







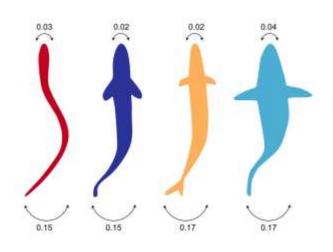




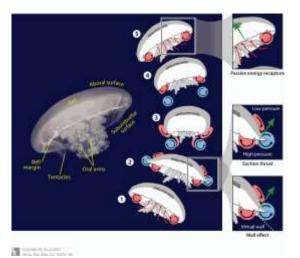
Learning to Control Free-Form Soft Swimmers

Changyu Hu · Yanke Qu · Qiuan Yang · Xiaoyu Xiong · Kui Wu · Wei Li · Tao Du

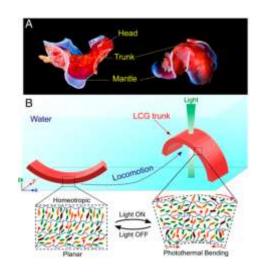
Swimming is Complicated



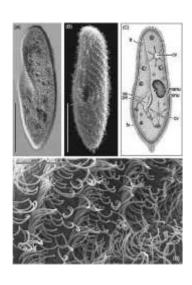
Fin/Body Undulation [Santo et al. 2021]



Jet Propulsion [Costello et al. 2021]



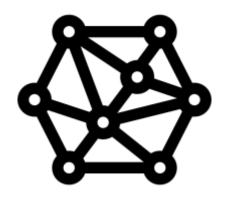
Undulatory Propulsion [Shimoga et al. 2021]

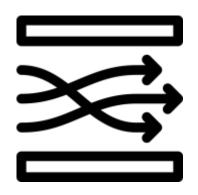


Ciliary Motion [Valentine et al. 2022]

Problem

How to find efficient swimming morphologies / skills?







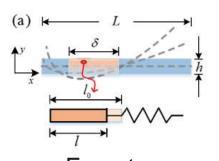
Shape & Control Modeling

Interaction with Fluid Environment

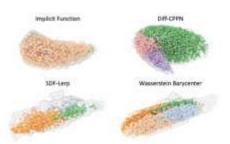
Policy Learning

Previous Research

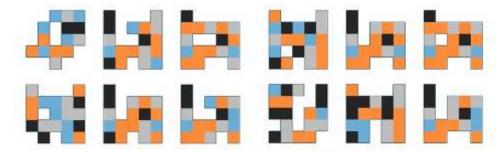
Control



Expert [Lin et al. 2019]

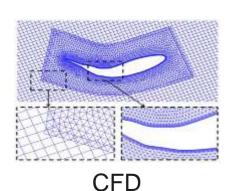


Clustering [Wang et al. 2023]

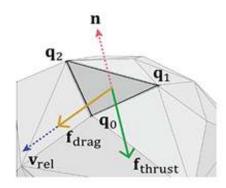


Per-Element [Bhatia et al. 2021]

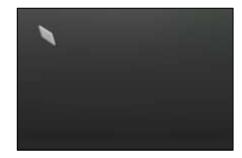
Simulation



[Zhang et al. 2022]



Lift & Drag [Min et al. 2019]



Flow Maps [Chen et al. 2024]

Methodology

Unified Representation for Shape & Control

Physics-Based Simulation

Al-Driven Controller Training

Methodology

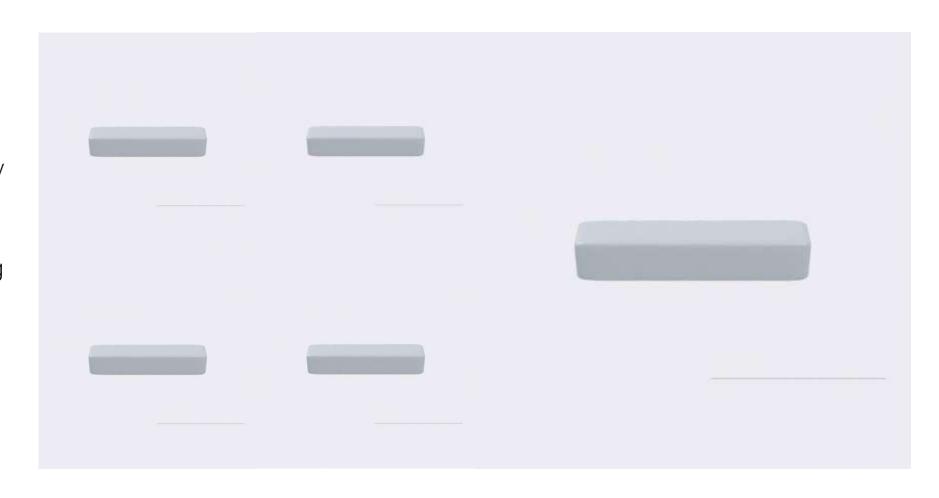
Unified Representation for Shape & Control

