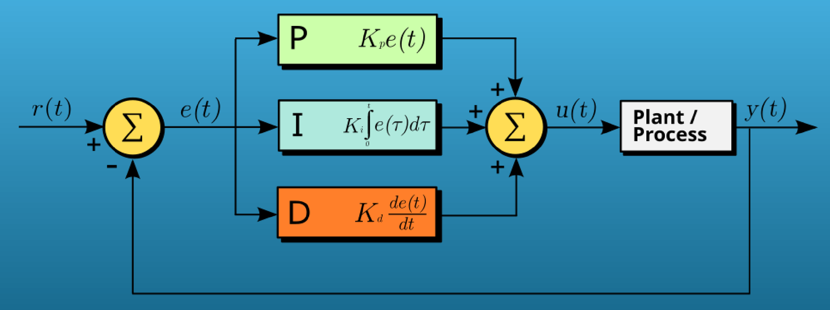


A block diagram of a PID controller in a feedback loop. r(t) is the desired process variable (PV) or setpoint (SP), and y(t) is the measured PV.

A BIO-INSPIRED FRAMEWORK FOR ADAPTIVE ROBOTIC GRIPPING

Bio-inspired Robotics: Adaptive Object Handling Through Cellular Mechanics and Artificial Intelligence

Syed Hamzah Rizvi

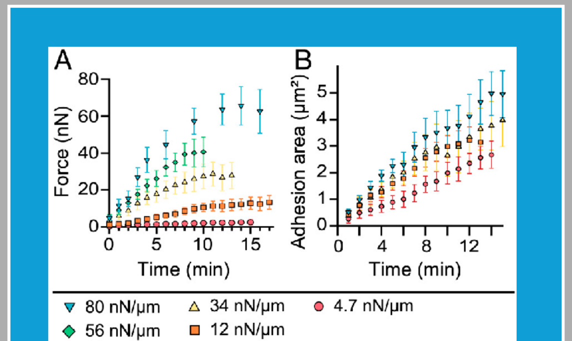
OVERVIEW

Robotic gripping operates under uncertainty because object stiffness, deformation behavior, and failure thresholds are unknown at the moment of contact. Conventional controllers, such as fixed-force and PID, assume a predictable material response, which can lead to slip or excessive force when conditions vary. This project introduces a clutch-inspired adaptive control framework that adjusts grip force in response to measured interaction forces. A physics-based simulation integrating force-dependent bond dynamics, stochastic state transitions, and spring-based interaction modeling was used to evaluate controller performance across diverse object conditions.

BACKGROUND

In biological systems, cells regulate traction forces through molecular clutch mechanisms, where adhesion bonds stochastically bind and unbind in response to applied force. This process governs how force is transmitted between the cell and its environment, enabling stable interaction under changing mechanical conditions. This principle motivates an alternative control strategy in robotics, where force regulation is driven by interaction dynamics rather than predefined assumptions. The adaptive framework developed in this study translates this behavior into a computational control model.

RESEARCH FRAMEWORK



1. Cells regulate force through stochastic bond dynamics
2. This enables stability across varying stiffness and load

Bell Model for Force-Dependent Bond Dynamics
↓
Monte-Carlo Process
↓
Modelling Gripper-Object Interaction
↓
Feature Extraction
↓
Unsupervised Learning, Clustering, and Statistical Analysis

