Mechanical Intelligence That Simplifies, Informs, and Integrates With Control for Robot Manipulation

Vatsal V. Patel
Yale University, *v.patel@yale.edu*

Robots need to be equipped with general-purpose hardware that is robust to model inaccuracies, sensor latencies, or perception failures so that they can perform complex tasks in unstructured environments. Intelligence that adapts to these deficiencies and even reasons about perturbations does not just have to reside in the robot's software.

Mechanical intelligence—the passive, mechanical response of systems leveraging properties such as compliance, differentials, kinematics, or constraints—embedded in the robot's hardware can absorb the slack and display intricate behaviors. As these mechanisms interact with the world, morphing and adapting as they go, they also gather information that can better inform the control actions of the system. Observing the adaptable behavior of mechanically intelligent systems replaces the data otherwise obtained through dedicated sensor arrays. But the hardware for intelligent robot systems cannot be developed in isolation from the algorithms and policies that operate it, and we need to integrate the design optimization of these mechanically smart architectures with the software.

My *research vision* is to design intelligence into robot agents so that they can perform complex tasks with limited data and basic models, while acquiring information from their interactions with the environment.

I. Contributed Research

A. Simplify: Mechanisms for Low-Level Control and Planning

Robot manipulation is traditionally done by grasping an object with a parallel jaw gripper, and object motions are brought about by the robot arm [15]. Dexterous skills with parallel jaw grippers may be possible with highly sophisticated control, but *in-hand* manipulation can be more efficient, safe, and accurate [17]. However, in-hand motions are incredibly challenging to execute because robot hands are often composed of anthropomorphic fingers with serial, fully actuated joints [32, 13]. These hands have many kinematic redundancies and require complex control logic that relies on a multitude of sensors. If there is insufficient sensor data, actuation latencies, or modeling inaccuracies, the object will be dropped. As a result, these hand designs limit in-hand manipulation paradigms to strictly controlled settings [3, 16].

Robot hands can instead be designed with mechanisms that take care of the low-level control goals such as grasp stability, contact dynamics, and robustness to perturbations – all without needing additional sensing or control. Passively adaptable mechanisms like underactuated fingers have been used widely in robot hands [1, 24, 11], and I have extended this work to design grippers that can blindly fixture unknown

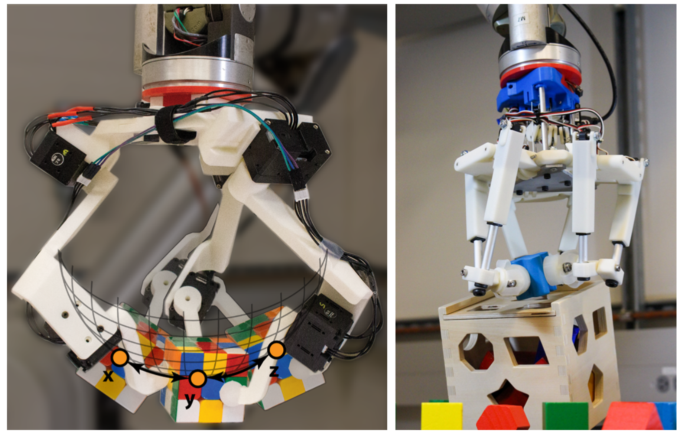

Fig. 1. Parallel mechanism-based hands can manipulate a variety of unknown objects over large workspaces even with simple open-loop control [27, 21].

objects with form closure guarantees [28], and in the finger design of a motor-augmented wrist orthotic device for people with spinal cord injuries [22].

I have also developed robot hand designs that kinematically embed motion into the hand topology in order to carry out open-loop in-hand manipulation of unknown objects over large workspace. My work has leveraged *parallel architectures* – where several independent kinematic chains link the end-effector to the base. The hand-object system is analogous to a parallel manipulator (the platform is similar to the object, the legs to the fingers, and the base to the palm) [4, 5], and in-hand motions have to contend with the kinematics of closed-loop chains formed by the fingers post-grasp. I have shown robot hands that are based on parallel architectures such as Stewart platforms [21] and spherical mechanisms [26, 27] have large manipulation envelopes with basic open-loop control and no tactile or visual sensing.

These mechanically smart architectures off-load some manipulation subgoals requiring lower-level, high-bandwidth control to the mechanism itself, while still having enough dexterity to execute higher-level objectives of reaching target object poses and even allow longer-horizon planning through finger-gaiting. Designing hand architectures to take on the low-level functions through mechanisms that absorb the slack allows robot systems to be far more generalizable and complete complex tasks in human environments.

