Tracing Energy Flow: Learning Tactile-based Grasping Force Control to Reduce Slippage in Dynamic Object Interaction

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***Abstract*—Regulating grasping force to reduce slippage during dynamic object interaction remains a fundamental challenge in robotic manipulation, especially when objects are manipulated by multiple rolling contacts, have unknown properties, and when external sensing is unreliable. We propose a physics-informed energy abstraction that models the object as a virtual energy container. The inconsistency between the fingers' applied power and the object's retained energy provides a physically grounded signal for inferring slip-aware stability. Building on this abstraction, we employ model-based learning and planning to efficiently model energy dynamics from tactile sensing and perform real-time grasping force optimization. Experiments in both simulation and hardware demonstrate that our method can learn grasping force control from scratch within minutes, effectively reduce slippage, and extend grasp duration across diverse motion-object pairs, all without relying on external sensing or prior object knowledge.**

I. Introduction

Grasping an object using fingertips to perform intended motion is common in tasks involving object manipulation or transport. In these *dynamic object interactions*, rolling contact occurs and slippage at the fingertips is often unavoidable [1]. Object stability thus depends on adjusting fingertip forces to reduce slippage. However, distinguishing slippage during dynamic object interaction is challenging due to the complex dynamics of multiple moving contacts, unknown object properties, and unreliable external sensing. This makes high-frequency force adaptation under dynamic conditions a fundamental requirement for reliable dexterous manipulation.

Despite these challenges, humans rapidly regulate grasping force purely by touch [2]. This raises a central question: *how can a robotic hand learn to adjust grasping force to minimize slippage during dynamic object interaction using only tactile sensing?*

While principled solutions exist for grasping force control [3, 4], they often fall short under real-world uncertainties. Moreover, existing tactile-based slippage detection [5]–[7] focuses on static or quasi-static scenarios, while motion and unknown surface conditions blur the boundary of slippage determination [8]. Energy-based reasoning has been applied to dexterous manipulation via hand-centric compliance models [9, 10], but not for object-centric slip-aware force control from tactile sensing.

To address these challenges, we propose a physics-informed energy abstraction that expresses slip-aware stability using only tactile sensing without requiring explicit supervision. The object is abstracted as a virtual energy container, and the inconsistency between the total applied power and the change in retained energy provides a compact and physically grounded signal for slip-aware stability (see Fig. 1).

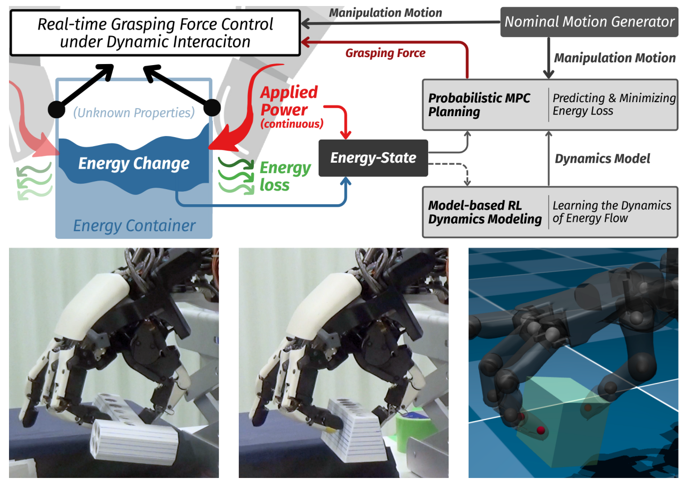

Fig. 1: Overview of the proposed framework. The object is abstracted as an energy container, where fingertip-applied power and retained energy are compared to infer energy loss as a physically grounded indicator of slippage. These quantities form an energy-state used in MBRL to learn energy-flow dynamics and optimize grasping force via pMPC.

To implement this abstraction for real-time control, we combine it with model-based reinforcement learning (MBRL) [11] and online planning via probabilistic Model Predictive Control (pMPC) [12], leveraging their synergy: the physics-informed abstraction provides a compact state for efficient dynamics learning [13], while MBRL and pMPC enable sample-efficient online adaptation and real-time force optimization. We validate the system in both simulation and hardware, demonstrating rapid acquisition of grasping force control from scratch within minutes.

Our contributions are:

- A physics-informed energy abstraction that infers slippage from tactile-based energy inconsistency.
- Integration with MBRL that achieves real-time force control comparable to observation-based methods, using only tactile sensing.
- Validation in simulation and hardware without external sensing or prior object knowledge.

