

THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Slip-Aware In-Hand Object Manipulation with Parallel Grippers

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Cover:

A single long exposure photo showing the gripper and sensors developed in this thesis, mounted on a UR3 robot, and performing rotational in-hand manipulation. Only the background has been edited (no AI), to be uniformly darkened.

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Abstract

Allowing controlled in-hand slip, rather than imposing rigid grasps, can substantially expand the manipulation capabilities of robotic systems equipped with parallel grippers. Such capabilities include more efficient object reorientation and increased effective reach. This thesis establishes the foundations for slip-aware in-hand manipulation with parallel grippers and demonstrates that such capabilities can be achieved using only a single-degree-of-freedom gripper and tactile sensing. To this end, the thesis contributes to advances in planar friction modeling and estimation, tactile sensing, gripper hardware design, and slip-aware control.

Robotic grippers interact with objects through the contact surface between their fingers and the object. We explore and model the friction at this interface, focusing on planar motion where translation and rotation occur simultaneously. This creates coupled tangential and torsional friction, which we model by extending the LuGre model using limit surface theory.

To experimentally realize slip-aware manipulation, we develop two generations of tactile sensors and gripper hardware. The first combines a high-performance force-controlled parallel gripper with commercial force/torque sensors and custom relative-velocity sensors based on optical mouse technology. This enables slip-aware manipulation using only in-hand perception. We use this system to estimate friction and contact properties and demonstrate several manipulation controllers, including gravity-assisted linear and rotational trajectory following, hinge control, and slip-avoidance. This framework is further extended with online estimation of contact properties, eliminating the need for a separate exploration phase.

The second-generation tactile sensor introduces a deformable sensing pad that measures sliding velocity, forces, torques, and pressure distribution. Using these sensors and an updated gripper, we demonstrate a variety of in-hand manipulation primitives by combining in-hand control with end-effector motion. Together, the extended friction model and contact-property estimation, tactile sensing and gripper hardware, and slip-aware manipulation controllers establish a unified basis for controlled slip and demonstrate versatile dexterous manipulation with simple parallel grippers.

Keywords: Robotics, In-Hand Manipulation, Tactile Sensing, Perception, Hardware, Grasp Control, Friction Estimation, Friction Modeling.

To those that aim for the stars and burn with passion.

List of Publications

This thesis is based on the following publications:

- [A] **Gabriel Arslan Waltersson**, Yiannis Karayiannidis, “Planar Friction Modelling with LuGre Dynamics and Limit Surfaces”. *Published in IEEE Transactions on Robotics (T-RO)*, vol. 40, no. 10, pp. 3166-3180, 2024.
- [B] **Gabriel Arslan Waltersson**, Yiannis Karayiannidis, “Perception, Control and Hardware for In-Hand Slip-Aware Object Manipulation with Parallel Grippers”. *Published in The International Journal of Robotics Research (IJRR)*, vol. 45, no. 10, pp. 1497-1519, 2026.
- [C] **Gabriel Arslan Waltersson**, Yiannis Karayiannidis, “Friction Estimation for In-Hand Planar Motion”. *Accepted in Experimental Robotics: The 19th International Symposium*, vol. TBD, no. TBD, pp. TBD, 2025.
- [D] **Gabriel Arslan Waltersson**, Yiannis Karayiannidis, “Deformable In-Hand Slip-Aware Tactile Sensor with Integrated Velocity Sensing, Force/Torque and Pressure Map Estimation”. *Conditionally accepted to RAL*.
- [E] **Gabriel Arslan Waltersson**, Marko Guberina, Yiannis Karayiannidis, “A Vocabulary of Slip-Aware In-Hand Motion Primitives”. *Submitted*.

Other publications by the author, not included in this thesis, are:

- [F] **G.A. Waltersson**, R. Laezza, Y. Karayiannidis, “Planning and Control for Cable-routing with Dual-arm Robot”. ICRA, *International Conference on Robotics and Automation*, Philadelphia, PA, USA, 2022.
- [G] R. Laezza, M. Shetab-Bushehri **G.A. Waltersson**, Y. Karayiannidis, “Offline Goal-Conditioned Reinforcement Learning for Shape Control of Deformable Linear Objects”. arXiv preprint arXiv:2403.10290, 2024.

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Acronyms

DoF:	Degree of Freedom
CoR:	Center of Rotation
CoP:	Center of Pressure
CoG:	Center of Gravity
CoM:	Center of Mass
F/T:	Force/Torque

Part I

Overview

CHAPTER 1

Introduction

What happens when you make an assumption, like that robot hands are supposed to firmly grasp an object, but instead allow it to slip?

There is a long-standing dream of creating intelligent robotic systems, with the versatility and object manipulation skills of humans. However, replicating these abilities has proven challenging, as what humans do instinctively is the result of eons of evolution. While humans excel in versatility, robots can achieve levels of precision far beyond us. It is as if the world of robotics is upside down—what seems easy for humans is challenging for robots, and what is difficult for humans is simple for machines, as though we have stepped into *Alice’s Adventures in Wonderland*. It is important to remember that robots and humans are inherently different—one is mechanical, the other biological. Replicating human-like qualities in machines has been difficult. Mechanical materials may be stronger and tougher, but they wear down over time, whereas humans, though fragile, can heal and adapt. A logical approach might be to continue enhancing the durability of mechanical components, further distinguishing robots from humans. Ultimately, we are left with two worlds, each with its own strengths and weaknesses. Yet, the goal remains the same: to

replicate the dexterity and versatility that humans possess.

Traditionally, when a robot grasps an object, the object is treated as though it is rigidly attached to the gripper. This approach imposes significant constraints on how the object can be picked up, moved, and placed, as the gripper must precisely match the object’s final orientation. In contrast, humans seamlessly adjust their grip on an object depending on the situation, often using only one hand. These subtle adjustments, such as sliding manipulations, happen so instinctively that we rarely notice them. For example, when holding a phone and preparing to place it on a surface, you do not go through a series of rigid, tedious steps to reorient it with both hands. Instead, you perform a near-magical demonstration of dexterity: by intuitively understanding the phone’s dynamics and through intricate hand contact, you allow it to slip and smoothly reorient within your hand, all while minimizing arm movement and conserving energy. Achieving this in-hand task with traditional robotics would require an inefficient and complex sequence of actions that bears little resemblance to human dexterity.

While we are not aiming to fully replicate human capabilities, this thesis seeks to enable simple robotic grippers to perform in-hand sliding manipulations. It is a problem with many facets, ranging from theory to hardware, and our contributions reflect a path through these challenges toward the goal of reliable in-hand manipulation. I envision a robot arm capable of picking up an object and effortlessly repositioning it within the hand, similar to how a human picks up a phone and adjusts it for comfortable use. For humans, this happens instinctively, but what would it take for robots to achieve a similar capability?

1.1 Research Overview

The path toward in-hand sliding manipulation begins at the contact interface between the gripper and the object. At this interface, the object’s motion is governed by the friction present under planar motion. Although many models have been proposed to capture frictional behavior, exact physical details are difficult to replicate, and different approaches require different compromises. For our scenario, the one-dimensional LuGre friction model effectively captures the critical transition dynamics between sticking and slipping. However, since in-hand slippage with parallel grippers follows planar motion, the model

must also capture the coupling between tangential and torsional forces. We contribute to planar friction modeling by extending the LuGre model to the planar case through the use of limit-surface properties, enabling precise simulation of in-hand slippage with arbitrary pressure distributions at the contact surfaces.

Moving from theory to real-world experimentation, my research approach initially resembled a game of Whac-A-Mole, constantly chasing the weakest link. On a hardware level, our system relies on the fundamental control loop of perception and actuation: the ability to perceive the world and act to change it. In this work, perception occurs at the fingertips through tactile sensing.¹

My guiding question became: how can I simplify this problem? What is the simplest solution that still fulfills our target capabilities? The breakthrough happened one day while looking at my desk. Noticing how well a standard computer mouse tracks a surface, an idea emerged. Although placing optical tracking sensors inside a robotic gripper was not entirely novel, I had identified a specific use case that played directly to their strengths. This realization inspired our second work: the development of a custom gripper setup equipped with optical tactile sensors, optimized for in-hand sliding manipulation. The resulting system is capable of sliding objects along both linear and rotational trajectories, relying solely on gravity and in-hand sensing.

Transitioning from theory to real-world experimentation revealed many interesting insights, the subsequent papers are the result of these observations. In our second work, we used a brief exploration phase during object grasping to determine friction and contact properties. However, these properties are not necessarily constant and can change as the object slides across different materials. Our third work therefore focused on estimating contact properties online, eliminating the need for the initial exploration phase.

There is a concept commonly referred to as embodied intelligence [1]: the principle that intelligence is not limited to computational decision-making, but can also be expressed through physical and mechanical properties. The human body is full of embodied intelligence, relying on compliance to naturally reduce the computational burden on the brain and nervous system. In the first version of our gripper setup, the tactile sensors utilized rigid contact pads due

¹“Tactile perception” is an umbrella term encompassing various modalities measured directly at the contact location, each modality comes with its own unique strengths and limitations. For instance, the classical approach heavily relies on measuring contact forces; however, it suffers from observability issues in the general case of planar sliding.

to the narrow focal range of the optical sensors. However, we observed that these rigid contact interface exhibited highly sensitive sliding dynamics. When manipulating rigid objects, stick-slip dynamics became pronounced, whereas softer object surfaces resulted in significantly smoother sliding. In essence, the compliance of the contact interface is a critical factor governing the sliding dynamics. This suggested that a soft, deformable contact pad integrated into the sensor could improve sliding behavior when manipulating rigid objects. This insight motivated the development of our next-generation tactile sensor, which features a deformable contact pad integrated with optical mouse sensors that move with the material’s deformation. By leveraging these deformations, the system can also estimate contact forces and pressure maps—providing a rich set of multimodal measurements alongside passive mechanical properties, which improve the in-hand manipulation behavior.

With these fundamental building blocks established, the question shifted from how to design the system to how to utilize it. In our final work, we demonstrate the capabilities of our system and structured a vocabulary for in-hand sliding manipulation.

1.2 In-Hand Object manipulation

In-hand object manipulation refers to the ability to adjust the position or orientation of an object relative to the gripper or hand. Implementations of this vary significantly depending on the underlying hardware. For instance, a simple parallel gripper—such as the one shown in Fig. 1.1, which is the focus of this thesis—operates with a single degree of freedom (DoF), meaning it can only open and close. This kinematic limitation naturally introduces constraints on its manipulation capabilities. In contrast, the human hand has 27 DoFs [2], which allows for highly flexible and intricate movements. However, a higher number of DoFs is not always desirable. In many industrial applications, reliability is paramount, which often raises concerns regarding complex systems, such as high DoF grippers [3]. Generally, simple mechanical systems offer greater robustness and predictability than their complex counterparts. While parallel grippers may lack the dexterity of more advanced systems, they offer greater grasp strength and simplicity. Consequently, for the study of slip-based in-hand manipulation, the parallel gripper provides a minimal platform where all re-positioning is achieved exclusively through

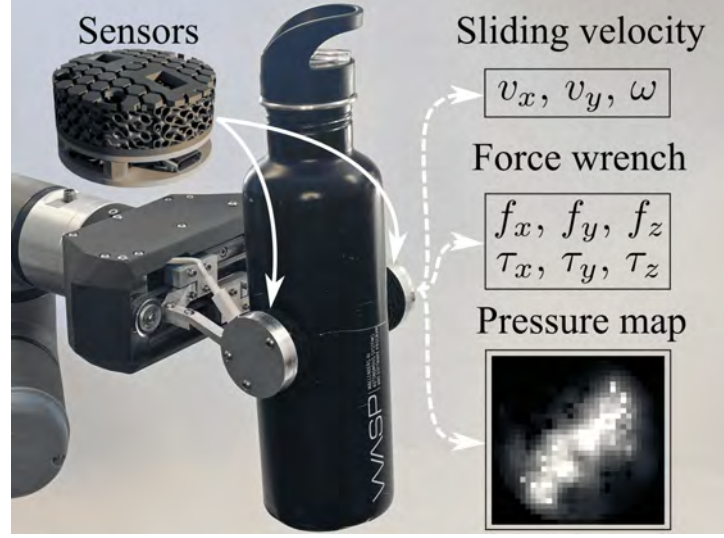


Figure 1.1: Picture of a custom parallel gripper mounted with custom sensors, capable of measuring sliding velocity, contact forces and the contact pressure distribution. The gripper is an updated version of the gripper presented in Paper B and the sensors are presented in Paper D.

controlled, slip-aware interactions.

Despite their structural simplicity, parallel grippers should not be underestimated in terms of their in-hand manipulation capabilities. Since the physical interaction is bounded by the contact pads, in-hand manipulation within a parallel gripper is in this thesis planar, meaning the object is constrained to two-dimensional linear translation and a single axis of rotation. Operating a 3-DoF object motion space with a single-DoF gripper means the system is inherently underactuated. However, by accurate control of the grasp force, the end-effector orientation, and dynamic motions with the robotic arm, a rich set of capabilities can be achieved. In this work, these capabilities are categorized into motion primitives and control modes. The distinction lies in their scope: motion primitives describe specific object motion patterns, whereas control modes define the underlying control behavior governing the interface between the object and the gripper. Hence, a single control mode can be used for multiple primitives, with the physical motion outcomes dictated by the system’s initial state and robot arm trajectories. To execute diverse in-hand motions despite underactuation, the system leverages extrinsic factors such as gravity, external environment contacts, or dynamic inertial movements—a concept known as extrinsic dexterity [4].

The majority of this thesis focuses on gravity-assisted in-hand manipulation,

as illustrated in Fig. 1.2. The basic motion primitives are categorized as:

1. **Slide:** The object slides within the gripper, altering its relative translation. This is typically, but not necessarily, executed when the object's Center of Gravity (CoG) is vertically aligned beneath the contact's Center of Pressure (CoP).
2. **Rotation:** The object rotates, changing its orientation with respect to both the gripper and the global frame. Typically performed with a gravity-induced torque, e.g. when CoG is horizontally offset from the CoP pivot point, and the object pivots towards the gravity vector.
3. **Hinge:** Hinge motion emphasizes changes in the gripper orientation rather than the object's orientation. It allows the object to remain stationary in the world frame while the gripper rotates around it, often with the object's CoG positioned directly beneath the contact's CoP.
4. **Hold:** The hold primitive prevents both linear and rotational motion.

The basic in-hand motions primitives are realized through four slip-aware controllers:

1. **Linear velocity control:** The controller modulates the grasp force to allow the object to slide and follow a linear reference velocity. The direction depends on the extrinsic forces acting on the object.
2. **Angular velocity control:** The controller modulates the grasp force to allow the object to follow an angular reference velocity.
3. **Passive hinge control:** The controller minimizes frictional torque while avoiding linear sliding motion, behaving like a passive hinge.
4. **Slip-Avoidance:** The controller dynamically adjusts the grasp forces to reject external disturbances while maintaining the minimum necessary force required for grasp stability [5]

Each slip-aware controller describes a particular contact behavior, while the resulting in-hand motion depends on the system configuration and the robot's motion. Thus, the same slip-aware controller can be used to achieve different in-hand motion primitives. For example, the hinge controller can be used

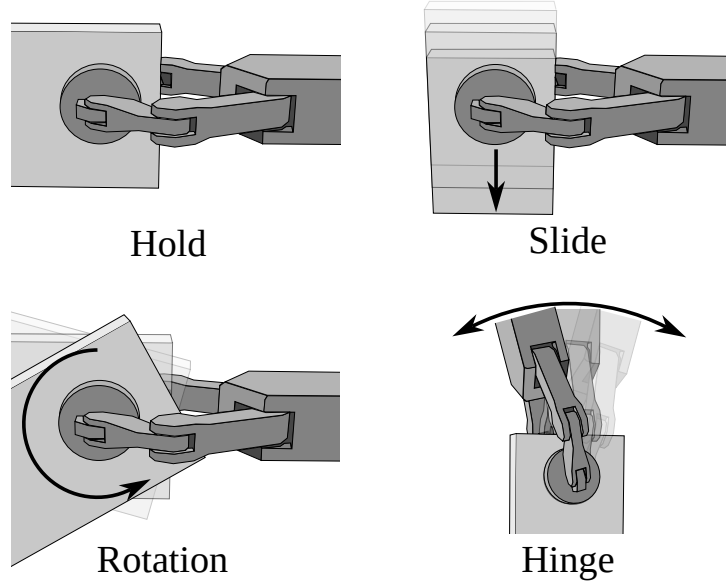


Figure 1.2: Illustration of slip-avoidance and gravity assisted slip motions.

both for the hinge motion depicted in Fig. 1.2 and for the dynamic swing-up motion presented in Fig. 1.4.