PROBLEM DEFINITION

Mechanical Uncertainty

- Unknown Stiffness (k)
- Unknown crush limit
- Variable deformation response

→

Traditional Control

- Fixed Force Control
- PID feedback control
- No explicit safety bounds

→

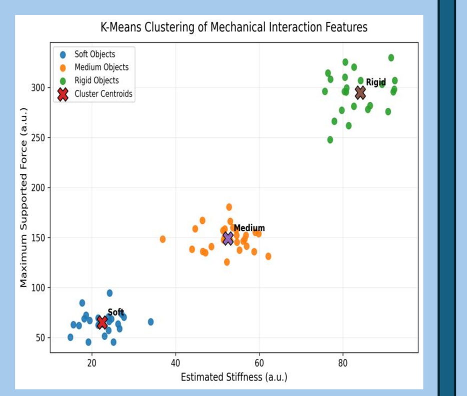
Failure Modes

- Under-grip = slip
- Over-grip = damage
- Instability under shift

MAIN METHODS AND PROCEDURES

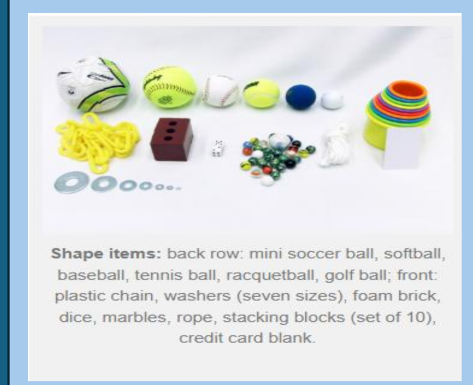
Python Implementation

Core Python libraries used for simulation, numerical computation, statistical analysis, and visualization in the adaptive gripping framework.

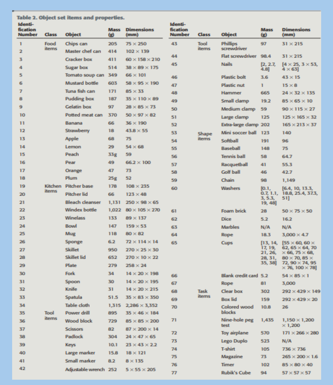


K-means clustering of mechanical interaction features showing three distinct object groups used for adaptive grip classification.

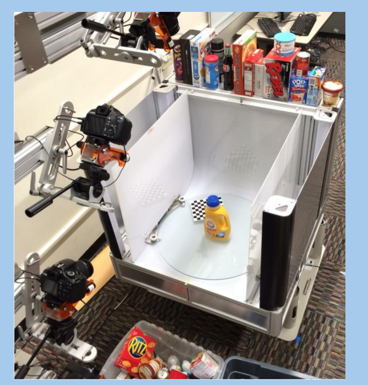
YCB Benchmark Dataset



For reproducibility purposes, the YCB Dataset was utilized throughout the project, paired with Python.



Objects and Physical Properties from the Yale-CMU-Berkeley (YCB) Object Set Used for Grasping Evaluation



Multi-camera imaging setup used to capture object geometry and visual data for the Yale-CMU-Berkeley (YCB) Object Dataset used in robotic manipulation research

Bell Model for Force-Dependent Bond Dynamics

- To simulate the clutch-like behavior, each element was modeled as either bound (attached) or unbound (not attached).
- Two equations can be derived from the Bell Model for force-dependent bond dynamics

$$k_{\mathrm{off}}(F) = k_{\mathrm{off},0}\, e^{F/F_b}$$

$$k_{\mathrm{on}}(F) = k_{\mathrm{on},0}\, e^{-F/F_b}$$

- F = Current force
- F_b = Characteristic bond force
- $k_{\mathrm{off},0}, k_{\mathrm{on},0}$ = base rates at zero force

Monte-Carlo Process

- Each clutch element is a two-state system: bound or unbound. This type of randomness can be modeled mathematically using a Poisson process, which describes the probability of events occurring in each time interval.
- The transition probabilities follow the definition that a rate multiplied by a small-time interval gives the probability of an event occurring during that time interval.
- This can be simulated to determine whether a clutch breaks or binds. A Monte Carlo step is used, where a uniform random number r ∈ [0, 1] is generated. If a clutch is bound and $r < P_{unbind}$, it unbinds; if it is unbound and $r < P_{bind}$, it binds.

Time to Slip t_{slip}

- Time to slip is defined as the earliest moment at which the force profile shows an unexpected, sudden drop, indicating that the object has begun to lose grip.
- This is implemented by scanning for the first index when the force decreases:

$$t_{\mathrm{slip}} = \min\{t_j \mid F(t_{j+1}) < F(t_j)\}$$

This feature identifies how long the system can sustain load before slipping occurs, which is important for separating stable and unstable grip conditions.