B. Inform: Mechanically Intelligent Information-Rich Systems

Robot systems may still need to close the feedback loop to adapt to novel objects, plan trajectories online, or update estimated system models [7, 34]. When these mechanically intelligent systems take on low-level control functions, feed-

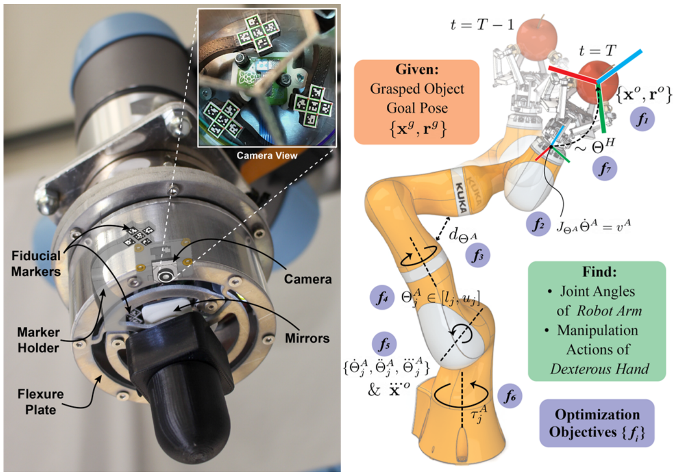

Fig. 2. Simple 6-axis FT sensor with a single, inexpensive RGB camera and mechanical amplifications (left) [31]. Motion optimization framework used to analyze unified arm and hand manipulation (right) [30].

back information is embedded in the passive response of these systems, instead of the data from dedicated sensor arrays. For example, compliant hands deflect under external forces that correlate to the magnitude/direction of that force. As such, this information is not "lost," and in fact, systems can be designed to perceive and gather data while interacting with the world [9]. Moreover, since these adaptive mechanisms can be more robust to disturbances, they can explore novel environments through contacts without task-critical failures.

One of the simplest methods of obtaining this high-dimensional information is through *vision*. Passive elastic systems are incredibly rich in visual information under forces [33], which can further augment recent algorithms that learn robot policies directly from images. We showed an implementation of using purely mechanical features to extract accurate 6-axis force/torque data without needing any signal conditioning or amplification, and with a simple linear calibration model [31]. This sensor consists of one inexpensive RGB camera module that tracks fiducial markers, and its components are easy to fabricate or obtained off-the-shelf. The flexure structure and angled mirrors in the sensor are designed to mechanically amplify the perceived motion of the markers in the camera view, resulting in a sensor that can resolve forces/torques within 1.5% relative to a commercial sensor. This work used design to mechanically program signal amplification in a standalone sensor device, although it can be directly incorporated into robot hands and arms, such as for distributed measurement of forces in whole-body tasks [14].

C. Integrate: Unifying Architecture and Motion Optimization

The design of robot hardware is inextricably coupled with its control and planning algorithms, and unifying the choice of mechanical architecture with the control optimization can significantly improve the robot's ability to complete the target task [25]. For example, rotational dexterity might be more important in a robot hand for bulb screwing in tight spaces. But on a manufacturing floor, a simple parallel jaw gripper may suffice on a 6-axis arm. My work has looked at coordinating robot arm and hand motions in order to leverage the capabilities of both subsystems, and subsequently analyze how well different hands perform on various manipulation tasks and environments [30]. The motion optimization frameworks we developed resolve the kinematic redundancy of adding dexterous hands to robot arms and synthesize a series of configuration states over the entire manipulation system. The resulting arm-hand motions are optimized for performance metrics of the overall system (e.g. pose accuracy, collision avoidance), while also achieving individual arm and hand subsystem goals (e.g. joint limits, manipulability, hand action costs). So, integrating the hand architecture into trajectory planning allows us to evaluate hand hardware and improve the resulting unified arm-hand manipulation motions [20].

II. Future Directions

Mechanical Control Pathways. Using mechanically smart architectures that adapt to uncertainties and perturbations is somewhat similar to the notion of manipulation funnels [19]. Subsequent works sequentially composed controllers for actuated systems with integrated sensors [6, 18]. Active control systems are certainly more easily programmable, but analytical methods need explicit model dynamics, and data-driven methods require a lot of compute and may still have limited real-world generalizability. I plan to explore how mechanisms that leverage physical constraints and take over low-level control can chain together skills for emergent behaviors [2, 23].

Co-optimizing Architecture and Policy. Co-design of hardware and control has seen recent developments [8, 12, 35]. These works incorporate design iterations and simulation into policy learning, although the parameters are simplified and limited (actuator attributes, stiffness, link lengths/angles), and the general kinematics of the systems are explored less (number and placement of links, joints). Extending our prior work on unifying design and motion optimization, hardware can be co-optimized with long-horizon policy to know what features – motion primitives, dexterity level, sensor information – need to be designed into the system for different task environments.

Architectures for Compute-Intensive Tasks. Applications requiring accurate local contact estimations, fast and dynamic motions, high number of contact instances, or interaction with soft or deformable materials can become computationally intractable. These challenges are exacerbated by hardware that struggles with over-constraints and poor manipulability. I plan to address the high-dimensionality, high-resolution, high-frequency response requirements of these problems with mechanically intelligent hardware paired with basic models and limited data [10].

Open-source Robot Hardware. Open-source hardware has high barriers in replicating physical components, comprehensive documentation, and long-term support. Our review paper highlighted the key benefits of open-source hardware for both the developers and the robotics community, as well as outlined best practices in sharing hardware projects [29]. I aim to continue disseminating research products as open-source projects and exemplify best practices that enable easy replication and reproducibility.

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