Physics-Based Simulation

Al-Driven Controller Training

Reduced Control Modeling

- Reduction on control space dimension
- Agnostic to morphology and robust to discretization
- Capable of representing diverse and characteristic deformations



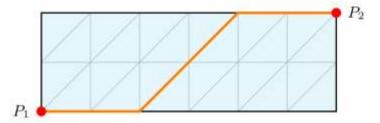
1. High Dimensional Volume Mesh



1. High Dimensional Volume Mesh



2. Iterative Sampling via Geodesic Distance

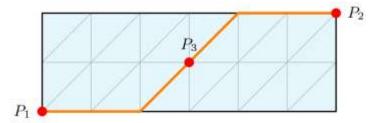


Path represents the shortest distance between points traveling through the **interior edges** of the volume mesh.

1. High Dimensional Volume Mesh



2. Iterative Sampling via Geodesic Distance

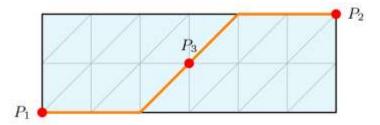


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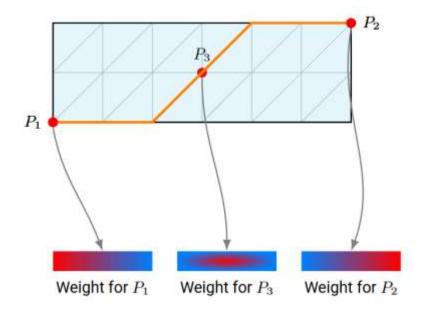


2. Iterative Sampling via Geodesic Distance

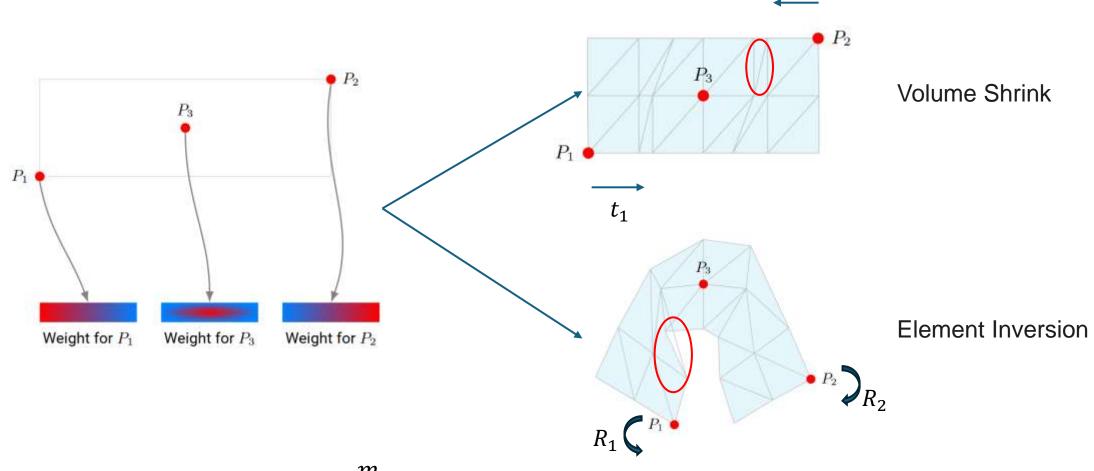


Path represents the shortest distance between points traveling through the **interior edges** of the volume mesh.