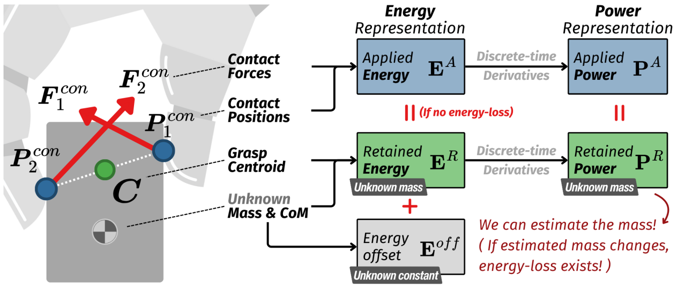

Fig. 2: Energy abstraction from multiple contact interaction. We compute the total applied power from all fingertip contacts and compare it with the object's retained power. Inconsistent mass estimates reflect energy loss attributed to slippage.

II. Related Work

Tactile sensing and slippage reasoning. Tactile sensing has been widely studied for slip detection using signal analysis [14], supervised learning [6, 7], or vibration-based methods [5]. However, these methods typically require explicit supervision and are developed under quasi-static settings, limiting their applicability to multi-finger dynamic interactions where object inertia and complex inter-finger forces make slippage reasoning difficult. In contrast, we infer slippage from energy consistency across multiple fingers, enabling label-free, real-time detection during dynamic manipulation.

Energy-based reasoning and model-based learning. Energy-based reasoning has been applied to dexterous manipulation via hand-centric compliance models [9, 10]. Model-based learning has also shown advantages in dexterous tasks [15, 16]. We combine both directions through an object-centric energy abstraction that aggregates multi-finger tactile input into a compact signal, enabling slip-aware force control without modeling contact mechanics or requiring external sensing.

III. Proposed Method

A. Energy Abstraction for Finger-Object Interaction

We assume a rigid, fixed-shape object with unknown but constant mass m, and adopt point contacts for all energy computation. The object is modeled as a virtual energy container, where the total energy $\mathbf{E}_t^A$ applied by n fingers is estimated by integrating contact forces ($\boldsymbol{F}^{con} \in \mathbb{R}^3$) and contact point velocities ($\dot{\boldsymbol{P}}^{con} \in \mathbb{R}^3$):

$$\mathbf{E}_t^A = \int_0^t \sum_{i=1}^{n} \boldsymbol{F}_{i,t}^{con} \circ \dot{\boldsymbol{P}}_{i,t}^{con}\, dt \in \mathbb{R}^3. \tag{1}$$

The object's hypothetical retained energy $\mathbf{E}_t^R$ is calculated using the grasp centroid $\boldsymbol{C}_t$ (mean of contact positions):

$$\mathbf{E}_t^R = m \cdot [\boldsymbol{g}^\top \boldsymbol{C}_t,\ \frac{1}{2}\dot{\boldsymbol{C}}_t^{\circ 2}] \in \mathbb{R}^4. \tag{2}$$

Under ideal energy conservation, the total applied and retained energies should differ by a constant offset. To eliminate this unknown offset, we take discrete-time derivatives to obtain the applied $\mathbf{P}_t^A$ and retained $\mathbf{P}_t^R$ power:

$$\mathbf{P}_t^A = \mathbf{E}_t^A - \mathbf{E}_{t-1}^A \in \mathbb{R}^3, \tag{3}$$
$$\mathbf{P}_t^R = \mathbf{E}_t^R - \mathbf{E}_{t-1}^R = m\tilde{\mathbf{P}}_t^R \in \mathbb{R}^4, \tag{4}$$

where $\tilde{\mathbf{P}}_t^R \in \mathbb{R}^4$ denotes the "massless" retained power. The object's mass is then estimated as:

$$\tilde{m}_t = \mathbf{1}^\top \mathbf{P}_t^A / \mathbf{1}^\top \tilde{\mathbf{P}}_t^R. \tag{5}$$

Under the constant mass assumption, $\tilde{m}_t$ should remain steady. In practice, slippage causes energy loss, leading to fluctuations in the estimated mass. We interpret these fluctuations as physically grounded signals of slip-aware stability (Fig. 2).

B. Dynamics Learning and Control

Using the energy abstraction, we define an energy-state for modeling finger-object energy flow using MBRL:

$$\boldsymbol{x}_t := [\mathbf{P}_t^A,\ \tilde{\mathbf{P}}_t^R,\ \boldsymbol{\Theta}_t] \in \mathbb{R}^{10}, \tag{6}$$

where $\boldsymbol{\Theta}_t \in \mathbb{R}^3$ is the orientation of the grasp centroid. The control signal $\boldsymbol{u}_t \in \mathbb{R}^7$ comprises desired centroid velocities (linear and rotational) and grasping force $F_t^\star$.