While gravity-based slip manipulations have been the primary focus of this thesis, slip-based manipulation can also involve external contact [4]. Figure 1.2 illustrates examples of such manipulations. External contacts, such as flat surfaces, can facilitate object manipulation through techniques such as pivoting, where the object is reoriented by leveraging a contact point on one of its corners [6], [7], [8], [9], [10], [11]. During the pivoting action the gripper contact point might slide to accommodate orientation change. Pivoting enables the handling of large objects, which may exceed the direct lifting capability of the robot [8], [9]. External surfaces share the load, allowing less powerful robots to effectively manipulate larger objects.

Another common method is non-prehensile sliding, which often involves pushing an object across a surface. This technique, explored in various studies [6], [12], [13], [14], is useful for aligning or packing objects in tight spaces [15]. Pushing objects on surfaces can involve a combination of in-hand slippage and sliding on a surface, as illustrated in Fig. 1.3. Additionally, objects can be repositioned within the gripper by pushing them against external contacts, which generates a force in the opposite direction of the gripper's motion

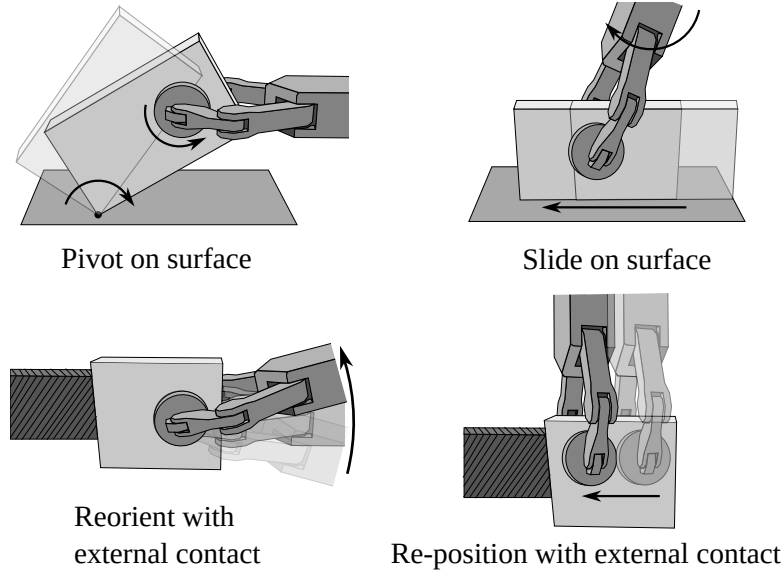


Figure 1.3: *Illustration of slippage control with external contacts.*

[16]. The bottom two illustrations in Fig. 1.3 show the reorientation and repositioning of objects based on external contacts.

Dynamic control can also be used for in-hand object manipulation, as shown in Fig. 1.4. An approach which is explored in paper E is dynamic swing-up control, which leverages an object’s inertia and momentum to alter its orientation, often against the direction of gravity [17], [18], [19]. Additionally, objects can be repositioned within the gripper by applying rapid accelerations, a method previously explored in studies, such as [4], [20]. These dynamic manipulation techniques offer the possibility to reorient or reposition objects without relying on gravity or external contacts, though they often require precise control and high accelerations.

The motion primitives presented above serve as an introduction to slip-aware control, though they do not encompass the full set of capabilities. A more comprehensive discussion on in-hand manipulation strategies can be found in Chapter 4. An advantage of in-hand manipulation is its ability to effectively extend the operational workspace of a robotic manipulator. In standard pick-and-place tasks, the required end-effector orientation heavily dictates the robot’s kinematic reach. This reach differs significantly depending on whether the gripper approaches the object from above or from the side, as illustrated in Fig. 1.5. Furthermore, environmental constraints during object

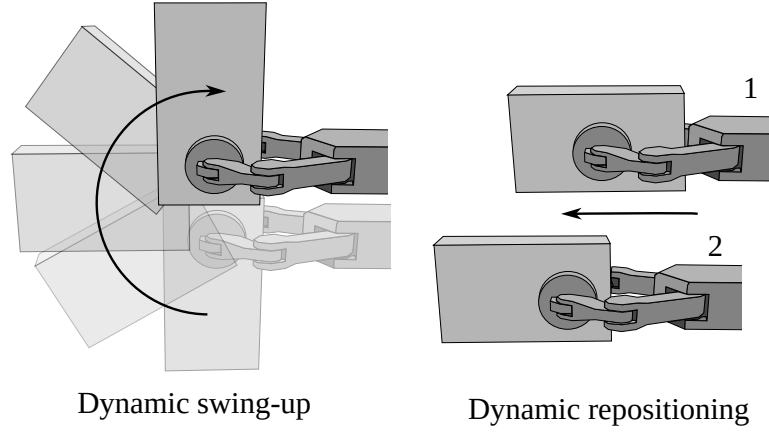


Figure 1.4: Illustration of dynamic slippage control.

pick-up often limit the available grasp poses. In-hand reorientation mitigates this problem by decoupling the picking grasp orientation from the placing orientation. This allows the robot to grasp the object using a kinematically favorable initial configuration, and subsequently adjust the grasp in transit to meet the specific orientation requirements for placing or further manipulation.

Another compelling application of slip-aware manipulation lies in enhancing dual-arm robotic systems, enabling them to dynamically adjust their relative grasp poses during cooperative tasks [6], [21], [22], as illustrated in Fig. 1.5. Rigidly grasping a shared object severely limits a dual-arm system’s workspace and constrains its allowable motions. However, by incorporating slip-aware control at the interfaces, the grasp points can be reoriented or repositioned as needed, significantly expanding the system’s overall dexterity and mobility. By extension, human-robot interaction (HRI) and robot-to-human handovers [23] can be modeled as a multi-arm manipulation problem. In these scenarios, slip-aware control can serve as an intuitive, haptic communication channel to convey user intent and safely provide a higher degree of cooperative flexibility.

While the specific application domains and capabilities discussed thus far focus on single DoF grippers, the principles of in-hand slip-aware manipulation also extend to more complex multi-fingered hands. Multi-fingered hands introduce a significantly higher degree of freedom to the manipulation problem, as they can achieve in-hand repositioning through combinations of both sliding and non-sliding (gaiting) contacts. In contrast, parallel grippers constrain all in-hand manipulation exclusively to sliding interactions. This struc-

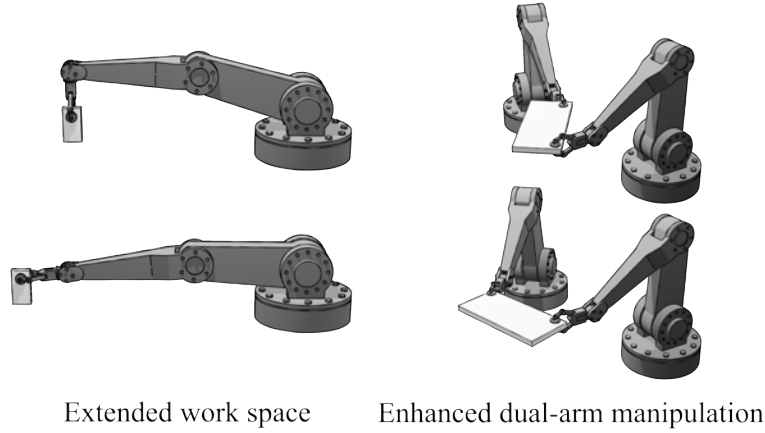


Figure 1.5: Illustration of slippage control with external contacts.

tural distinction makes parallel grippers an ideal platform for isolating and exploring pure slip-aware manipulation, building the foundations to be used in industry or transferred to highly articulated systems, such as multi-fingered robotic hands or advanced prostheses. Furthermore, the work provides an insight into contact behaviors under planar motions, which extends far beyond in-hand manipulation, to fields such as sports science and rehabilitation [24], vehicle and tire dynamics [25], and manufacturing processes [26].

1.3 Contributions

This thesis aims to advance in-hand manipulation capabilities for parallel grippers. The work is presented in five main papers, each addressing different aspects of the problem. The following summarizes the contribution of each paper to the field.

Paper A focuses on modeling the contact and friction between the gripper and object, specifically simulating friction under planar motions. The key contributions are:

1. We propose a distributed planar friction model for an arbitrary contact surface and pressure distribution, capable of capturing the stick-slip scenarios. This is achieved by extending the LuGre friction model with the limit surface theory.
2. To mitigate the computational complexity of the distributed planar fric-

tion model, we propose a computationally efficient reduced planar friction model. The reduced planar friction model utilizes a pre-computed limit surface and reduces the number of bristles needed for the simulation to three.

3. The Elasto-Plastic model is extended to planar motion. The LuGre model can experience drifting under oscillating loads, even if they are under the required loads necessary for slippage, the Elasto-Plastic model mitigates the drifting by introducing an elastic part in the bristle model.

Paper B addresses the hardware limitations in the field of in-hand manipulation, focusing on enhancing the capabilities of parallel grippers and sensors. The contributions are:

1. A high performance parallel gripper. For in-hand manipulation, parallel grippers only have control of the grasping force. It is crucial that grasp force can be controlled fast and accurately, commercial grippers typically have closed architecture for their low level controller and do not offer the capabilities of fast closed-loop force control.
2. Planar velocity sensors. General in-hand manipulation of objects relies on sensing. We propose planar velocity sensors that can be placed on-top of force sensors and accurately measure the sliding velocities. The sensor combination allows us to solely rely on in-hand sensing.
3. In-hand estimation of contact properties. The developed hardware allows for rapid estimation of contact properties at object pick-up.
4. By leveraging the gripper hardware, sensor hardware, and contact estimation algorithms, we propose four simple slip-aware controllers to demonstrate the capabilities of the developed system. The four slip controllers achieve trajectory-following for gravity-assisted linear and rotational slippage, hinge control, and slip-avoidance, illustrated in Fig. 1.2.

Paper C deals with online friction estimation. In paper B, the friction estimation was performed during the pick-up of an object and was kept static for the entire manipulation duration. However, an object may have patches of different materials or change properties due to wear, temperature or other

factors. Furthermore, the typical friction models used in estimations are approximations and do not capture all physical properties. Therefore estimating the friction in an online fashion could overcome these shortcomings. The contributions are:

1. An online contact property estimator for Coulomb μ_c and static μ_s friction, and the contact radius r , as well as an analysis of coupling in the estimation of μ_c and r .
2. Validation through simulations and real-world experiments.
3. Insights into sim-to-real challenges and a filtering heuristic for real-world estimation.

Paper D presents the development of a new tactile sensor that integrates velocity, force, torque, and pressure map estimation into a single device. The primary motivation for this sensor stems from Paper B, where the sensor’s contact pad was rigid. In contrast, the sensor developed in Paper D features a deformable contact pad, allowing for better slip dynamics and improved tracking of non-flat objects. The contributions are:

1. A tactile sensor featuring a deformable contact pad that enables optical measurement of planar sliding velocity, estimation of full 6-DoF force/torque, and reconstruction of contact pressure distribution through pad deformation using Hall-effect sensors. The novelty with respect to existing tactile sensors lies in the integration of multiple sensing modalities not previously combined within a single system.
2. Enhanced contact dynamics and increased contact torque authority enabled by the deformable contact pad, compared to the rigid design in [27], enabling smoother and more stable manipulation, and in-hand manipulation of objects with curved surfaces.

Alongside the sensor development, a new robotic gripper was designed and machined. While the gripper itself does not represent a standalone theoretical novelty, it serves as an engineering contribution for future researchers working on in-hand slip-aware control. Compared to the gripper used in Paper B, this new version is machined from aluminum rather than 3D-printed plastic, providing a significantly smaller physical footprint without compromising its capabilities while improving durability.

Paper E focuses on structuring in-hand manipulation through a vocabulary of motion primitives and demonstrating the capabilities enabled by this framework. The main contributions of this work are:

1. We propose a vocabulary of slip-aware in-hand motion primitives that abstracts desired object motions from the underlying control methods.
2. We present a dynamics level trajectory optimization approach enabling motion planning for dynamic pivoting.
3. We experimentally demonstrate a broader range of slip-aware in-hand manipulation capabilities for parallel grippers than has previously been reported in the literature [20], [27], [28], [29], including dynamic swing-up manipulation.

In total, the Papers A to E contribute to advancing the field of in-hand manipulation both theoretically and technologically. The theoretical contributions include improved contact and friction modeling and motion planning, while the technological contributions include the design and implementation of specialized hardware for slip-aware in-hand manipulation.

1.4 Thesis Outline

Part I introduces the field and provides the background necessary for understanding the papers presented in Part II. The thesis is organized as follows: Chapter 1 introduces the concept of in-hand manipulation, while Chapter 2 covers contact modeling and estimation of the interactions between the gripper and object. Chapter 3 provides an overview of the hardware development and tactile sensing for in-hand perception. Chapter 4 discusses the slip-aware control modes and an overview of the system. Finally, Chapter 5 summarizes the included papers, and Chapter 6 reflects on the field and discusses possible future directions.

CHAPTER 2

Contact Modeling and Estimation For In-Hand Manipulation

Contact modeling plays a fundamental role in in-hand manipulation, particularly in the design of slip-aware controllers. When a parallel gripper interacts with an object, that interaction is governed by the contact surfaces between the gripper’s fingers and the object, as illustrated in Fig. 2.1. The material properties of both surfaces strongly influence this contact behavior. Well-behaved contact dynamics can minimize unwanted stick-slip phenomena, allowing the controller to focus on the desired motion rather than compensating for unpredictable friction transitions. This concept is typically referred to as embodied intelligence. Furthermore, the contact area size and pressure distribution directly govern planar motion, dictating how linear forces transition into torsional torques and vice versa. While analytical models and simulations only approximate reality, they provide a powerful tool to study these interactions in a fully controlled environment, such as the estimation of physical properties, and synthesize control algorithms. To that end, this chapter focuses on two key areas: friction modeling for simulations, and real-world contact estimations.

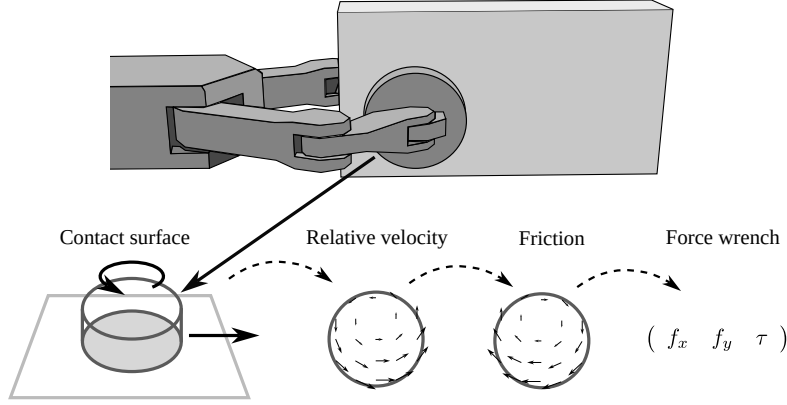


Figure 2.1: Interaction between the object and gripper under planar motion.