3. Influence Weights Precomputation

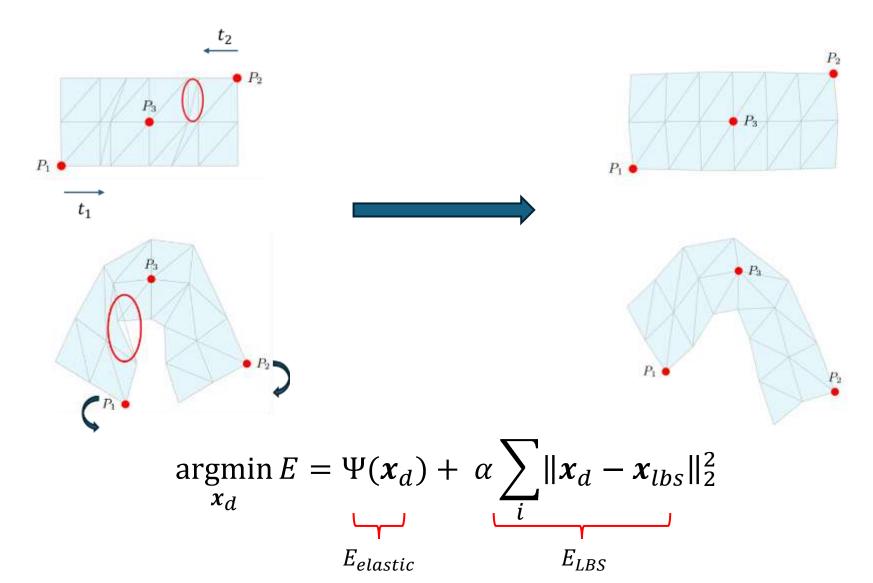


Kinematic Displacement (LBS)



$$\boldsymbol{u}_k = \sum_{i=0}^m w_i(\boldsymbol{X}, \boldsymbol{p}_i) (\boldsymbol{R}_i(\boldsymbol{x}_k - \boldsymbol{c}) + \boldsymbol{t}_i + \boldsymbol{c})$$

Dynamic Correction



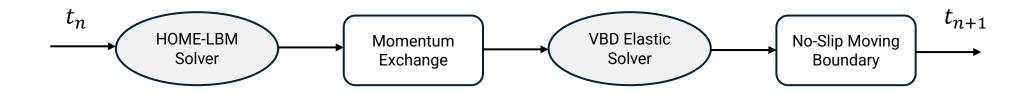
Methodology

Unified Representation for Shape & Control

Physics-Based Simulation

Al-Driven Controller Training

Efficient and Accurate Simulator



- SOTA fluid and elastic solver
 - Fully GPU-parallelized
- Weak two-way coupling scheme
 - Carefully optimized for time consuming parts (e.g. intersection detection)

	Fluid Domain Size	Elastic Body DOFs	Time per Step
2D Fish	1200x400	~300 Triangles	2.7ms
3D Clownfish	512x128x12 8	~3.5k Tetrahedra	18.3ms

Methodology

Unified Representation for Shape & Control

Physics-Based Simulation

Al-Driven Controller Training

Unified RL Training Pipeline

Local Frame Unified state space representation **Target Point** v_{mean} Control Points $s = \{x_{local}, v_{local}, v_{mean}, d, l, a_{last}\}$

- Capture the local deformation patterns of the soft swimmer efficiently
- Ensure the learned policy is rotation- and translation-invariant by construction