We model the system as a discrete-time transition:

$$\boldsymbol{x}_{t+1} = f(\boldsymbol{x}_t, \boldsymbol{u}_t) + \epsilon, \tag{7}$$

where ϵ denotes Gaussian noise. We learn f using a Fourier-featured Linear Gaussian Model [13], which provides a probabilistic prediction $p(\boldsymbol{x}_{t+1}) \approx \mathcal{N}(\boldsymbol{\mu}_{t+1}, \boldsymbol{\Sigma}_{t+1})$ with complexity $\mathcal{O}(DM^2)$ independent of sample size, enabling real-time control. The grasping force is optimized by pMPC [12]:

$$\min_{\boldsymbol{F}_t^\star} \sum_{k=2}^{H+1} \mathbb{E}[\ell(\hat{\boldsymbol{x}}_k)],\ \text{s.t.}\ \hat{\boldsymbol{x}}_{k+1} = f_M(\hat{\boldsymbol{x}}_k, \hat{\boldsymbol{u}}_k),\ \hat{\boldsymbol{x}}_1 = \boldsymbol{x}_t \tag{8}$$

where $\ell(\hat{\boldsymbol{x}}_k)$ penalizes fluctuations in estimated mass as a proxy for energy inconsistency. The optimized force is distributed among fingers via force closure [4]. Note that any unmodeled effects, such as torque from an unknown center of mass, are implicitly captured through the learned energy dynamics, allowing the system to compensate without explicit modeling.

C. Online Learning Pipeline

We adopt an iterative MBRL strategy. At each step, a nominal motion generator induces object motion, while pMPC optimizes grasping force by minimizing expected energy loss. Initial trials rely on random exploration, and the dynamics model is updated after each trial. This enables learning real-time grasping force control without external sensing or object knowledge.

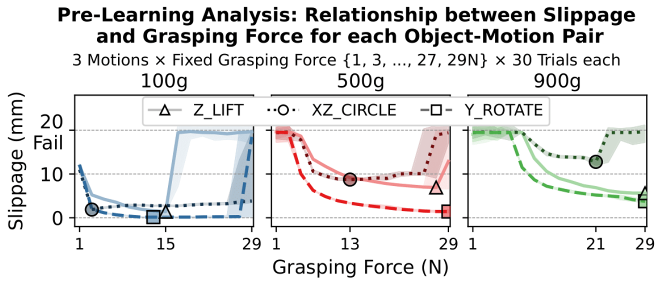

Fig. 3: Pre-learning analysis of slippage vs. grasping force. Each column shows slippage under three motions for objects of different masses with fixed forces. The optimal force varies per object-motion pair.

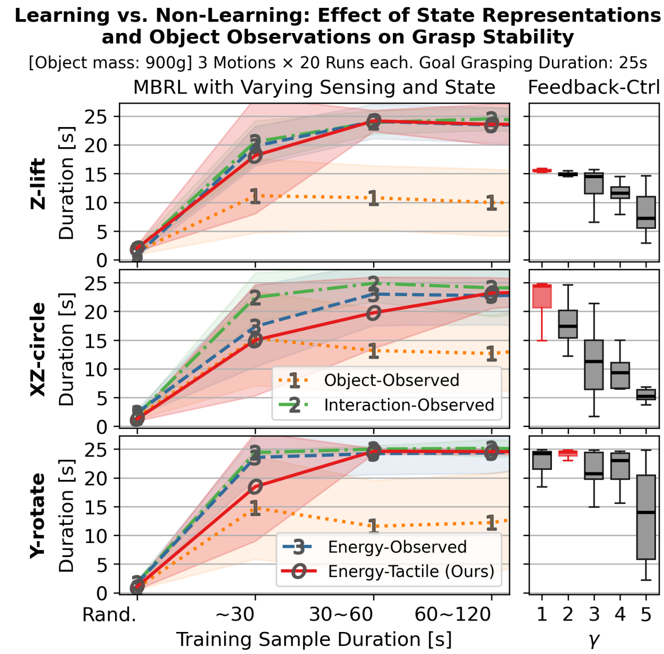

Fig. 4: Comparison of learning and non-learning baselines for grasping force control (900g object, three motions). Despite lacking object observation, Energy-Tactile (Ours) achieves comparable final performance to observation-based methods.