Friction has been studied across numerous academic fields [30], each developing specific models tailored to its distinct requirements. While our primary focus is on in-hand manipulation, planar friction models extend far beyond this use case. They are foundational to planar pushing problems [31], object throwing [32], vehicle and tire dynamics [25], sports science and rehabilitation [24], and manufacturing processes [26].

Naturally, these friction models are highly adapted to their specific applications. Multi-purpose physics simulators—such as PhysX (utilized by Isaac Gym [33]), Algorix [34], MuJoCo [35], and Drake [36]—each strike a distinct compromise between model accuracy, computational complexity, and ease of use. Among these, Drake stands out for its fidelity in capturing planar friction and contact mechanics especially for in-hand manipulation tasks.

In the field of control theory, LuGre-style friction models have gained significant traction. By utilizing internal state variables modeled as deflecting elastic bristles, the LuGre framework smoothly captures complex stick-slip dynamics and pre-sliding displacement [37]. However, these classical formulations are typically defined for 1D motions. In this chapter I introduce 1D friction models before formalizing the contact surface representations and standard planar friction models. Building on this foundation, LuGre-style models are extended to planar motion, followed by techniques to mitigate the resulting computational overhead. I discuss how the capacity of these models to accurately simulate physical behaviors is tightly coupled to the choice of numerical integration schemes, which significantly dictates both the emergent dynamics and the overall computational complexity. Finally, online friction estimation

for in-hand planar motions is discussed.

2.1 Friction Models for 1D Motions

The modern study of friction dates back to the 18th century with the Coulomb friction model, attributed to Charles-Augustin de Coulomb [38]. This model describes friction as a force opposite to the direction of motion, proportional to the normal force:

$$f_f \leq \mu_C f_n \quad (2.1)$$

where f_f is the frictional force, f_n is the normal force, and μ_C is the coefficient of friction. The Coulomb friction model is static and does not account for changes in friction with velocity. Despite these limitations, its simplicity has made it widely used in grasping and multi-body simulators. The friction model is often represented as a friction cone [39], where no slipping occurs as long as the force applied on the surface remains within the cone. When the force reaches the boundary of the cone, incipient slip occurs—a transition state between sticking and slipping, where some parts of the contact surface slip while others remain adhered. Further increases in tangential forces result in full slippage. Most multi-body simulators smooth these transitions out and utilize heuristics to simulate sticking behavior, which trades numerical efficiency for accuracy.

In the early 20th century, Stribeck observed that friction depends on the velocity [40]. Initially, when the object is static, friction follows the static friction coefficient μ_S . As the object begins to move, the friction force drops to the Coulomb friction coefficient μ_C . As the velocity increases further, a viscous friction force is observed. This phenomenon is known as the Stribeck effect, illustrated in Fig. 2.2. Several model variations describe the Stribeck effect [41]. Here, we follow the derivation [42]:

$$f_f(v) = (\mu_C + (\mu_S - \mu_C)e^{-(v/v_s)^\gamma} + \mu_v v) f_n \quad (2.2)$$

where v is velocity, v_s and γ control the transition between μ_S and μ_C , and μ_v is the viscous friction coefficient. In this model, the viscous friction is linearly dependent on the sliding velocity.

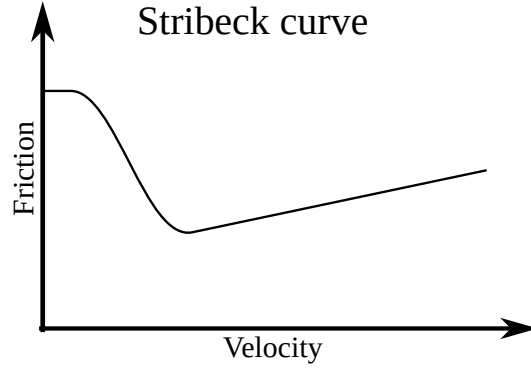


Figure 2.2: Conceptual illustration of the Stribeck effect and the velocity dependence of friction.

Dynamic Friction Models

While the Coulomb and Stribeck models are memoryless, experimental data indicates that friction exhibits dynamic behavior [43]. Dahl introduced a model that accounts for friction dynamics by estimating friction forces from velocity and micro-displacements [44]. In this model, the friction force is represented as bristle deflections modeled by the state variable z :

$$\dot{z} = v - \frac{\sigma_0 |v|}{f_c} z \quad (2.3)$$

where f_c is the Coulomb friction and σ_0 is the stiffness coefficient. The friction force is thereafter given by:

$$f_f = \sigma_0 z. \quad (2.4)$$

As can be seen in (2.3) and (2.4), the Dahl model does not capture the Stribeck effect. To address this, the LuGre friction model was developed [37], extending Dahl's model to include the Stribeck effect. Similar to the Dahl model, the LuGre model represents friction through bristle deflection, as shown in Fig. 2.3. In the LuGre model, the bristle deflection z evolves according to:

$$\dot{z} = v - \sigma_0 \frac{|v|}{g(v)} z, \quad (2.5)$$

where

$$g(v) = f_c + (f_s - f_c) e^{-|\frac{v}{v_s}|^\gamma}. \quad (2.6)$$

Here, f_c and f_s represent Coulomb and static friction, respectively. The fric-

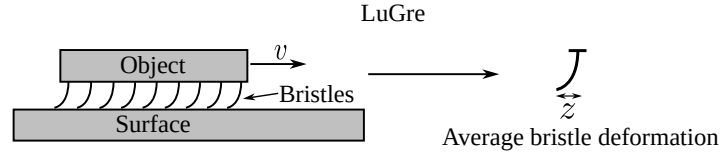


Figure 2.3: Illustration of the bristle deflection analogy of the Dahl and LuGre friction models.

tion force is then given by:

$$f_f = \sigma_0 z + \sigma_1 \dot{z} + f(v), \quad (2.7)$$

where σ_1 is a damping coefficient and $f(v)$ is viscous friction.

The original LuGre assumes a constant normal force. In [45] the LuGre model has been extended for varying normal loads, often referred to as the amended LuGre model [46]. This model evaluates the bristle deflection for the friction coefficient instead of the force. Similar to (2.5) the bristle deflection is governed by:

$$\dot{z} = v - z \frac{\sigma_0^A |v|}{g^A(v)}, \quad (2.8)$$

where $g(v)$ and σ_0 has been replaced with $g^A(v)$ and σ_0^A . The new steady state bristle deflection $g^A(v)$ is given by:

$$g^A(v) = \mu_C + (\mu_S - \mu_C) e^{-|\frac{v}{v_s}|^\gamma}. \quad (2.9)$$

This results in the friction force:

$$f_f = (\sigma_0^A z + \sigma_1^A \dot{z} + \sigma_2^A v) f_n. \quad (2.10)$$

LuGre models capture the stick-slip phenomenon, where objects alternate between sticking and slipping, as detailed in [47]. This effect occurs due to the difference in static friction and Coulomb friction. For example, consider an object resting on a surface pulled by a spring. The object begins to slip when the force exerted by the spring exceeds the maximum static friction force. Once the object starts slipping, the friction transitions to Coulomb friction, which is typically lower than the static friction force. As a result, the net force on the object becomes positive, causing it to accelerate. As the object accelerates and reaches a velocity greater than that at which the spring is

being pulled, the spring force acting on the object decreases until the object sticks again, and the process repeats. In reality, this phenomenon can occur on very small spatial scales and at high frequencies.

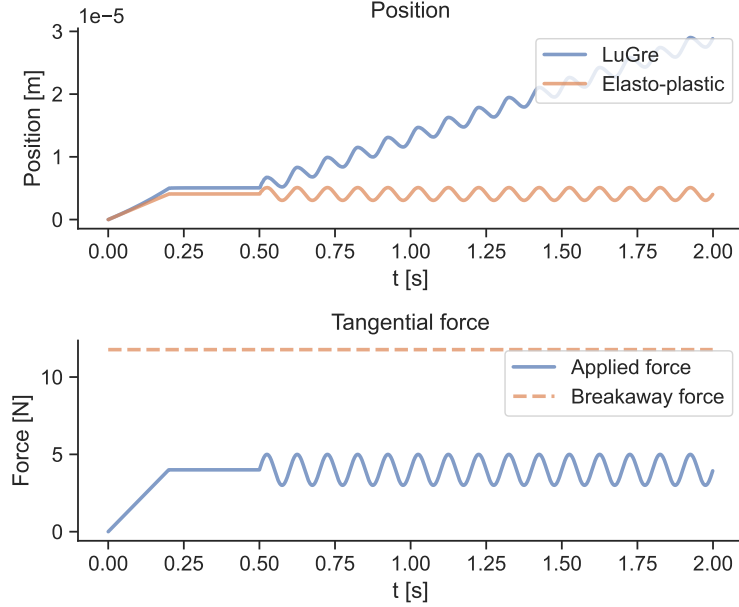


Figure 2.4: Displacement drift in the LuGre model under a small oscillating load and its mitigation by the Elasto-Plastic model under the same conditions.

Elasto-Plastic Friction Model

The Elasto-Plastic model [48], an extension of the LuGre model, addresses drifting under varying tangential loads, also in sub-slip conditions, as shown in Fig. 2.4. The Elasto-Plastic model introduces an elastic regime for bristle deflection, thus preventing drifting. Equation (2.8) which governs the rate of the bristle deflection is in this case modified to:

$$\dot{z} = v - \alpha(z, v)z \frac{\sigma_0 |v|}{g(v)} \quad (2.11)$$

where $\alpha(z, v)$ is a function that governs the elastic versus plastic regimes described by:

$$\alpha(z, v) = \begin{cases} 0 & \text{sgn}(v) \neq \text{sgn}(z) \\ \begin{cases} 0 & |z| \leq z_{\text{ba}} \\ \alpha & z_{\text{ba}} \leq |z| \leq z_{\text{max}} \\ 1 & |z| \geq z_{\text{max}} \end{cases} & \text{sgn}(v) = \text{sgn}(z) \end{cases} \quad (2.12)$$

where z_{ba} is a breakaway threshold. The transition between plastic and elastic regimes is described by:

$$\alpha = \frac{1}{2} \sin \left(\pi \frac{z - (z_{\text{max}} + z_{\text{ba}})/2}{z_{\text{max}} - z_{\text{ba}}} \right) + \frac{1}{2}. \quad (2.13)$$

The elastic behavior in the sticking regime ensures that the friction force is proportional to the micro-displacement and hence preventing drift. The maximum bristle deflection z_{max} is the steady state deflection $z_{\text{max}} = z_{\text{ss}} = \frac{g^A(v)}{\sigma_0}$. As seen in Fig. 2.4, the Elasto-Plastic model mitigates the drifting under varying tangential loads on an object.

2.2 Contact Surfaces under Planar Motions

Planar motion adds another dimension to friction modeling. The behavior is now also dependent on the contact shape and size. In this work, the shape and size are more generally defined with the contact pressure distribution. The contact will dictate how the coupling between torsional and tangential friction behave when subjected to planar motions. This coupling means that the torsional and tangential friction are not independent from each other. First, a short overview of the contact surface is presented, followed by a description on how the 1D LuGre models can be extended for planar motion.

Contact Surface

When a robotic gripper grasps an object, the contact pad on the robot's finger presses against the object's surface, forming a contact area, shown in Fig. 2.5. The size and pressure distribution of this contact surface significantly influence the frictional forces and torque generated during planar motion.

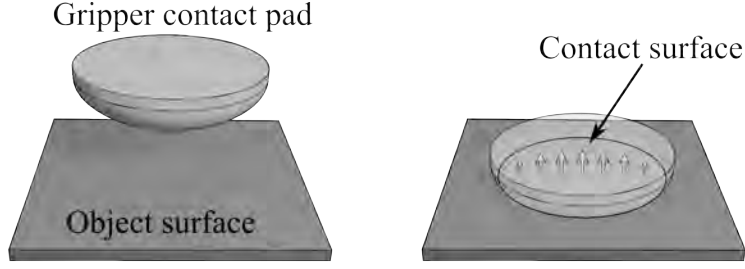


Figure 2.5: Illustration of the contact surface when a soft contact pad is pressed against a rigid object.

Larger contact surfaces with pressure concentrated towards the edges can produce more frictional torque than smaller surfaces. Soft contact pads, their deformation, and the resulting pressure distributions have been extensively studied in works such as [49], [50], [51], [52], [53], [54], [55].

The shape and rigidity of the object also play a crucial role in determining the pressure distribution. For example, a cylindrical object, like a bottle, produces a different contact pressure distribution than a flat surface. In this thesis, modeling is simplified by assuming that the contact interface is flat. The pressure distribution at the contact is typically not constant. Mechanical flexing of the gripper’s finger under load (see Fig. 2.6) affects the size and distribution of the contact surface, making the contact area force-dependent even for rigid objects and contact pads. However, the effect of finger flexing is less pronounced for deformable contact pads, whose deformation contributes more directly to the contact pressure distribution under load. For linear slippage, variations in the contact pressure distribution generally have a minor effect, although they may cause small orientational changes as the CoP shifts. In contrast, during slip-avoidance or rotational slippage, the contact pressure distribution directly affects the amount of torsional friction that can be generated.

During the modeling in Paper A and the tactile measurements in Paper D, we let $p(x, y)$ represent the pressure at the location (x, y) , see Fig. 2.7. This representation contains a large amount of information; however, it is computationally inefficient and cumbersome for use in control or estimation. To address this issue, the contact surface was approximated with a rim-contact model, see Fig. 2.8. This representation is characterized by a single parameter, the contact radius r . Although it sacrifices accuracy, it is easy to incorporate into control and estimation problems and captures an approximation of the

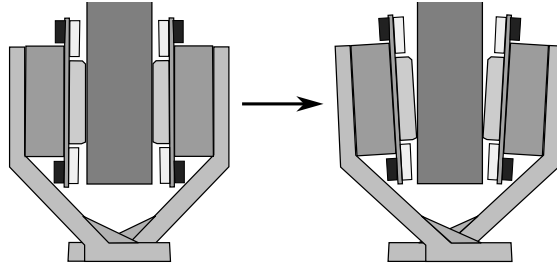


Figure 2.6: Illustration of how a rigid contact pad and rigid object might not be aligned under high grasping forces due to mechanical flexing.

coupling between torsional and tangential forces under planar motion.

Other interesting behaviors emerge when considering the contact surface and the properties of the contact pad. Incipient slip is the phenomenon in which part of the contact surface experiences slip while other regions remain stuck. In other words, the entire contact area does not transition to slip simultaneously [56]. Instead, slip typically initiates at the edges of the contact and propagates inward. Previous studies have shown that elastic contacts exhibit a partial-slip regime in which local slip precedes gross sliding. Furthermore, compliant materials undergo larger deformations and often generate larger contact areas under equivalent loading conditions. Consequently, it is reasonable to hypothesise that increased compliance may broaden the observable partial-slip regime, potentially slowing the transition from sticking to sliding. However, I was unable to find literature explicitly demonstrating a direct relationship between contact compliance and the extent of incipient slip. Nevertheless, it is noteworthy that the setup in Paper B employed a rigid contact pad, whereas Papers D and E utilized deformable tactile sensors. Interestingly, when a deformable contact pad was used, a reduction in stick-slip behavior was observed. While many factors may contribute to this difference, the observation is consistent with the hypothesis that increased contact compliance may influence the transition between sticking and slipping.