Unified RL Training Pipeline

Unified reward function

 Use a target point to control the locomotion of swimmers

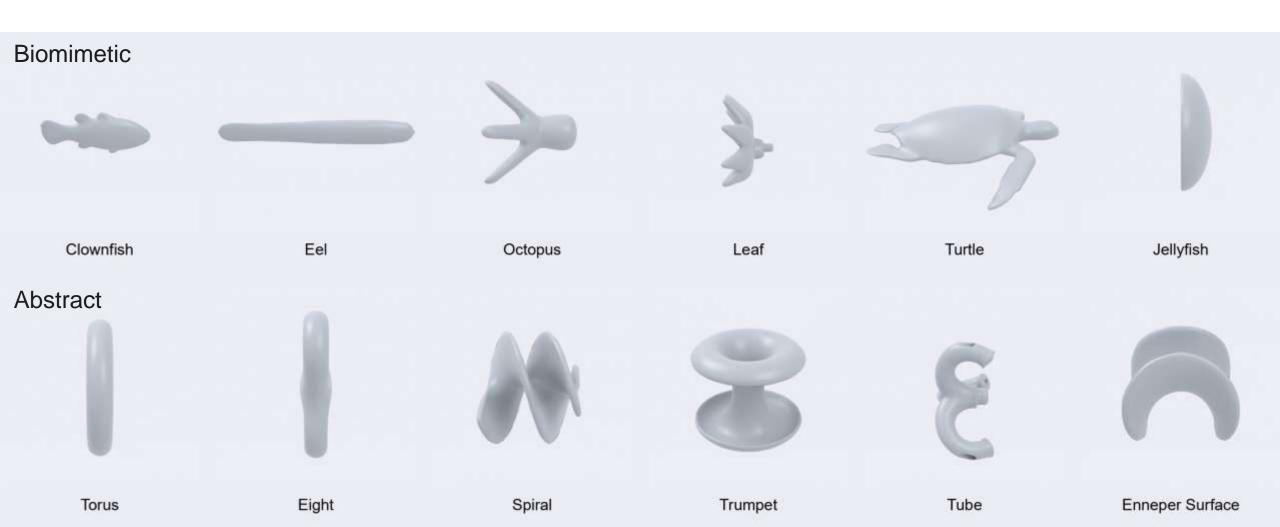
$$R = R_{\text{task}} + \lambda_{\text{smooth}} p_{\text{smooth}} + \lambda_{\text{reg}} p_{\text{reg}},$$
 $R_{\text{task}} = \boldsymbol{v}_{\text{mean}} \cdot \boldsymbol{d},$
 $p_{\text{smooth}} = -||\boldsymbol{a} - \boldsymbol{a}_{\text{last}}||_2^2/(6m),$
 $p_{\text{reg}} = -||\boldsymbol{a}||_2^2/(6m).$

Swimming forward: right

Navigation: randomly generated

Flow Resistance: center of solid

Collection of Morphologies



Main Results: Forward Swimming



Clownfish



Torus



Enneper Surface



Eight

Comparison with Baselines









Ours

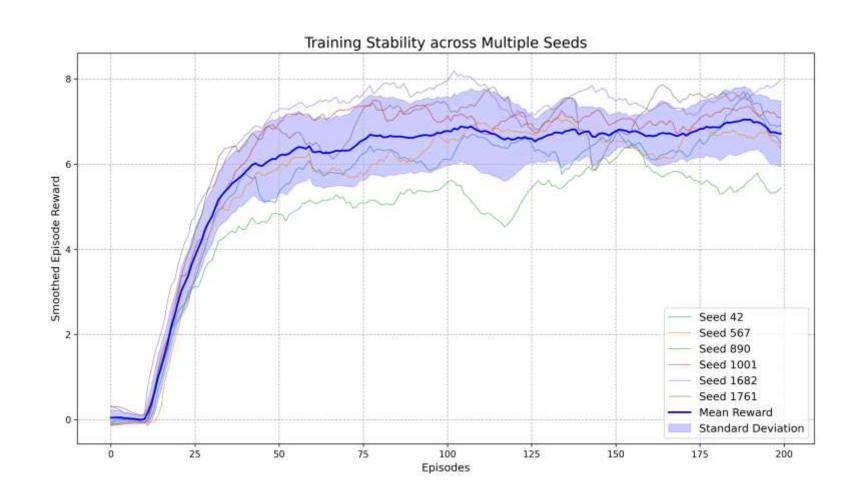
Clustering (Adapted from Wang et al. 2023)

Main Results: Energy-efficient Swimming

w/o energy penalty

with energy penalty

Training Stability



Conclusions

- We introduced a unified framework automating controller learning via:
 - Morphology-agnostic control representation
 - High-fidelity, GPU-accelerated simulator
- We demonstrated emergence of effective gaits for diverse morphologies, significantly outperforming baselines on unconventional shapes.

Thank You for Watching

Acknowledgements

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Webpage