SIMULATION RESULTS

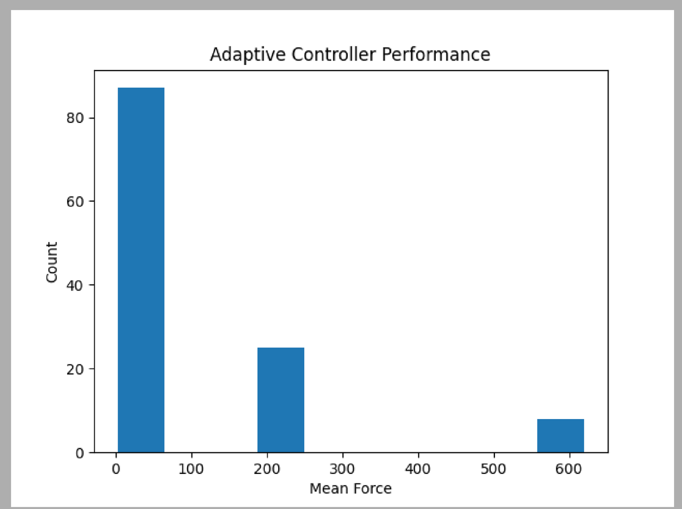


Figure 1: Distribution of forces applied by the adaptive controller across YCB objects

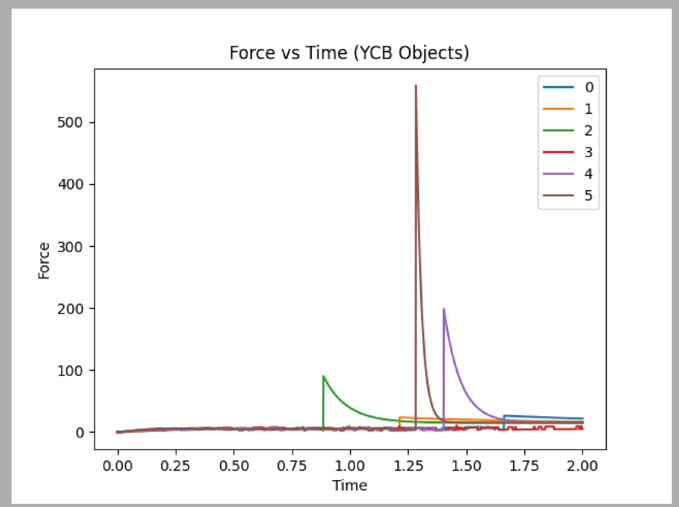


Figure 3: Time-dependent force profiles for YCB objects

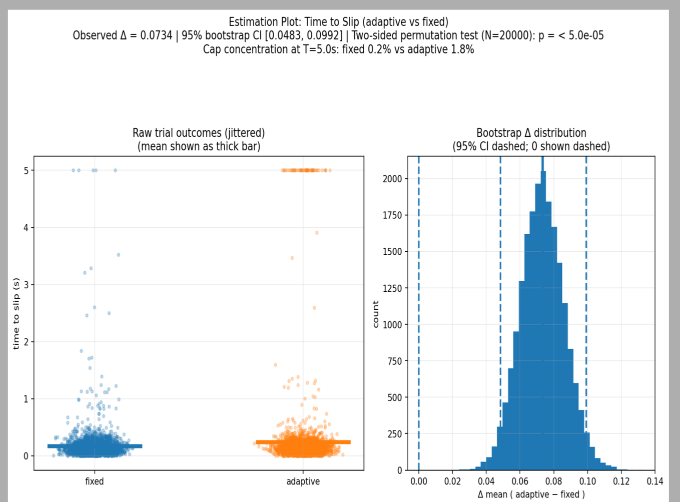


Figure 5: Estimation plot of time-to-slip for the adaptive controller compared with fixed-force control. The adaptive controller increases mean time-to-slip (, 95% bootstrap CI [0.0483, 0.0992] and the difference is unlikely under the permutation null