Friction under Planar Motions

When surfaces exhibit planar motion (both angular and tangential velocities), tangential friction and torsional friction forces are coupled. The combined force can be described by a force wrench, as shown in Fig. 2.1. For example, an object undergoing linear motion requires minimal torque to start spinning. As the object spins faster, torsional friction increases, while tangential friction

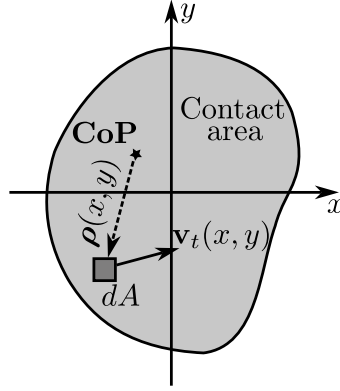


Figure 2.7: Illustration of the contact surface for the limit surface friction model.

decreases. The limit surface theory [57], [58] provides a mathematical description of this coupling under Coulomb friction. The tangential forces $[f_x, f_y]^T$ and torque τ are defined by:

$$[f_x, f_y]^T = - \int_A \mu_C \hat{\mathbf{v}}_t(x, y) p(x, y) dA \quad (2.14)$$

and

$$\tau = - \int_A \mu_C [\boldsymbol{\rho}(x, y) \times \hat{\mathbf{v}}_t(x, y)] p(x, y) dA, \quad (2.15)$$

where $\boldsymbol{\rho}(x, y) = [x \ y]^T$ is the position vector with its origin at the CoP, as depicted in Fig. 2.7, and $\hat{\mathbf{v}}_t(x, y)$ is the unit velocity vector at the point (x, y) . The function $p(x, y)$ represents the pressure distribution at that point, illustrated by the arrows in Fig. 2.5.

In robotics literature, an ellipsoid approximation of the limit surface is typically used [20], [49], [59], [60], [61], [62]. It can be described by:

$$[f_x \ f_y \ \tau]^T = \mu_C f_N \frac{\mathbf{S} \mathbf{v}_S}{\|\mathbf{v}_S\|_2}, \quad (2.16)$$

where $\mathbf{S} = \text{diag}([1 \ 1 \ r])$ and $\mathbf{v}_S = [v_x \ v_y \ r\omega]$. The ellipsoid approximation follows the coupling behavior of a rim-contact.

In Paper A, the extension of LuGre-type friction models to the planar case is investigated. The goal is to develop a friction model that accurately captures stick-slip behavior for planar motions and contact surfaces, which is essential for in-hand manipulation with robotic grippers. However, such simulations can quickly become computationally expensive. To address this issue, we

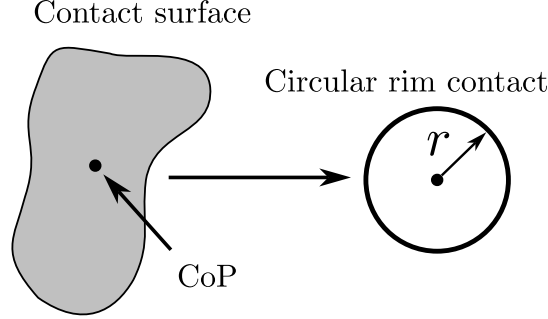


Figure 2.8: Illustration of the rim-contact approximation of a contact surface.

propose an approximate model that utilizes a pre-computed limit surface, thereby significantly reducing the computational cost.

Paper A presents two main models: the distributed and reduced planar LuGre models. The distributed planar LuGre model discretizes the contact surface and simulates a two-dimensional LuGre model in each cell. However, this approach is computationally demanding, as each cell contains two bristle states. For a $[20 \times 20]$ discretization, this results in 800 hidden state variables.

The reduced planar LuGre model instead relies on a pre-computed limit surface. The bristle dynamics are simulated using an ellipsoidal approximation, requiring only three bristle states. While this approximation substantially reduces the computational complexity, it also discards a significant amount of information about the true contact surface. To compensate for this loss, the ellipsoidal approximation is scaled using the pre-computed limit surface, allowing it to locally follow the dynamics of the true contact surface, while retaining a low computational cost.

2.3 Simulation Integration Schemes

Simulating multi-body dynamics requires a careful interplay between mathematical modeling and numerical integration schemes. The classical dynamics

of a mechanical system are governed by Newton's second law:

$$f = ma \quad (2.17)$$

where the force f acting on a body is equal to its mass m multiplied by its acceleration a . Since acceleration represents the second derivative of position with respect to time, (2.17) defines an ordinary differential equation (ODE) describing the continuous motion of the system. Given the applied forces and the system mass, the acceleration can be computed directly, allowing the velocity and position to be updated by integrating the underlying ODE over time.

The simplest approach to numerically solving such ODEs is the forward Euler integration method. Given a system state $x(t)$ and its time derivative $\dot{x}(t) = f(t, x(t))$, the subsequent state is approximated linearly as

$$x(t + \Delta t) = x(t) + \Delta t \cdot f(t, x(t)) \quad (2.18)$$

where Δt denotes the discrete integration time step. A smaller time step generally improves the accuracy, as the state derivative is assumed to remain constant throughout the interval. However, reducing the time step also increases the computational cost for every second simulated. For example, utilizing a time step of $\Delta t = 10^{-6}$ s requires one million discrete integration steps to simulate just a single second of motion. For simulations with fixed time steps, these small time steps are often necessary when system dynamics changes rapidly, such as during contact collisions or stick-slip transitions.

For systems characterized by smooth, slowly varying accelerations, discrete fixed-step integration can approximate the true trajectory with high accuracy. However, systems involving contact dynamics and friction introduce discontinuities; contact forces can appear or vanish instantaneously, and friction forces can rapidly reverse direction over microsecond time scales. For simple friction models, such as Coulomb friction, high-frequency numerical oscillations are commonly observed when using fixed-step explicit schemes, as illustrated in Fig. 2.9. For more complex formulations, such as the LuGre friction model, explicit schemes can become unstable unless a sufficiently small time step is used. This is illustrated in Fig. 2.10, where two of the three explicit solvers become unstable.

Fortunately, across large intervals of a typical simulation, the dynamics

evolve slowly enough that larger time steps can be used without a significant loss of accuracy. This behavior has motivated the deployment of adaptive integration methods, where the time step is adjusted dynamically based on the local truncation error of the system. Rapidly changing dynamics are integrated using tightly constrained steps, whereas smoother regions leverage larger steps, thereby balancing simulation accuracy with computational efficiency.

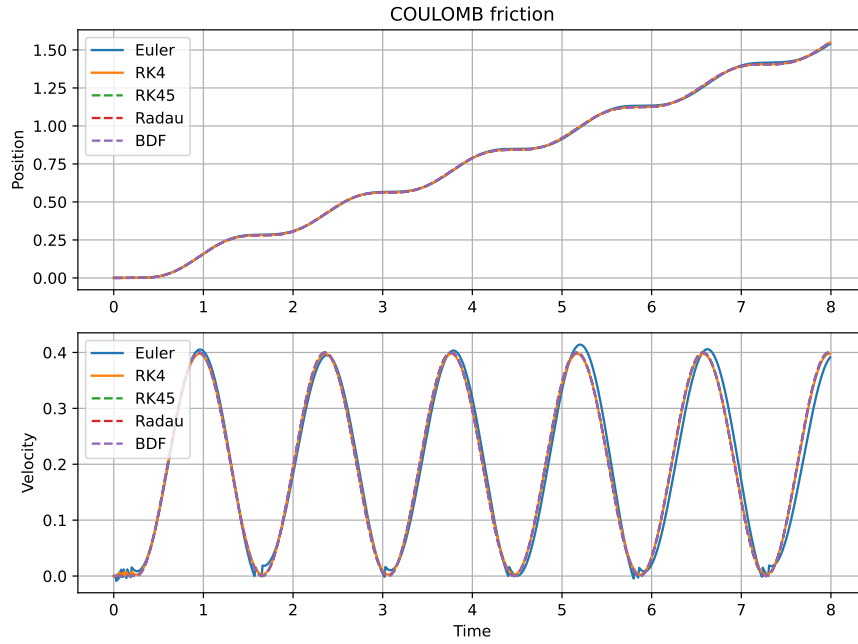


Figure 2.9: Comparison between different integration schemes applied to a mass-spring system subject to Coulomb friction.

Explicit solvers compute the next state of a system directly from the current state and its derivatives [63], making them straightforward to implement and computationally efficient per time step. For instance, the forward Euler method represents the foundational explicit integration scheme. Among more sophisticated explicit approaches, Runge–Kutta methods are widely utilized. The classical fourth-order Runge–Kutta (RK4) variant employs a fixed time-step and approximates a fourth-order Taylor expansion using a weighted sum of four internal slope samples. The adaptive Runge–Kutta–Fehlberg (RK45) method extends this approach by simultaneously calculating fourth- and fifth-order expansions. By evaluating the difference between these two estimates,

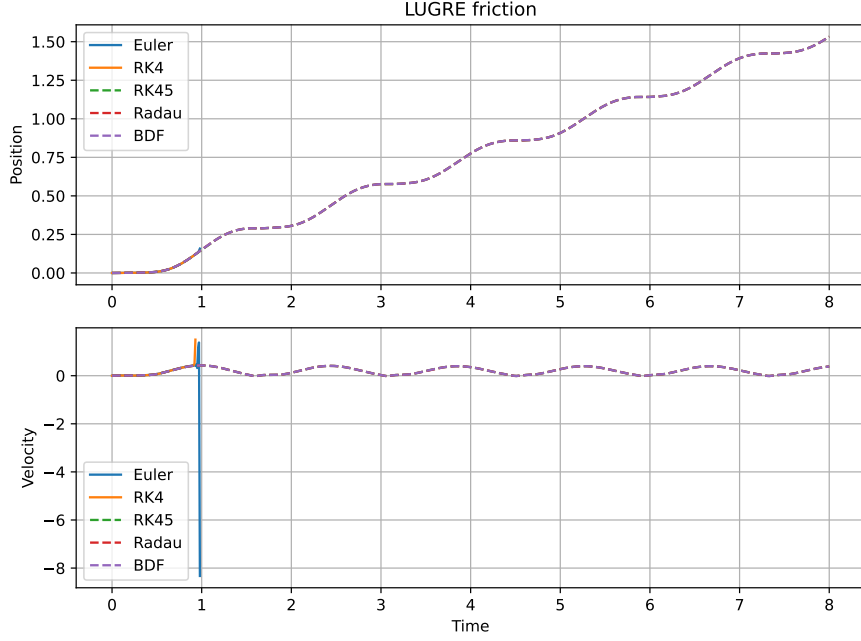


Figure 2.10: Comparison between different integration schemes applied to a mass-spring system subjected to LuGre friction.

the algorithm dynamically scales the step length to ensure a predefined error tolerance is satisfied. Despite their efficiency, explicit solvers can become unstable when applied to stiff systems, often requiring undesirably small time steps to maintain numerical stability.

In contrast to explicit schemes, implicit solvers [64] determine the future state of a system by evaluating the governing equations at the next time step, t_{n+1} . This formulation results in an implicit algebraic system of the form $y_{n+1} = y_n + h(t_{n+1}, y_{n+1})$. If the underlying physics or constitutive laws are nonlinear, this approach necessitates solving a coupled nonlinear system of equations at every discrete time step, typically using iterative techniques such as the Newton–Raphson method. Consequently, implicit methods has a significantly higher computational cost per time step.

Despite this increased computational overhead, implicit solvers offer a critical advantage. Many implicit integration schemes possess favorable stability properties that permit substantially larger time steps than explicit methods, particularly when solving stiff systems. However, numerical stability does not necessarily imply accuracy, and excessively large time steps can still lead to

inaccurate simulation results. In contact-rich systems, implicit formulations often provide improved robustness and permit larger stable time steps, frequently reducing constraint drift and improving the handling of stiff contact interactions. These properties make implicit methods particularly attractive for the planar LuGre models considered in Paper A, which exhibit both stiffness and a large number of coupled internal states.

2.4 Friction Estimation and Real-World Behavior

While many physical phenomena can be described accurately using relatively simple models, friction remains notoriously difficult to characterize. Empirical friction frequently deviates from standard models, which typically capture only the primary properties necessary for a given task in order to balance accuracy and computational tractability. In practice, friction depends on a multitude of coupled factors, including surface roughness, sliding velocity, contact area, temperature, humidity, wear, contact duration, surface residue, and the rate of applied force [65], [66], [67], [68], [69]. Accurately modeling all of these phenomena is generally impractical for real-time control applications. Although more detailed models can improve predictive accuracy, they often do so at the expense of increased complexity, making them more difficult to implement and substantially increasing the number of parameters that must be identified. Consequently, the controllers considered in this work rely on simplified friction models, while discrepancies between the model and the physical system are compensated for through feedback control.

Our objective is to use friction models for real-time control while updating their parameters online. This approach allows the parameters of the model to adapt dynamically to changing surface properties during sliding, thereby mitigating the effects of modeling inaccuracies. In this work, we focus primarily on estimating the static friction coefficient, μ_S , and the Coulomb friction coefficient, μ_C , between the tactile sensor’s contact pad and the grasped object. In paper B and C, we also estimate the contact radius, whereas in paper E, the contact radius can be directly calculated from the tactile pressure map reading.

The estimated friction coefficients, together with the measured contact forces, are used to assess the contact state during sticking. In particular, they enable the evaluation of grasp stability and the computation of the min-

imum grip force required to prevent slip. Previous work [70] has explored tactile sensors capable of detecting incipient slip, which serves as a precursor to gross slippage. The sensors developed in this work do not directly measure incipient slip. Instead, the tactile setup in paper B measures contact forces and sliding velocities, while the sensor in paper D additionally measures the contact pressure distribution. Combined with online estimates of the friction coefficients, these measurements are used for active slip-avoidance and in-hand manipulation.

Friction estimation fundamentally requires some form of slip to occur, whether localized (e.g., incipient slip) or global/gross slip (where the entire contact surface moves). Static friction can typically only be measured during the transient switch from sticking to slipping. Once continuous sliding begins, the contact shifts to Coulomb friction. The actual mechanisms used to estimate friction and slip heavily depend on sensor properties and sensing modalities (see [69] for a review of tactile sensors applied to friction estimation). For example, Okatani et al. [71] successfully estimated static friction from sensor deformation during initial contact compression. This method exploits the behavior of deformable and low-compressible materials like silicone, which exhibit localized slip at the contact edges when pressed against a surface. The resulting local strain is thereafter correlated to the friction coefficients. While friction estimation relies on localized measurements, Le et al. [72] took a macro-level approach, utilizing a camera to segment an object by material type and applying tactile sensing to estimate friction coefficients for a specific region, which were then mapped to all other segmented parts of the same material class.

Our work utilizes sensors that measure sliding velocity and forces via separate sensing modalities. This dual-modality architecture is significant because it provides highly reliable, high-frequency data during slip events. For friction estimation we investigate two distinct experimental paradigms: in Paper B, we employ an initial exploration phase during object pick-up to estimate contact properties, whereas in Paper C and E, we track these properties continuously using an online estimator.

External contact vs gravity driven estimation

In the exploration phase of Paper B, the object rests on a fixed surface while the gripper applies a constant grasp force and intentionally induces slip. First,

the gripper translates the object against the surface and subsequently applies a rotational motion, enabling estimation of both friction coefficients and the contact radius. The resulting in-hand velocities and contact forces are recorded and used in a simple linear regression framework to estimate the friction parameters.

In contrast, Paper C considers an object that is already grasped and lifted. Slip is induced passively by gravity as the grasp force is gradually reduced. Although both scenarios involve in-hand slip within the contact frame, their dynamics differ significantly.

When a gripper moves against a fixed object, the induced slip typically generates large changes in tangential force, providing a clear signal for slip detection. In contrast, during gravity-driven in-hand slip, the tangential force remains nearly constant. The resulting force variations are often of the same order as the sensor noise floor and may be difficult to separate from manipulator-induced vibrations. Consequently, force-based slip detection becomes considerably more challenging.

