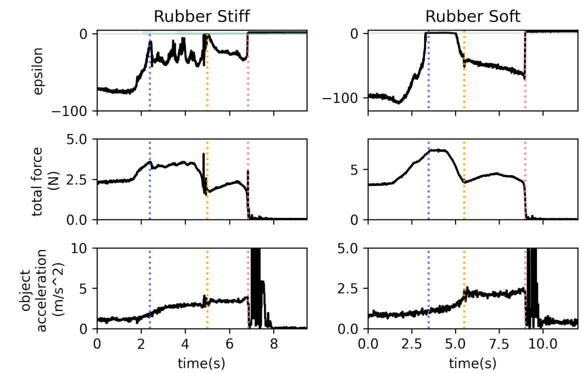

Fig. 3. Grasp analysis results for the rubber cases. Epsilon is a metric of grasp stability that goes to zero at the onset of object slip [1]. The blue, yellow, red lines are when the object first starts to slip, the first finger loses contact, and the object completely drops out of the robot hand, respectively.

We applied grasp analysis to all four cases using the median value from Figure 2(C). Figure 3 shows grasp stability estimation of the rubber cases using the epsilon metric from grasp analysis [1]. A negative epsilon value indicates that the grasp is secure, and an epsilon of zero indicates slip. Here we see that the stability estimation is cleaner and more accurate in the soft case. When the object is slipping during three-fingered grasp, the stiff case shows considerable variability in epsilon while the soft case is a constant zero for epsilon, correctly indicating an insecure grasp.

IV. Discussion

In general, effective grasping depends on friction to generate stabilizing forces. Unfortunately, friction is a complex phenomenon, and as these results demonstrate, friction for compliant materials friction varies greatly depending on materials, temperature, load and pressure, slip velocity, and other parameters [2]. Without the ability to sense friction (or at least the main parameters that influence it), the results presented here suggest that grasp stability predictions, whether from analytical grasp models or from machine learning methods, will be unreliable (Figure 3). This implies that machine learning methods will require inputs from contact sensors that directly sense friction [10]. Alternatively, it may be possible to use conventional tactile sensors to lightly slide against the object surface at the start of the grasping process to estimate friction. This is similar to the capabilities of human fingers, which possess sophisticated mechanoreceptor nerve endings that allow the central nervous system to quickly estimate friction during the first fraction of a second after the fingertip makes contact [11]. Without such sensing capabilities, robots will be constrained to use grasps that minimize dependence on frictional forces, which will greatly restrict the range of objects that can be reliably grasped[12].

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