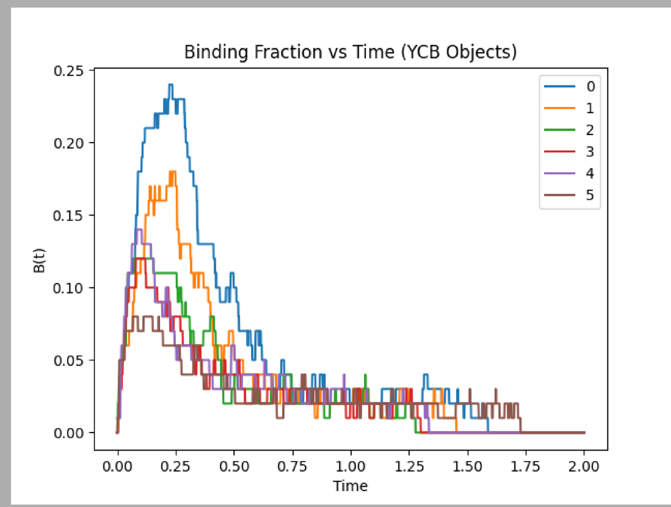


Figure 2: Binding fraction evolution over time under fixed-force control

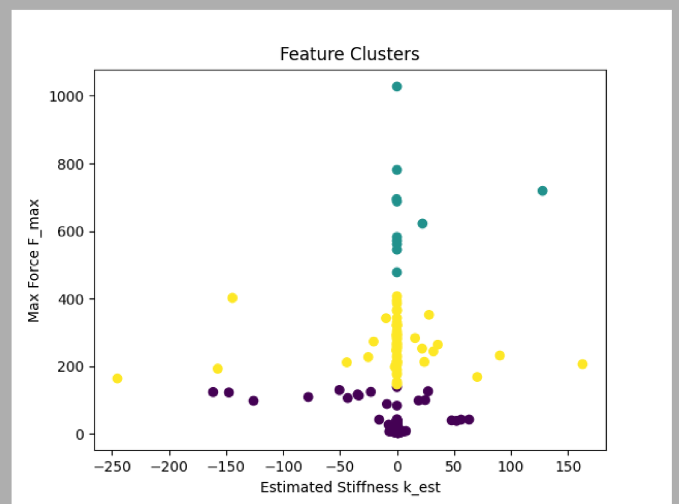


Figure 4: Feature space clustering revealing three mechanically distinct object categories

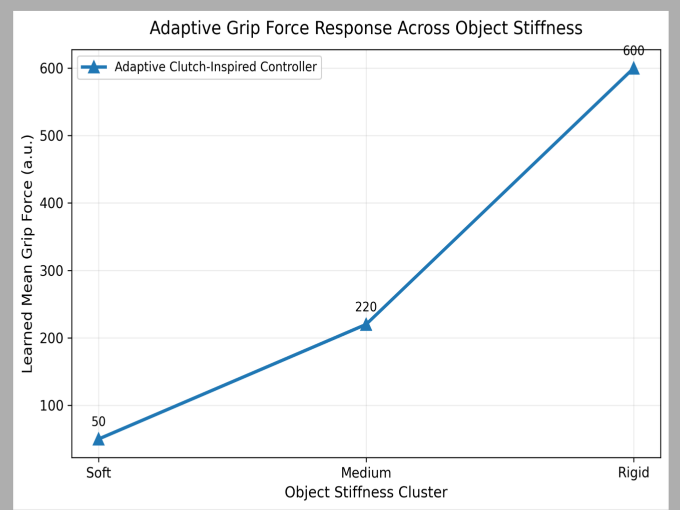
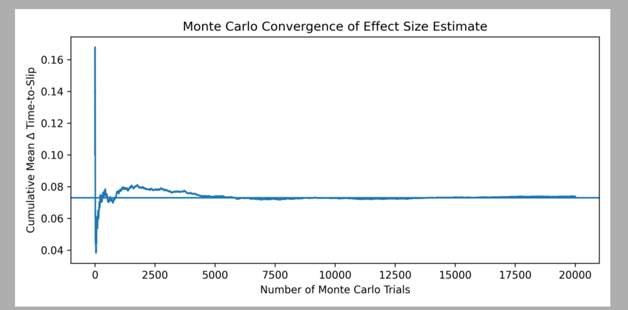
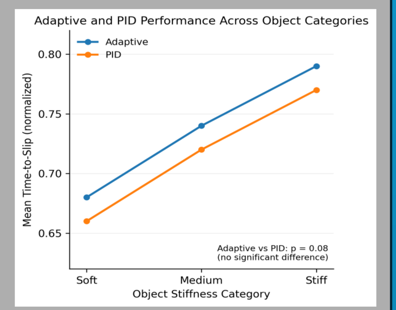


Figure 6: Adaptive grip force increased across soft, medium, and rigid object clusters, showing cluster-specific force regulation by the clutch-inspired controller.