Furthermore, the dynamics of in-hand sliding are often extremely rapid. In Paper C, using the hardware developed in Paper B, the complete transition from sticking to slipping and back to sticking typically occurs within 0.05 s. Even with a sensor sampling rate of 120 Hz, estimating parameters during the transients reliably is difficult. In addition, the normal force is no longer constant during the slip event. Together, these factors make friction estimation during in-hand slipping more challenging than during a controlled exploration phase. Paper C addresses these challenges through the practical implementation of online friction and contact-size estimation under planar motion.

The tactile sensors in Paper D have a deformable contact pad, which produces more gradual stick-slip transitions and, therefore, slower contact dynamics. These sensors, used in Paper E, substantially simplify the friction estimation problem and enable more reliable online parameter estimation during manipulation.

Online Friction Estimation

The primary objective in Paper C is to estimate the static friction coefficient μ_S , the Coulomb friction coefficient μ_C , and the equivalent rim contact radius r (illustrated in Fig. 2.8). We formalize this by partitioning the estimation task into distinct operational regimes. Because μ_S is only observable during

the brief stick-to-slip transition, its estimation is treated separately from μ_C and r . This section focuses only on the estimation of μ_C and r . Under

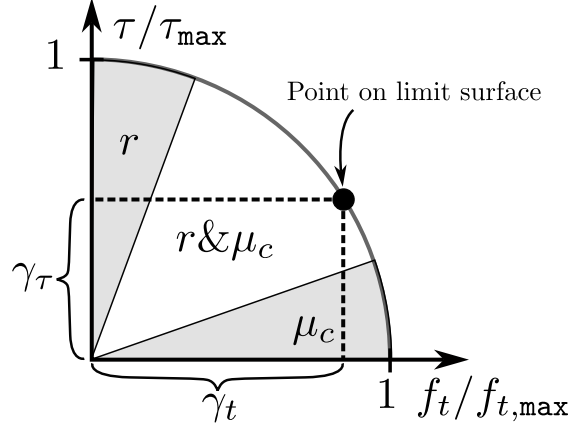


Figure 2.11: Illustration of the normalized limit surface and the corresponding estimation regions.

planar motion, torque and tangential friction forces are intrinsically coupled. For Coulomb friction, this coupling is governed by the limit surface (see Fig. 2.11). Our estimator approximates this surface using an ellipsoid assuming a rim-contact model (see Fig. 2.8), where the tangential force f_t and torque τ are modeled as:

$$f_t = (\gamma_t f_n) \mu_C \text{ with } \gamma_t = \frac{v_t}{v} \quad (2.19)$$

$$\tau = (\gamma_\tau \mu_C f_n) r \text{ with } \gamma_\tau = \frac{|r\omega|}{v} \quad (2.20)$$

where f_n is the grasp force. Using (2.19) and (2.20), an online estimator can be constructed to track μ_C and r during planar motion.

However, several observability constraints emerge. During pure linear slip-page (zero rotation), the system yields no information regarding the contact radius r . Conversely, during pure rotational motion, the individual effects of increasing μ_C or r are indistinguishable; only their mathematical product is fully observable. This naturally divides the estimation problem into different regimes based on the system's current state on the limit surface. Our approach in paper C uses thresholds on γ_t and γ_r , see Fig. 2.11. Under predominantly linear motion, only μ_C is updated; under planar motion, both r and μ_C are actively estimated; and under predominantly rotational motion,

only r is updated while μ_C is held constant.

While this multi-regime estimator performs well in simulation, real hardware introduces unmodeled physical dynamics that degrade performance. As previously noted, a stick-slip-stick event can occur in under 0.05 s. While our force/torque sensors sample at 1 kHz, the velocity sensing modality is set to 120 Hz to balance sampling frequency and accuracy. A significant amount of sticking and slipping dynamics can unfold within a single 1/120 th of a second. At these micro-time scales, components traditionally modeled as perfectly rigid experience micro-flexions and high-frequency structural oscillations, especially from the slip to stict transition. These structural dynamics corrupt the force measurements, leading to estimator degradation. To mitigate these unmodeled behaviors, we implement a simple yet effective practical heuristic: if the transient rate of change of the grasp force exceeds a predefined threshold, parameter estimation is temporarily paused. This ensures the estimator operates on data collected when the system dynamics are slow enough to be accurately modeled. The resulting estimation problem is therefore constrained by both theoretical observability and practical sensing limitations. A successful estimator must satisfy both requirements simultaneously.

The challenges described above arise largely because r is not directly observable and rapid stick-slip dynamics corrupting the measurements used by the estimator. The tactile sensors developed in Paper D address both issues. The deformable contact pad produces more gradual stick-slip transitions, while the measured pressure distribution allows the contact radius to be estimated directly. As a result, the estimator presented in Paper E can estimate μ_C across the entire limit surface without requiring force-rate-based heuristics.

CHAPTER 3

Hardware, Tactile Perception and Low-Level Control

If designing hardware has taught me anything, it is that the avenues for unforeseen setbacks are truly endless—and yet when the system finally comes alive, there is nothing quite like it.

While there is a wide array of commercially available tactile sensors and parallel grippers, they are typically not designed specifically for in-hand, slip-aware manipulation. This gap motivated the development of custom sensors and gripper hardware, bypassing the inherent compromises of using platforms built for alternate purposes. Now, after two complete design iterations of both the sensors and the gripper (see Fig. 3.1), the hardware is finally enabling the in-hand manipulation capabilities originally envisioned.

3.1 Grippers

In this thesis, we work exclusively with parallel grippers. Because these grippers only possess a single DoF of control—opening and closing—in-hand slip-aware manipulation places significant demands on this single axis. Slip dynamics can occur rapidly, hence, maintaining smooth motion during slip requires

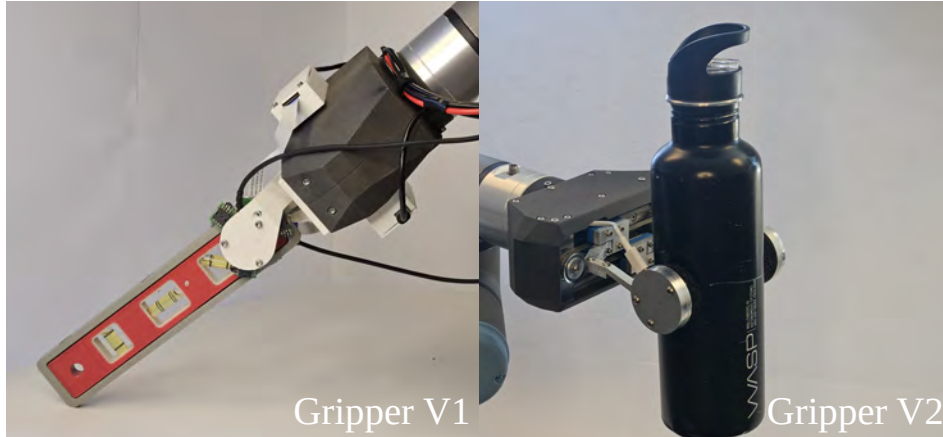


Figure 3.1: The gripper V1 and V2 setups with the sensors, mounted on a UR3e arm.

fast and accurate responses from the gripper control loop.

Mechanically, parallel grippers are inherently simple, and both versions developed in this thesis share the same fundamental architecture (see Fig. 3.2). The drivetrain features a brushless DC (BLDC) motor designed for stalled conditions—a type typically found in large camera gimbal systems. This motor is coupled to a 1:2 gear reduction to increase torque output, which subsequently drives a belt-and-pulley system. Two fingers, each mounted to a linear bearing, are directly actuated by the belt. An integrated motor encoder measures the rotor position, from which the linear position of the fingers can be inferred. This architecture functions as a quasi-direct-drive system, making it exceptionally well-suited for high-speed, force-transparent control. The primary tradeoff compared to traditional grippers is the higher current required to maintain a grasp, a direct consequence of the backdrivable, quasi-direct transmission.

Low-level actuation is managed by an onboard microcontroller and motor driver. Both gripper iterations employ Field Oriented Control (FOC) to regulate the current supplied to the BLDC motor. FOC measures the rotor position to determine the optimal current phase, thereby maximizing motor efficiency. This embedded algorithm executes at approximately 20–40 kHz, while higher-level external control is maintained at 500 Hz via a USB interface. In Paper B, gripper V1 was commanded via voltage, which correlates closely with gripping force under the stalled conditions typical of a grasp. Similarly, Paper D utilized voltage control for gripper V2. However, in Paper

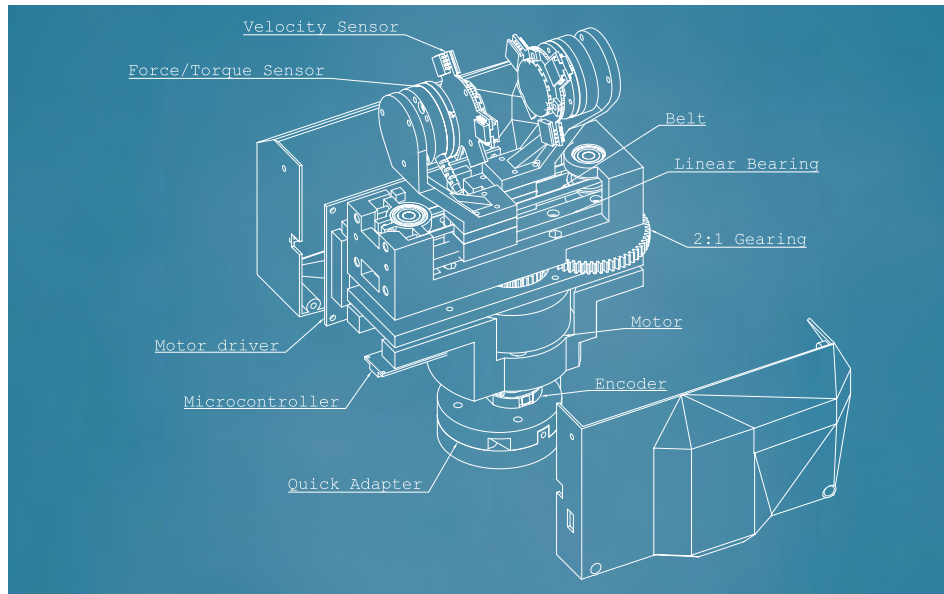


Figure 3.2: Exploded view of gripper V1.

E, gripper V2 was updated to support both voltage and motor angle control, enabling instantaneous switching between the two modes. Executing the position loop directly on the microcontroller allows the control loop to run at a significantly higher frequency, enabling more aggressive position tracking.

Gripper V1 was primarily constructed from 3D-printed components, allowing it to be fabricated using standard rapid prototyping techniques. With the exception of the gears, all structural plastic components illustrated in Fig. 3.3 are 3D printed. While this approach offers distinct advantages in terms of manufacturing simplicity and low cost, the primary drawbacks of these 3D-printed elements are their limited structural integrity, low thermal conductivity, and poor heat resistance. Because the motor and drive electronics generate thermal energy during operation, heat can accumulate within the assembly. Above approximately 60°C —corresponding to the glass transition temperature of PLA [73]—the printed components begin to lose structural integrity. In practice, this thermal degradation is only an issue during continuous, high-force grasping tasks over extended durations.

The second iteration of the gripper (V2) is constructed primarily from aluminum (shown in Fig. 3.4), which I machined using a small benchtop CNC mill. The primary improvements over the V1 design are enhanced structural durability and an optimized form factor. In a research lab, exposing custom

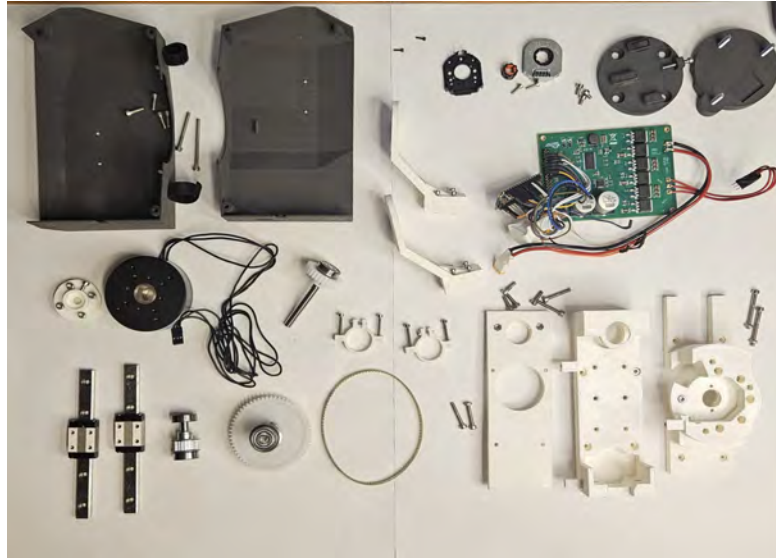


Figure 3.3: The components of the gripper V1.

prototypes to other users is often the fastest way to identify their practical limitations. While I had developed an intuitive sense of the physical limits of gripper V1, that implicit knowledge does not easily transfer to other users. To ensure that the hardware could withstand operation by others without constant maintenance, gripper V2 was engineered using higher strength materials, and the entire structure was designed to dissipate heat generated by both the motor and the tactile sensors. Furthermore, despite its significantly reduced size, the design provides greater clearance between the finger contact points and the gripper body, allowing for the manipulation of larger objects. While gripper V2 does not claim standalone mechanical novelty, it directly enables novel experimental capabilities.

3.2 Tactile Sensors

Humans possess multimodal sensory capabilities that enable the perception of diverse object properties, including shape, weight, dimensions, surface roughness, humidity, and temperature [39]. These sensory inputs are typically classified into static and dynamic modalities. Dynamic sensing captures transient changes, such as vibrations, and exhibits a faster response profile than static sensing, which measures the steady-state magnitude of a given stimulus. There

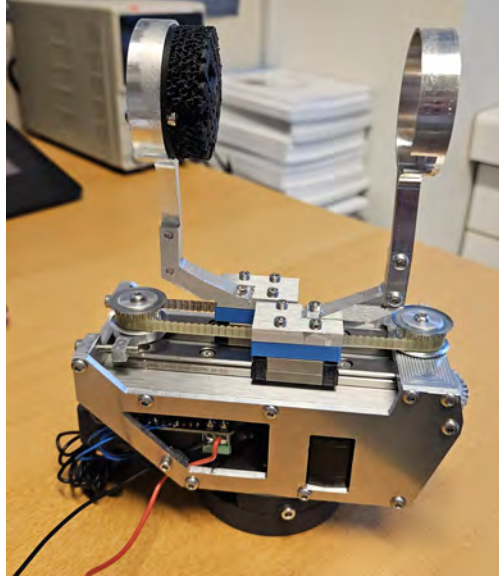


Figure 3.4: Gripper V2 without the outside shell.

are numerous comprehensive reviews that detail the vast landscape of tactile sensing [65], [74], [75], [76].

Tactile sensors specifically refer to sensors that detect local properties of a contact, such as force or temperature. Haptic sensing is a broader term that encompasses tactile sensing as well as other types of perception related to contact, including information that is indirectly influenced by the contact. For example, an object’s weight can be inferred from the effort required to lift it or from the shift in balance when carrying it. An F/T sensor located at the wrist of a robot can similarly infer information about the contact and is a typical example of haptic sensing. While substantial progress has been made in the development of robotic tactile sensors, widespread industrial adoption has been limited [39]. This is largely because tactile sensors can be challenging to integrate into robust systems and often suffer from issues such as drift and non-linear behavior. Tactile sensing in robotics is typically divided into several modalities: force, optics, vibration, and temperature.