IV. Experiments

A. Setup

We evaluate in both simulation (Shadow Hand in MuJoCo [17]) and hardware (a dexterous robotic hand [18] with four DOF per finger). In simulation, objects are cuboids with masses $\in \{0.1, 0.5, 0.9\}$ kg. In hardware, two 3D-printed objects (320g "Trapezoid" and 350g "Hammer") are used. Three periodic manipulation motions are tested: Z-lift, XZ-circle, and Y-rotate. The system communicates with MBRL at 10Hz.

B. Simulation Results

Energy abstraction as a slip-aware signal: Pre-learning analysis with fixed-force trials (Fig. 3) shows that the optimal grasping force varies significantly with each object-motion pair, and no single predefined value can handle diverse conditions. Furthermore, energy-based mass estimates correlate with grasp stability: successful trials yield accurate mass estimates, while failing trials show larger estimation errors and higher slippage, confirming the energy abstraction as a reliable slip-aware signal.

Comparison with baselines: We compare our tactile-only method (Energy-Tactile) against four baselines using a 900g object across all three motions (Fig. 4): (1) **Feedback-Ctrl**, a non-learning controller that adjusts force proportionally to energy-based mass estimate deviation, tested across five gain values; (2) **Object-Observed**, MBRL using only object motion state, with pMPC maximizing z-height as a naive heuristic; (3) **Interaction-Observed**, MBRL with full object and grasp centroid state, minimizing their discrepancy as an upper-bound under full observability; and (4) **Energy-Observed**, using our energy abstraction but computed from direct object observation. Feedback-Ctrl demonstrates that energy-based mass estimates encode slip-relevant information, but the optimal gain varies by condition and fails to achieve the target 25s grasp duration for Z-lift, highlighting the need for learning-based strategies. Object-Observed also fails under dynamic motions, revealing the limitations of heuristic-based learning. While Interaction-Observed performs best under full observability, Energy-Tactile (ours) achieves comparable final performance using only tactile sensing, with minimal learning delay, demonstrating the effectiveness and practicality of our energy abstraction under sensing constraints. Our results suggest that, at least for dynamic force control tasks, tactile sensing can serve as more than a complement to vision — it can independently drive effective manipulation without external observation.

Learn-from-scratch across conditions: We conducted 20 MBRL runs per object-motion pair (Fig. 5). Our method rapidly improves grasp duration within two minutes of interaction, energy-based mass estimates converge toward ground truth, and grasping forces converge to distinct ranges for each condition, demonstrating robust generalization using only tactile sensing.

C. Hardware Results

We evaluate on two objects with unknown properties across three motions (Fig. 6). Our method consistently improves grasp duration within one minute, despite learning from scratch using only tactile sensing. Mass estimates converge toward ground truth, and grasping forces adaptively converge to higher values for the heavier and geometrically more challenging object. The full learning process averages 512 ± 30.4s.

V. Conclusion

We presented a physics-informed energy abstraction that enables tactile-based grasping force control to reduce slippage during dynamic object interaction. By leveraging energy consistency, the approach provides a compact and physically grounded signal for slip-aware reasoning without object priors or explicit supervision. Integrated with MBRL, the system

