Research Statement

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1. Research Vision and Motivation

The progression of robotics toward general-purpose physical intelligence is fundamentally constrained by the ability to master interaction with unstructured environments. Unlike the idealized rigid-body dynamics often assumed in classical control, the physical world is characterized by continuous compliance and complex deformation. Whether in the structural flexibility of a manipulator or the surface compliance of a tactile sensor, the mechanics of deformation govern the fundamental capabilities of robotic agents to move, manipulate, and perceive. Consequently, I posit that the mastery of these systems requires a fundamental shift from rigid-body assumptions to models that can accurately represent and exploit continuum behavior.

However, establishing a high-fidelity representation of this physics creates a bottleneck for robot learning. Modern algorithms like Reinforcement Learning require millions of interactions. Collecting this data in the real world is unscalable due to hardware fragility and time constraints. Conversely, numerical simulators like the Finite Element Method are computationally intractable for learning. My research addresses this simulation gap. My central thesis is that the complex behavior of continuum systems can be compressed into low-dimensional, differentiable inference models. By using high-fidelity physics as an offline teacher rather than a runtime solver, I develop data-driven abstraction frameworks. This approach realizes accelerated simulation engines, providing the essential infrastructure to train contact-aware and physically intelligent robots.

2. Summary of Research Accomplishments

My doctoral research focused on developing a unified methodological framework for **data-driven physics abstraction**. I systematically addressed the simulation of deformable systems by bifurcating the problem into two topologically distinct domains, the dynamics of the robot body (Action) and the mechanics of the contact interface (Perception), and developing tailored abstraction strategies for each.

1. Modeling Deformable Body Dynamics (Action): To enable learning-based control for soft manipulators, I developed a **surrogate modeling framework**. Traditional analytical models often lack the generality required for complex morphologies, while raw FEM simulations are incompatible with standard control stacks. I proposed a method to abstract continuum deformation into a **virtual kinematic chain**. By training a Transformer-based dynamics model on offline FEM data and mapping it to a rigid-link surrogate, I achieved a simulation environment that retains physical compliance while maintaining compatibility with fast rigid-body solvers. This framework was validated through the zero-shot Sim-to-Real transfer of RL policies for trajectory tracking and force control on a physical pneumatic robot.

2. Modeling Soft Contact Mechanics (Perception): To address the data scarcity in tactile perception, I developed a **Neural Physics Engine (NPE)**. Vision-based tactile sensors provide rich data but lack physical ground truth labels. I constructed a bidirectional pipeline connecting real-world images with calibrated FEM physics, creating an automatic annotation engine. Building on this, I developed a geometry-aware Graph Neural Network (GNN) to replace the iterative contact solver. By enforcing a topological inductive bias, this Neural Physics Engine learns the local rules of force propagation, enabling real-time, high-fidelity simulation of contact deformation that generalizes to unseen object geometries. This work demonstrated that learned inference models could effectively replace numerical solvers to generate physically grounded tactile data for manipulation tasks.

3. Future Research Interest

My long-term research goal is to establish the computational foundations for **Physics-Aware Foundation Models**. While current generalist models excel in vision and language, they lack a fundamental intuition for physical interaction such as force, compliance, and dynamics. I aim to bridge this gap by developing scalable representations of physical contact that can be integrated into large-scale learning architectures.

Short-Term: Generalized Contact Simulation in Accelerated Environments

In the immediate future, I aim to expand the scope of my Neural Physics Engine beyond specific sensors to model general contact interactions, including the deformation of manipulated objects. Current simulators like Isaac Lab provide high-throughput rigid-body physics but lack a differentiable, high-fidelity model for soft-body interaction. I plan to develop a modular differentiable contact primitive that can be integrated into widely used GPU-accelerated simulators. This involves extending the GNN-based abstraction to handle mutual deformation (soft-on-soft contact) and dynamic viscoelastic effects. The objective is to provide the robotics community with a "plug-and-play" deformable physics engine that operates at the speed of rigid-body dynamics, enabling the massive-scale training of contact-rich manipulation policies.

Medium-Term: Learning the Latent Space of Physical Interaction

As robot learning moves toward multi-modal foundation models, a critical open question is how to represent physical information. Current approaches often concatenate raw sensor data, relying on black-box scaling to discover correlations. I argue that this is computationally inefficient and fails to capture the underlying conservation laws of physics. I propose to investigate the universal contact manifold, a compact, shared latent space that encodes the essential features of physical interaction, such as geometry, force, friction, compliance, independent of the specific sensor modality. By leveraging data-driven abstraction to compress high-dimensional continuum mechanics into efficient physics tokens, I aim to develop architectures that fuse force and deformation data with vision and language in a structured, physically grounded manner. This research will focus on discovering what constitutes the minimal sufficient statistic for contact-rich manipulation, moving beyond raw data dumping toward efficient, physics-informed representation learning.

Long-Term Vision: Physics-Grounded World Models for Generalist Humanoids

Ultimately, I view my research as the cornerstone for building next-generation world models for humanoid robotics. As humanoids enter unstructured environments, they face a reality gap that current video-based models cannot bridge. Predicting pixels is fundamentally different from predicting forces. My vision is to scale data-driven abstraction to create a neural reality engine. This simulation environment will model every interaction with FEM-level fidelity at real-time speeds, from the deformation of a fingertip to the compliance of a whole-body embrace. This capability will enable humanoids to learn complex, contact-rich skills entirely within simulation, such as using power tools or handling fragile organic objects. By embedding the true laws of continuum mechanics into the learning loop, I aim to solve the data scarcity crisis for embodied intelligence. This will allow humanoids to acquire years of physical experience in a matter of hours.