Force-based tactile sensors measure contact forces, ranging from simple normal force measurements to more complex 6-axis F/T data, or even force fields distributed over a surface. Such tactile sensors have been used for dexterous manipulation tasks with both parallel grippers [77] and multi-fingered robotic hands [78]. They are also often combined with friction-based methods for slip



Figure 3.5: F/T sensors mounted on the fingers of gripper V1.

avoidance [39]. However, there are also many sensors that are not dedicated F/T sensors, but that can be used to estimate the contact forces [79], [80], [81], [82].

Optical tactile sensors have gained significant traction in recent years, driven by the popularity of platforms such as GelSight [82] and DIGIT [81], as well as easily reproducible alternatives such as the TacTip [83]. While the broader landscape encompasses several distinct optical sensing architectures [84], the most prevalent designs rely on measuring surface deformation at a contact interface. These systems typically embed a camera and a lighting array behind a transparent elastomer coated with a reflective membrane. When an object presses into the surface, the membrane deforms, altering the reflection of light from its surface and creating distinct shading and color gradients in the camera frame. This optical approach provides exceptionally high-resolution spatial information, enabling the direct application of computer vision and deep learning techniques to tactile perception tasks.

Sliding and object manipulation often generate micro-vibrations that can be detected via dynamic tactile sensing modalities [85]. The BioTac sensor [86], for instance, leverages an internal fluid-pressure sensor to capture acoustic pressure waves while simultaneously monitoring thermal fluxes. Other techniques include tracking the mechanical vibration of tactile surface nibs [85], utilizing piezoelectric slip elements, or embedding microphones to detect

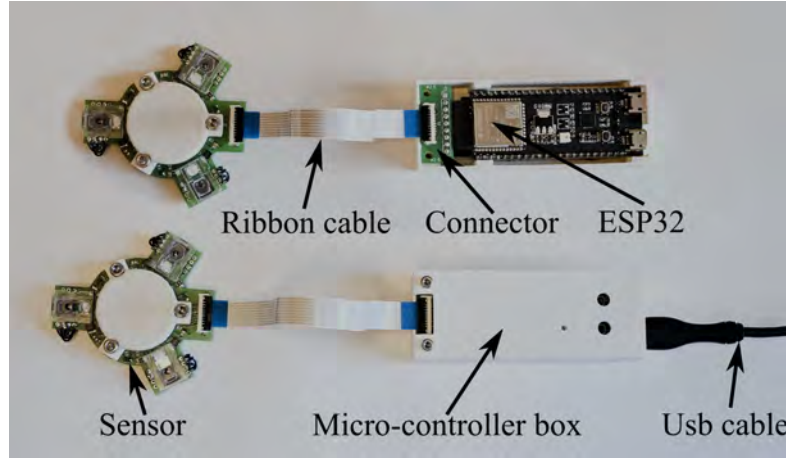


Figure 3.6: Velocity sensors 1.0, from paper B.

acoustic emissions [39]. However, a core limitation of vibration-based sensing is the difficulty of filtering out non-slip noise. Because the frequencies generated during sliding are highly dependent on the unique material pairings and roughness of the object surface, isolating these signals from the structural vibrations of the robot itself remains challenging.

The tactile sensing developed in this thesis is designed to complement rather than replace other modalities, such as computer vision [87]. Each approach has distinct trade-offs. For example, computer vision is well suited for locating objects across a workspace, but cannot directly measure contact properties. Conversely, tactile sensing can detect when an object is about to slip—a state that external cameras cannot easily capture. Furthermore, vision is susceptible to line-of-sight occlusions, and its resolution degrades with the distance from the camera. Fusing these two modalities allows them to mitigate each other’s weaknesses while leveraging their respective strengths.

Tactile Sensor V1

Initially, my research focused on a fundamental question: how can an object be tracked in-hand purely through tactile force feedback? However, after encountering the complexity of inferring precise dynamic displacements solely from force measurements, the research question shifted to an alternative approach: why not track the sliding velocity directly?

In Paper B, we designed V1 of our tactile sensor specifically to realize this

concept for slip-aware in-hand manipulation. The sensor combines traditional F/T sensing with planar velocity tracking—specifically, linear velocity in v_x and v_y alongside rotational velocity ω . This dual sensing approach allows us to simultaneously monitor both the contact forces and the exact sliding movement at each finger contact. The resulting hardware design is straightforward: the foundation consists of a commercially available F/T sensor attached to the gripper (see Fig. 3.5), upon which a custom printed circuit board (PCB) is mounted containing three optical mouse sensors arranged radially (see Fig. 3.6).

Implementing this idea, however, revealed significant hardware bottlenecks. Commercially available optical mouse sensors that can be ordered in low volumes with the correct lens, LED, and an accessible datasheet are exceptionally difficult to source. Beyond the lack of documentation, most standard sensors are fundamentally incompatible with this application. Nearly all wired mice integrate the main microcontroller inside the sensor housing; while this simplifies commercial manufacturing, it embeds a native USB output. Running three independent USB streams within a tiny fingertip footprint is highly impractical. Fortunately, certain wireless mice decouple the sensor from the main microcontroller. To overcome the sourcing barrier, these specific optical sensors, lenses, and LEDs were salvaged from commercial computer mice. Their communication protocols were then reverse-engineered and implemented on an ESP32-S3 development board. This custom embedded system aggregates the data from all three optical chips into a unified stream, preventing the host computer from incorrectly registering the sensor array as standard cursor-control peripherals.

These optical sensors are highly effective at tracking sliding motions, capable of detecting displacements as small as 0.01 mm. However, they present distinct operational limitations: they typically fail to track on transparent or highly specular (glossy) surfaces, and they require a highly constrained focal distance to maintain tracking accuracy. To accommodate this distance constraint in our initial design, we chose to employ a rigid contact pad. The contact surface plays a critical role in in-hand, slip-aware manipulation, serving as the primary physical interface between the gripper and the object. While the sensor architecture in Paper B proved highly successful for executing slip-aware manipulation tasks, the practical insights gained during experimental evaluation directly inspired the development of a second-generation tactile

sensor, presented in Paper D.

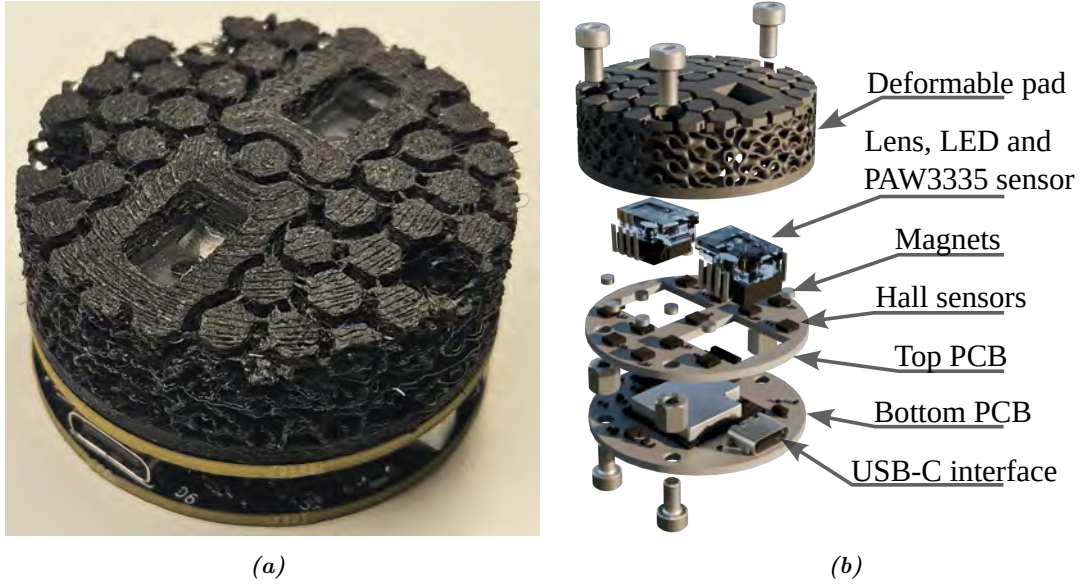


Figure 3.7: Tactile sensor V2.

Tactile Sensor V2

There is a well-established paradigm in robotics known as embodied intelligence—the concept that desired functionalities and control behaviors can emerge directly from physical mechanics and structural properties rather than computation alone [88]. Through the experimental evaluations conducted in Paper B, two primary mechanical requirements were identified to improve our in-hand slip-aware framework: a reduction in stick-slip phenomena and a more uniform contact pressure distribution. We hypothesized that introducing a deformable contact pad could mitigate stick-slip behavior through broader incipient slip regions. This insight inspired the development of a second-generation tactile sensor that retains the optical displacement sensors but embeds them within a compliant medium.

The finalized sensor is shown in Fig. 3.7a, with its internal components detailed in the exploded view in Fig. 3.7b. This self-contained sensor measures the contact wrench, pressure distribution, and planar sliding velocities, utilizing a USB-C port for both power delivery and data communication.

The defining advancement of this iteration is the integration of the deformable contact pad. By embedding the optical mouse sensors directly within

the contact pad, the sensing elements actively conform to the geometry of the object. This design yields two primary advantages for velocity tracking. First, it enables robust velocity estimation across curved object surfaces. Second, because the tracking mechanics are fully integrated within the active contact area, it drastically minimizes the risk of individual optical sensors moving outside the geometric boundary of the manipulated object. Furthermore, the compliant nature of the pad inherently dampens stick-slip transitions and provides a more uniform contact pressure distribution. Combining these enhanced contact mechanics with real-time pressure distribution estimation significantly simplifies the online estimation of the friction properties.

However, these compliance benefits introduce specific trade-offs relative to the initial design. Since this version bypasses the expensive commercial F/T sensor in favor of a single sensor design, the raw accuracy of the measured contact wrench is reduced. Instead of direct strain-gauge measurement, the contact wrench is estimated by tracking the structural deformation of the pad itself, utilizing permanent magnets embedded within the elastomer paired with an array of Hall effect sensors.

3.3 Grasp Control

This section outlines the low-level grasp controllers that interface directly with the high-level slip-aware control loops. For the first-generation gripper hardware (used in Papers B and C), the grasp controller tracked a desired normal force f_d using the commercial F/T sensors for closed-loop feedback. The control law was formulated as:

$$f_c = f_d + \frac{k_P}{\eta}e + k_I I_c(e), \quad (3.1)$$

where f_c represents the control command, which is mapped to a motor voltage V via a fixed proportional gain. The parameters k_P and k_I denote the positive proportional and integral gains, respectively, and $e = f_d - f_n$ defines the force error between the measured grasp force f_n and the desired force.

To mitigate transient overshoot, an error-dependent scaling factor $\eta = \gamma(\Delta e)^2 + 1$ was introduced, where $\Delta e = e(t) - e(t - t_s)$ denotes the discrete error derivative given a sampling time step t_s . The physical intuition behind this scaling factor leverages the intrinsic back-EMF of the voltage-

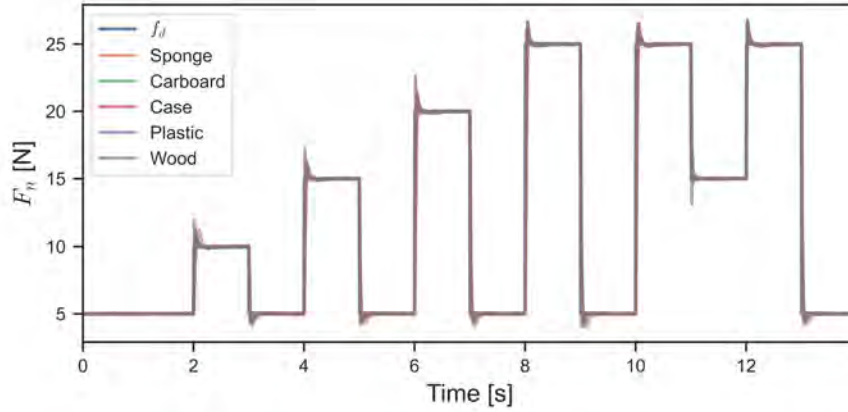


Figure 3.8: Step tracking with gripper V1 for different objects.

controlled BLDC motor, which provides natural viscous damping. For large dynamic errors, the feedforward action drives the system rapidly towards the target with minimal overshoot. However, under steady-state conditions with small errors, the feedforward term exhibits a residual bias caused by internal transmission friction and motor temperature fluctuations.

Temperature variations alter the phase resistance of the BLDC windings, subsequently shifting the voltage-to-force ratio under stalled conditions. While active current control could bypass this temperature dependence, it would simultaneously eliminate the natural back-EMF damping of the system and require highly sensitive, low-noise current-sensing circuitry. The proposed scaling factor η resolves this trade-off as it allows the gripper to act primarily as a feedforward system when the error changes rapidly, while effectively increasing the proportional gain as the error rate decelerates. To prevent integrator wind-up, the clamped integral term I_c is bounded by $I_b = \frac{I_{\max}}{\eta k_I}$ according to:

$$I_c(e) = \max \left(-I_b, \min \left(\int e(t)dt, I_b \right) \right). \quad (3.2)$$

The resulting controller exhibits highly responsive tracking characteristics across varying object stiffnesses, as demonstrated by the step response evaluation in Fig. 3.8.

For the second-generation gripper architecture (V2) featuring the deformable tactile sensors, explicit closed-loop force control is bypassed for certain tasks, such as linear or rotational sliding. While force control remains feasible via the

new tactile sensors, its absolute accuracy is lower than that of the commercial strain-gauge F/T sensors. Instead, the gripper can switch instantaneously between position or voltage control. When position control is utilized, the physical compliance of the deformable pads acts as a mechanical buffer during contact. The primary advantage of utilizing low-level position control is that the high-bandwidth controller on the gripper directly rejects internal actuator friction. Consequently, the slower, high-level slip-aware controller running at 250 Hz does not need to compensate for the internal non-linear actuator dynamics.

With the V1 hardware, the closed-loop force controller actively mitigated internal friction using direct force measurements. In contrast, the V2 architecture pairs position control with tactile compliance, which results in smoother in-hand motions despite the lower force estimation accuracy of the soft sensor. To maintain operational flexibility, the gripper V2 is capable of switching between position and voltage control modes within a single control cycle, enabling distinct control strategies depending on the active slip-aware manipulation controller.

CHAPTER 4

In-Hand Slip-Aware Manipulation

The goal of this chapter is twofold: first, to introduce the in-hand control modes that dictate the contact behavior and provide physical intuition regarding the motion primitives enabled by these control modes. Second, to outline the high-level architecture of the entire integrated system. Conceptually, this approach aims to construct a fundamental “vocabulary” for in-hand sliding manipulation. These primitive actions can subsequently be sequenced into “sentences”, ultimately allowing the gripper to execute arbitrary object regrasping. The specific implementation details of the controllers are covered in Paper E.

4.1 In-Hand Control Modes

As introduced in Chapter 1 and illustrated in Fig. 1.2, slip-aware manipulation comprises four primary control modes: rotational, hinge, linear, and slip-avoidance. While these modes fundamentally dictate the local contact behavior at the fingers, they do not map one-to-one onto specific trajectories. Instead, with the exception of slip-avoidance, each control mode can be leveraged to synthesize multiple distinct in-hand motion primitives. The control

modes govern the interactions at the contact interface. When combined with specific end-effector trajectories and the initial state of the system, they give rise to the distinct motion patterns that we call motion primitives.

Rotational Control Mode

One of the fundamental in-hand control modes is rotational control, which allows the object to pivot with a target angular velocity ω_c in the gripper as long as an external torque-generating force acts upon it. The basic primitive utilizing the rotational control mode is illustrated in Fig. 4.1. The object initially has its center of mass (CoM) offset horizontally from the CoP, and the gravity vector induces a torque at the contact point. During rotation, the gripper remains fixed and the induced torque changes as the rotation evolves. Since this torque depends on the position of the CoM, it is possible to perform closed-loop feedback using only force and torque sensing, which for a system with LuGre friction has been proven to be locally weakly observable [89]. In our framework, we directly measure the sliding velocities and utilize both velocity and force measurements.