STATISTICAL ANALYSIS

Controller performance was evaluated across 20,000 Monte Carlo trials using nonparametric statistical methods. Time-to-slip was used as the primary stability metric due to its ability to capture continuous grip behavior. Two-sided permutation testing was used to evaluate whether observed differences between controllers could arise under the null hypothesis, while bootstrap resampling was applied to compute 95% confidence intervals for performance differences. These approaches allow for robust inference without relying on distributional assumptions. Convergence analysis was additionally performed to verify that the estimated effect size stabilized as the number of trials increased, supporting the reliability of the simulation-based results.





CONCLUSION

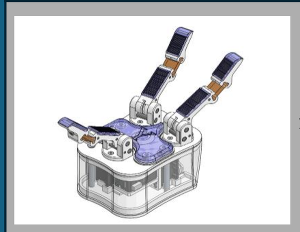
The results demonstrate that clutch-inspired adaptive control improves grip stability by increasing time-to-slip and reducing excessive force application under uncertain conditions. Compared with fixed-force control, the adaptive strategy shows a statistically significant improvement and provides more controlled force regulation than PID-based approaches. These findings support the use of interaction-driven control strategies for robotic manipulation in environments where object properties are unknown or variable.

Comparison	Mean Δ Time-to-Slip	95% CI	p-value
Adaptive vs Fixed	+0.073	[0.048, 0.099]	5×10^-5
Adaptive vs PID	+0.021	[-0.003, 0.046]	0.08

FUTURE WORK

This framework provides a foundation for translating clutch-inspired adaptive control into physical robotic systems. Future work will focus on implementing the controller on robotic grippers equipped with force and tactile sensing to evaluate performance under real-world conditions such as sensor noise, actuator delay, and friction variability. As illustrated in the images, the approach could enable adaptive object manipulation in applications such as automated warehouse picking, assistive robotics, and prosthetic gripping devices. The prototype gripper shown represents a potential hardware platform for integrating the controller and experimentally evaluating how grip forces adapt to objects with varying stiffness and geometry.

Adaptive gripping for object manipulation in uncertain environments, such as warehouse automation.



Prototype robotic gripper for future physical implementation of the clutch-based adaptive controller.

REFERENCES

- [1] Bell, G. I. (1978). Models for the specific adhesion of cells to cells. Science, 200(4342), 618–627. https://doi.org/10.1126/science.347575
- [2] Calli, B., Singh, A., Bruce, J., Walsman, A., Konolige, K., Srinivasa, S., Abbeel, P., & Dollar, A. M. (2015). Yale-CMU-Berkeley dataset for robotic manipulation research. International Journal of Robotics Research, 36(3), 261–268. https://doi.org/10.1177/0278364917706967
- [3] Chan, C. E., & Odde, D. J. (2008). Traction dynamics of filopodia on compliant substrates. Science, 322(5908), 1687–1691. https://doi.org/10.1126/science.1163595
- [4] Gillespie, D. T. (1977). Exact stochastic simulation of coupled chemical reactions. The Journal of Physical Chemistry, 81(25), 2340–2361. https://doi.org/10.1021/j100540a008
- [5] Halliday, D., Resnick, R., & Walker, J. (2013). Fundamentals of Physics (10th ed.). Wiley.
- [6] MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations. In Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability (Vol. 1, pp. 281–297). University of California Press.
- [7] ˚Astr¨om, K. J., & H¨agglund, T. (1995). PID Controllers: Theory, Design, and Tuning (2nd ed.). Instrument Society of America.
- [8] Calli, B., Walsman, A., Singh, A., Srinivasa, S., Abbeel, P., & Dollar, A. M. (2015). *Benchmarking in manipulation research: Using the Yale-CMU-Berkeley object and model set*. IEEE Robotics & Automation Magazine, 22(3), 36–52. https://doi.org/10.1109/MRA.2015.2448951