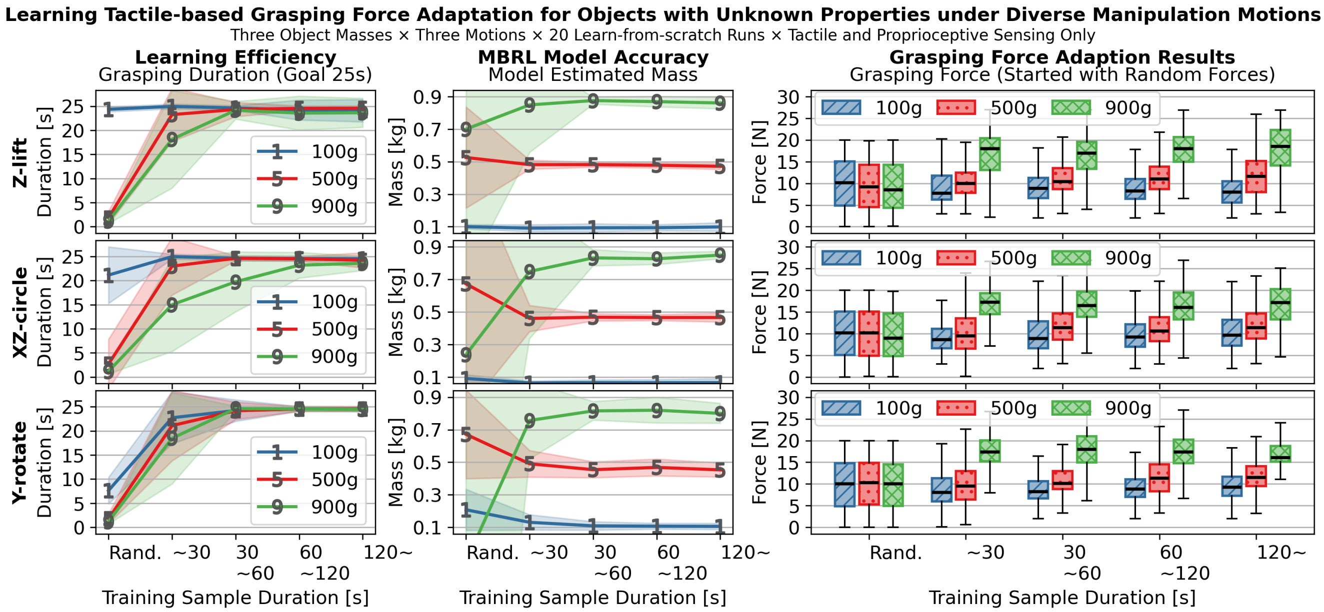

Fig. 5: Learning grasping force control using only tactile sensing in simulation. Experiments cover three masses (100g, 500g, 900g) and three motions, each repeated 20 runs. *Left*: Grasp duration increases as learned dynamics improve. *Middle*: Mass estimates converge toward ground truth. *Right*: Grasping force converges to distinct ranges for different conditions.

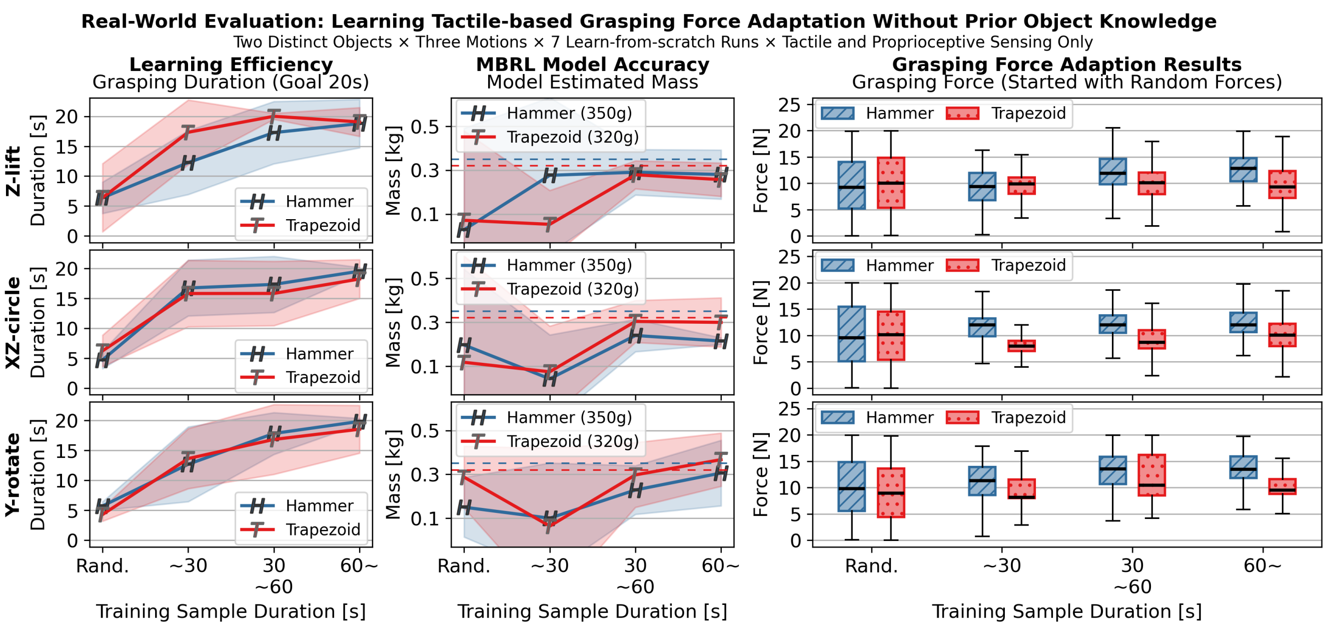

Fig. 6: Hardware evaluation of tactile-based grasping force control without prior object knowledge. The robot learns on two objects across three motions. *Left*: Grasp duration increases within one minute. *Middle*: Mass estimates approach ground truth. *Right*: Forces converge to motion-specific values.

achieves rapid learning and real-time control in both simulation and hardware. Current limitations include the assumption of rigid objects with fixed mass. Future work may extend the framework by integrating RL policies and leveraging energy abstraction as a reward signal.

Note

This work has been accepted for publication [19].

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