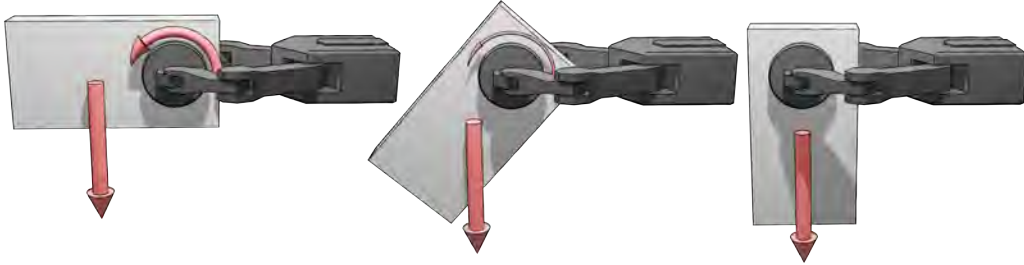


Figure 4.1: Illustration of rotate down motion.

Gravity-based rotational slippage can only rotate the object in the direction of the force-induced torque. When the CoM is located directly beneath the CoP and aligned with the gravity vector, the net torque on the object drops to zero. This creates an interesting control problem. Although the goal is to follow a reference trajectory, the rotational velocity can only be indirectly controlled by modulating the grasp force. In this situation, since tracking a

reference angular velocity is no longer possible, the controller instead switches to minimizing torsional friction while maintaining sufficient grasp force to avoid linear sliding.

Furthermore, the control problem is inherently asymmetric. The gripper often has high control authority when stopping the object, whereas acceleration toward the gravity vector is fundamentally bounded. Once this limit is reached, further release of the object does not increase its acceleration but instead causes the object to lose contact and enter free fall.

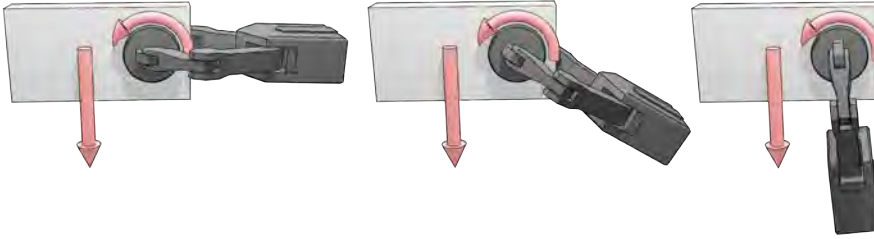


Figure 4.2: Illustration of hinge motion, where the gripper rotates and the object remains fixed.

During the motion primitive illustrated in Fig. 4.1, the gripper remains fixed; however, this constraint is not imperative. By allowing the gripper to rotate around the object, as illustrated in Fig. 4.2, the force-induced torque can be maintained throughout the manipulation, thereby extending the achievable manipulation range. This primitive enables the in-hand angle to change while maintaining a fixed global orientation of the object. This capability is crucial when manipulating objects that cannot tolerate changes in global orientation, such as open containers filled with liquid.

The gripper does not have to remain perfectly vertical during the rotational motion. It is sufficient that the projected force vector generates enough torque to overcome the contact friction without causing the object to fall out, see Fig. 4.3a. As demonstrated in Fig. 4.3b, it is possible to maintain a substantial tilt on the gripper and still successfully execute the rotational motion. This robustness allows for much more flexible initial conditions during manipulation and can also be exploited by the hinge controller.

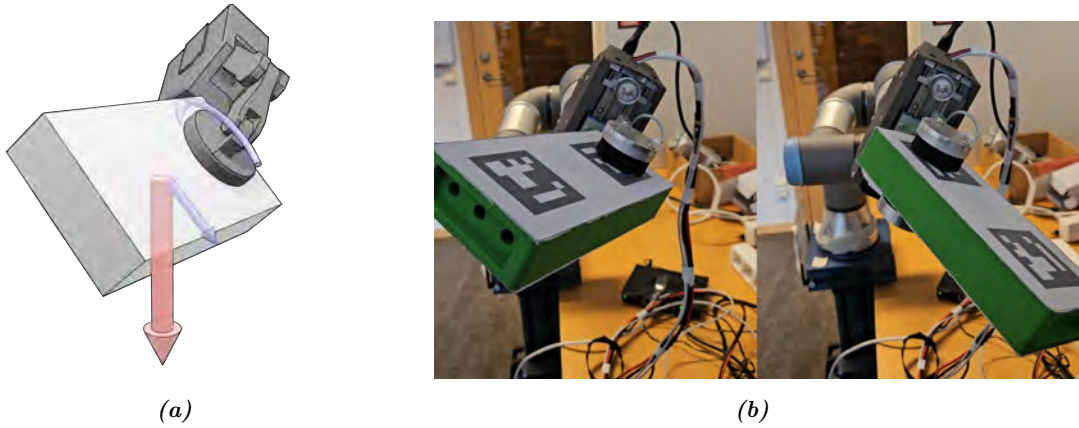


Figure 4.3: Rotation with tilted gripper.

Hinge Controller Mode

The hinge controller is a variation of the rotational controller, with the important distinction that it does not command a target angular velocity. Instead, the hinge controller attempts to minimize torsional friction while preventing the object from sliding linearly. Essentially, the grasp contact becomes a passive revolute joint and functions as a mechanical hinge. A basic use case of the hinge controller enables motions such as the one illustrated in Fig. 4.4, where the CoM and CoP of the object are aligned with the gravity vector, allowing the gripper to rotate around the object while the object itself remains fixed in the world frame.

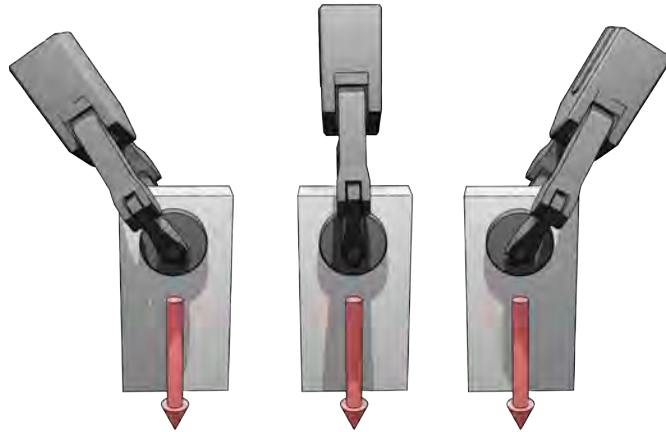


Figure 4.4: Illustration of hinge motion with object aligned with gravity.

The hinge primitive can be viewed as a passive revolute joint, making it uniquely suited for tasks such as pivoting an object against an external surface, as illustrated in Fig. 4.5. This decoupling allows the high-level trajectory planner to focus exclusively on moving the end-effector, while the lower-level hinge controller independently regulates the local in-hand behaviors.



Figure 4.5: Illustration of hinge control while pivoting on an external surface.

The scenarios involving the rotational pivot primitive described so far can only rotate the object in one direction. However, by changing the orientation of the gripper, the relative direction of the gravity vector experienced by the object can be altered. To effectively rotate an object upward, the gripper can be rotated, allowing the object to pivot with hinge control, activate slip-avoidance once the target has been reached, and then rotate the gripper back, as illustrated in Fig. 4.6. Provided that the CoM and CoP are sufficiently far apart and the object does not collide with the gripper, this sequencing allows the object to be rotated to any arbitrary angle by strategically utilizing the gravity vector.

The hinge controller can also be deployed for dynamic maneuvers, such as a swing-up motion (illustrated in Fig. 4.7). This paradigm allows the trajectory optimization for the swing-up phase to focus solely on the global end-effector kinematics, while the required grasp force is regulated in real-time by the low-level hinge controller.

Linear Sliding Control

The linear sliding control mode initially appears very straightforward. Its basic variant is illustrated in Fig. 4.8. In this scenario, the CoM is located

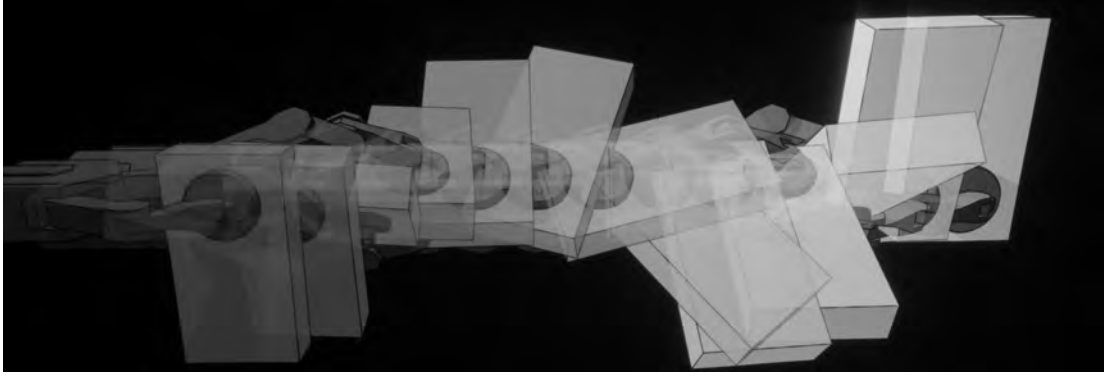


Figure 4.6: Illustration of rotate up motion.



Figure 4.7: Time series of swing-up motion with hinge control.

below the CoP of the contact pad, and the object slides downward while tracking a reference velocity magnitude. The direction of this slide is governed entirely by the direction of the gravity vector.



Figure 4.8: Illustration of linear slide motion.

Unlike the rotational controller, which regulates angular velocity while actively minimizing linear slippage, the linear sliding primitive does not explicitly attempt to suppress rotational motion. This design choice stems from the fact that suppressing angular velocity typically demands a higher grasp force

than linear slippage. Furthermore, if any external torque acts on the contact surface, the limit surface theory dictates that pure linear slippage is physically impossible. The consequences of this coupling are illustrated in Fig. 4.9. If the CoM is not perfectly aligned with the gravity vector and the CoP, a rotational motion will occur first. This rotation continues until the CoM settles directly beneath the CoP, at which point pure linear sliding follows.



Figure 4.9: *Illustration of the linear slip controller, starting with an initial torque that induces rotation followed by linear slip motion.*

It is also possible to achieve controlled planar motion using the linear slip controller. This is accomplished by rotating the gripper and controlling the linear slippage simultaneously, as illustrated in Fig. 4.10. While this behavior is kinematically similar to sequentially executing a linear motion followed by a hinge motion, this approach allows both actions to be performed concurrently. Essentially, the linear controller doubles as a hinge controller equipped with active linear velocity control.

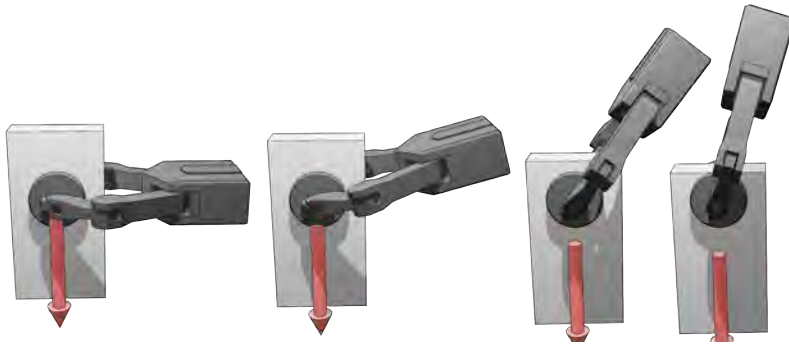


Figure 4.10: *Illustration of planar motion with linear slippage controller.*

So far, the linear sliding scenarios described have all regulated the linear velocity in a manner where the CoM moves away from the CoP. For the CoM to slide toward the CoP, it must for non-dynamic motions, be located above

the CoP. This configuration is an inherently unstable system, structurally analogous to an inverted pendulum. While it would certainly be possible to actively stabilize the object, it is practically far simpler to allow the object to rest against the palm of the gripper. This additional contact point mechanically stabilizes the object, enabling it to slide linearly with the CoM positioned above the CoP, as illustrated in Fig. 4.11. Furthermore, depending on the orientation of the gripper, the direction of sliding can be controlled within a specific range, bounded by the physical requirement that the CoM must remain between the CoP and the palm contact point.

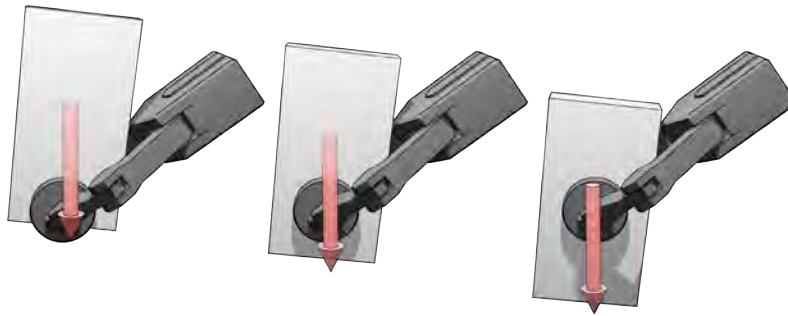


Figure 4.11: Illustration of linear slippage with palm contact.

Adaptive Slip-Avoidance

The adaptive slip-avoidance is perhaps the most straightforward control mode. Its primary goal is to completely avoid slippage while continuously adjusting the grasp force to the minimum value required to maintain stability. This mode, along with the hinge primitive, relies heavily on measured contact forces and friction parameters. While simple in concept, the slip-avoidance primitive has wide utility: it is deployed whenever any other in-hand primitive has achieved its target state and must bring the relative motion to a halt. For instance, an extreme use case occurs during the dynamic swing-up maneuver, where the object reaches high in-hand velocities before approaching a target angle. Instead of carefully stabilizing the object through precise end-effector trajectories—as is typical for inverted pendulum problems with passive joints—the system can plan for a small overshoot and then simply halt the object almost instantly at the desired angle by switching to the adap-

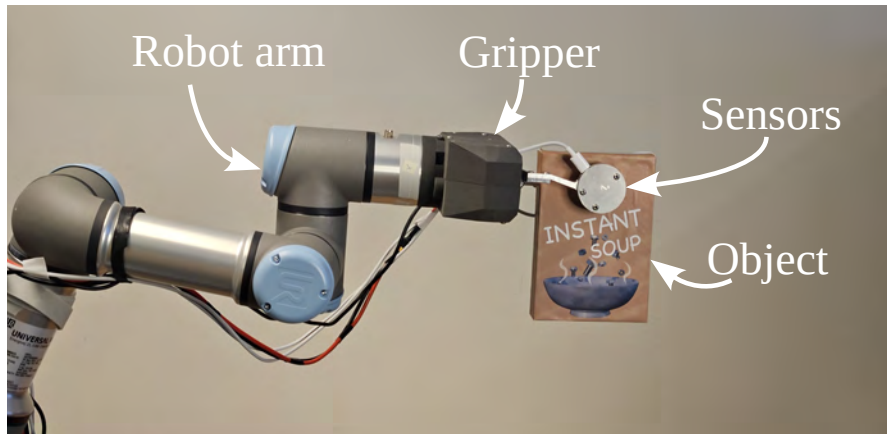


Figure 4.12: Image of the experimental setup.

tive slip-avoidance mode. This approach provides a powerful capability to instantly freeze an object’s motion or grasp it as lightly as possible without risk of dropping it.

All of these described behaviors emerge from a single-DoF parallel gripper by strategically leveraging the sensing modalities and contact mechanics. These motions can be chained together and executed sequentially, allowing the system to achieve a wide envelope of feasible in-hand poses. Ultimately, this demonstrates that the capabilities of a mechanically simple parallel gripper can be significantly extended through slip-aware in-hand control.

4.2 The Complete System

An overview of the experimental setup is shown in Fig. 4.12. The setup consists of a gripper mounted on a UR3 robotic arm, with two tactile sensors mounted on the gripper, one for each finger. The gripper grasps an object and performs slip-aware in-hand manipulation.

There are many possible approaches to designing the underlying control architecture of a robotic system, each with its own trade-offs. This section describes the architecture developed for the system presented in this thesis. A robotic system is typically not implemented as a single sequential chain of logic or instructions. Instead, it consists of multiple processes operating in parallel and continuously communicating with one another. This structure allows the control problem to be divided into different hierarchical levels,

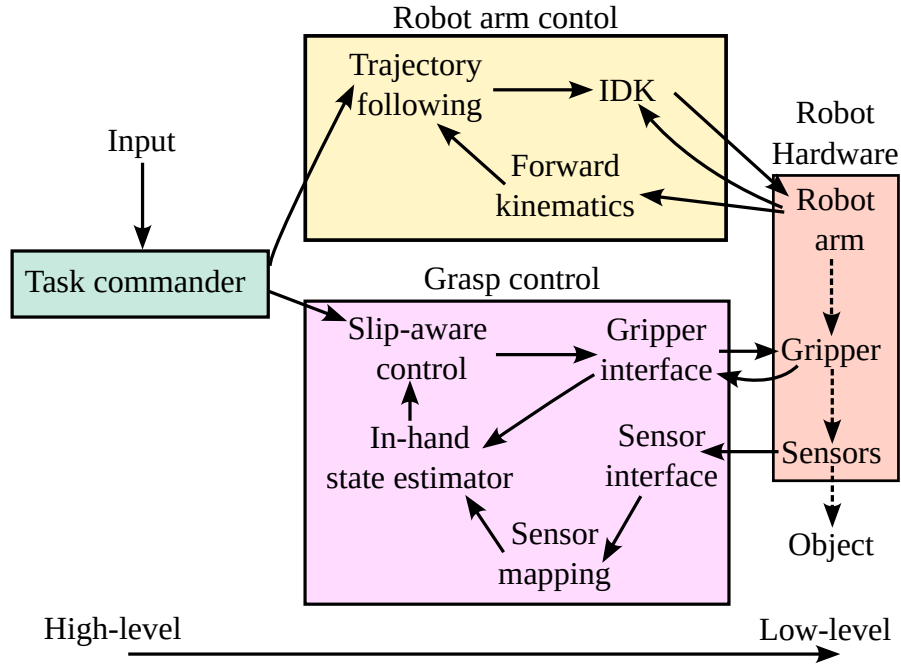


Figure 4.13: An illustration of the information flow of the robotic system. The dashed lines represents a physical connection.

as illustrated from left to right in Fig. 4.13. Such a hierarchy is particularly important because the hardware and software components of a robotic system may operate at substantially different rates. For example, the low-level motor controller of the gripper may operate at frequencies well above 10 kHz, whereas the tactile sensors provide measurements at 250 Hz.

The terms low-level and high-level control generally refer to the degree of abstraction from the underlying physical process and hardware. Low-level control operates close to the physical system. For example, a motor controller running on an embedded system is directly responsible for regulating the motor. In contrast, high-level tasks abstract away implementation details and instead specify a desired outcome, such as rotating an object by 30° . Achieving such a high-level objective requires several lower-level processes to translate the task into command signals that can be executed by the hardware.

An illustration of the information flow from a user command to a sliding manipulation is shown in Fig. 4.13. The process begins with a command such as “rotate 40° in 3 s” or “slide 30 mm in 2 s”. In the current implementation, these commands are provided by a human operator. Although the current

implementation relies on direct human input, the same interface is intended to support a planning algorithm for achieving more complex manipulation tasks. The input request is first processed by a task commander, which repackages the command and forwards it to the robotic arm and gripper controllers.

On the robotic arm side, the process is relatively straightforward. The request is first translated into a set of waypoints, from which a task-space trajectory is generated. A trajectory controller then calculates the desired end-effector velocities required to follow this trajectory based on the current time and the estimated end-effector pose. These velocities are converted into joint velocities using inverse differential kinematics. The resulting joint-velocity commands are sent to the robot, where the actuators at each joint are responsible for tracking their respective target velocities. The measured joint angles are thereafter used to calculate the end-effector pose through forward kinematics.

On the grasp-control side, the system is more application-specific. The task commander activates one of the four slip-aware controllers, which use information from the tactile sensors to calculate either a target grasp force or a target motor position for the gripper. These commands are sent to the gripper at 500 Hz and executed by the onboard microcontroller at a higher control rate. The tactile sensors measure magnetic fields and sliding displacement. The sliding displacement is represented as sensor counts, with a resolution of approximately 200 counts per mm. These measurements are transmitted to the computer at 250 Hz, where the magnetic readings are converted into contact forces and pressure maps, while the displacement counts are converted into sliding velocity. The resulting measurements are collected by the in-hand state estimator, where they can be combined with external measurements, such as vision-based object tracking.

The slip-aware controllers obtain the required information from the state estimator and use it to close the control loop. In addition to following high-level commands, the slip-aware controllers can also be commanded to directly track target sliding velocities. This provides greater flexibility within the control architecture and enables the controllers to serve as a lower-level interface for more advanced optimization and motion-planning methods.

CHAPTER 5

Summary of included papers

This chapter provides a summary of the included papers.

5.1 Paper A

Gabriel Arslan Waltersson, Yiannis Karayiannidis
Planar Friction Modelling with LuGre Dynamics and Limit Surfaces
Published in IEEE Transactions on Robotics (T-RO),
vol. 40, no. 10, pp. 3166-3180, 2024.
©2024 IEEE DOI: 10.1109/TRO.2024.3410455.

Paper A extends the LuGre friction model to planar motion and arbitrary contact surfaces. First, the contact surface is discretized, and a 2D version of the LuGre model with an Elasto-Plastic extension is proposed. The 2D LuGre model is then integrated over the contact surface to describe the resulting force wrench, which we refer to as the distributed planar LuGre model. While this model provides a detailed representation of the frictional interactions, it is computationally demanding. To address this, we propose the reduced planar LuGre model, which leverages a pre-computed limit surface for the

contact area. By reducing the simulated bristle dynamic equations to three, the computational cost is significantly lowered. Both models are tested and compared in various simulated scenarios to evaluate their performance.

G.A.W. is the main contributor to this work. Y.K. is the supervisor.

5.2 Paper B

Gabriel Arslan Waltersson, Yiannis Karayiannidis

Perception, Control and Hardware for In-Hand Slip-Aware Object Manipulation with Parallel Grippers

Published in The International Journal of Robotics Research (IJRR), vol. 45, no. 10, pp. 1497-1519, 2026.

©2026 Sage DOI: 10.1177/02783649251397549.

Paper B explores the development of custom hardware for in-hand slip-aware control. A custom parallel gripper is designed specifically for closed-loop force control, a feature not typically available in commercial grippers. For perception, we develop custom sensors capable of measuring planar velocity on flat surfaces using optical mouse sensors. These relative velocity sensors are mounted on F/T sensors, which are then placed on the fingers of the gripper, enabling independent measurements of both velocity and force. This setup allows for contact property estimation and we demonstrate four slip-aware controllers, each relying solely on in-hand sensing. The four slip controllers include trajectory-following for gravity-assisted linear and rotational slippage, hinge control, and slip-avoidance. The complete system is mounted on a UR10 robot and undergoes extensive testing to evaluate its performance.

G.A.W. is the main contributor to this work. Y.K. is the supervisor.

5.3 Paper C

Gabriel Arslan Waltersson, Yiannis Karayiannidis

Friction Estimation for In-Hand Planar Motion

Accepted in Experimental Robotics: The 19th International Symposium, vol. TBD, no. TBD, pp. TBD, 2025.

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Paper C presents a method for online estimation of contact properties during in-hand sliding manipulation with a parallel gripper. We estimate the static and Coulomb friction as well as the contact radius from tactile measurements of contact forces and sliding velocities. The method is validated in both simulation and real-world experiments. Furthermore, we propose a heuristic to deal with fast slip-stick dynamics which can adversely affect the estimation.

G.A.W. is the main contributor to this work. Y.K. is the supervisor.

5.4 Paper D

Gabriel Arslan Waltersson, Yiannis Karayiannidis
Deformable In-Hand Slip-Aware Tactile Sensor with Integrated Velocity Sensing, Force/Torque and Pressure Map Estimation
Conditionally accepted to RAL.

Paper D introduces a novel tactile sensor for in-hand manipulation with slip-aware control that integrates velocity, force/torque, and pressure map sensing into a single device with a deformable contact pad. To the best of our knowledge, this is the first sensor to combine these sensing modalities within a single compliant structure. The sensor features a deformable contact surface and can robustly track both flat and curved surfaces across a wide range of materials. Its performance is evaluated through a comprehensive set of experiments that highlight both its capabilities and limitations. The sensor is designed for rapid and low-cost fabrication, using a combination of standard PCB manufacturing and rapid prototyping techniques.

G.A.W. is the main contributor to this work. Y.K. is the supervisor.

5.5 Paper E

Gabriel Arslan Waltersson, Marko Guberina, Yiannis Karayiannidis
A Vocabulary of Slip-Aware In-Hand Motion Primitives
Submitted.

Paper E presents a framework for slip-aware in-hand manipulation using simple robotic parallel grippers. We introduce a vocabulary of in-hand motion primitives that separates desired object motions from their underlying

control methods. By combining tactile sensing, end-effector movements, and external forces such as gravity and contact with the gripper palm, the system achieves a range of manipulation capabilities including dynamic regrasps. The work focuses on planar objects and demonstrates a broader set of slip-aware manipulation skills on a single platform than has previously been shown, providing a foundation for future planning and reasoning in robotic manipulation.

G.A.W. and M.G. jointly contributed to the conceptual development and implementation of the work, as well as the experimental results and their analysis. G.A.W. was primarily responsible for the writing of the Introduction, Related Work on tactile sensing, Contributions, Vocabulary of Motion Primitives, Slip-Aware Controllers, and Results sections. M.G. was primarily responsible for the writing of the Introduction, Related Work on regrasping and dynamic pivoting, Contributions, Dynamic Pivoting, and Results sections. Y.K. is the supervisor.

CHAPTER 6

Concluding Remarks and Future Work

This thesis takes a step towards enabling robots with dexterous manipulation capabilities. While sliding objects within the grasp of a parallel gripper represents only one of many challenges on the path towards this broader goal, it contributes to the development of the sensing and manipulation capabilities required for increasingly dexterous robotic systems.

In-hand sliding has received relatively little attention compared to other aspects of robotic manipulation, with only a limited body of work establishing the foundations of the field. This thesis builds on these foundations by advancing in-hand sensing and manipulation capabilities towards a level at which they can be integrated into a larger robotic system. The aim is to provide a platform for future research on motion planning, sequencing of manipulation primitives, dynamic sliding, and extrinsic contact manipulation within a common system. In the existing literature, these capabilities have largely been investigated individually, often using separate experimental setups tailored to specific tasks. In contrast, this thesis presents a versatile gripper system that integrates several of these capabilities within a single experimental platform.

The central idea behind the gripper system is simple: sliding manipulation becomes significantly more tractable when both contact forces and sliding ve-

locities can be measured directly. At its core, the system combines optical sensing with force sensing to enable controlled sliding. While the system has inherent limitations and operating bounds, it is designed to operate reliably within these bounds without requiring task-specific tuning or prior knowledge of the manipulated object. The system does not require prior information about object properties, and the controllers adapt online to changes in characteristics such as weight and friction. Although the system is primarily designed for in-hand sliding manipulation, these capabilities also make it well suited for other tasks, such as slip-avoidance.

Ultimately, dexterous manipulation requires robots to do more than maintain a stable grasp. They must be able to deliberately change contacts, exploit friction, and move objects within and beyond the grasp. The work presented in this thesis contributes to this broader objective by focusing on the sensing and control of sliding within the grasp, with friction playing a central role in enabling these behaviours. In doing so, it provides a foundation for future research towards more capable robotic systems. Furthermore, planar sliding is not unique to robotics. The methods developed in this thesis for modelling, sensing, and controlling planar sliding could therefore have applications beyond in-hand manipulation with parallel grippers.

6.1 Future Work

There are many avenues for future work. The most apparent is to combine the system developed in this thesis with a motion planner and external sensors, allowing for higher-level reasoning and complementary sensing. This work focuses primarily on what happens within the hand, while tasks such as locating and identifying an object on a table are better suited to external sensing, such as computer vision. Combining these sensing modalities could allow their respective strengths to complement each other. The broader question then becomes how in-hand sliding manipulation can be incorporated into a larger robotics framework, and under which circumstances sliding manipulation is beneficial compared to other available manipulation strategies.

A second research direction is to take a more fundamental approach to contact mechanics. There is still much to understand about how contact surfaces can be designed to achieve desired contact dynamics. Furthermore, the mechanics of soft contact pads during sliding, together with the mechanical

properties of the materials, influence the resulting manipulation behavior. A deeper understanding of these interactions could enable the design of contact surfaces specifically tailored to reduce stick-slip dynamics.

Friction simulation is another avenue which could be further explored. One possibility would be to modify and incorporate the planar friction models developed in this thesis into a simulator. Efficient and accurate simulation of friction remains a challenging problem, particularly in multi-body systems where multiple contacts and frictional interactions occur simultaneously. Developing models that capture the relevant frictional behavior without making simulation prohibitively expensive could enable more realistic simulation-based planning and control.

In the real world, however, the interaction between an object and a contact surface is determined by more than the surface material alone. Texture, geometry, shape, and other physical properties can all influence the resulting behavior. There is, therefore, considerable fundamental work remaining in understanding how objects interact during planar motions, and in determining how material, texture, and shape could be designed and optimized to achieve particular manipulation behaviors.

The current tactile pad is 3D-printed from TPU. While this enables relatively simple and accessible manufacturing, the material also introduces hysteresis into the pad. Collaboration with researchers in materials and manufacturing science could provide opportunities to improve the mechanical properties of the pad while simultaneously reducing its size. Such developments could improve the accuracy and reproducibility of the tactile sensing while enabling more compact gripper designs.

The sensing and perception system could also be improved by developing fallback strategies for situations where one sensing modality becomes unreliable. For example, if the system could detect that the sliding-velocity estimate is becoming unreliable while e.g. the force measurement remains trustworthy, it could adapt its behavior to reduce the risk of dropping the object. This could be particularly useful for objects with surface properties that are difficult for the optical tracking system to measure reliably.

Another promising direction is online calibration of the tactile sensing using other sources of information. Haptic measurements or signals already available from the gripper, such as motor current, could potentially be used to estimate the grasp force independently of the tactile sensor. This information could

then be used to detect and compensate for sensor drift during operation. More generally, online compensation of sensor drift and hysteresis would be valuable for improving the long-term accuracy and reliability of the tactile sensing.

Finally, while this work has focused on parallel grippers, in-hand sliding manipulation is not limited to this type of end-effector. More dexterous, human-like hands can also benefit from the ability to deliberately slide and reposition objects within the grasp. In fact, during human manipulation, many motions naturally involve behaviors similar to those of a parallel gripper, where the grasp force is actively controlled while the object is allowed to move relative to the fingers. A deeper understanding of sliding, contact dynamics, and control in parallel grippers may therefore provide useful intuition that extends beyond simple grippers and towards more dexterous robotic hands.

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