Simulating the Body and Brain

Advances in Science Paradigm

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Outline

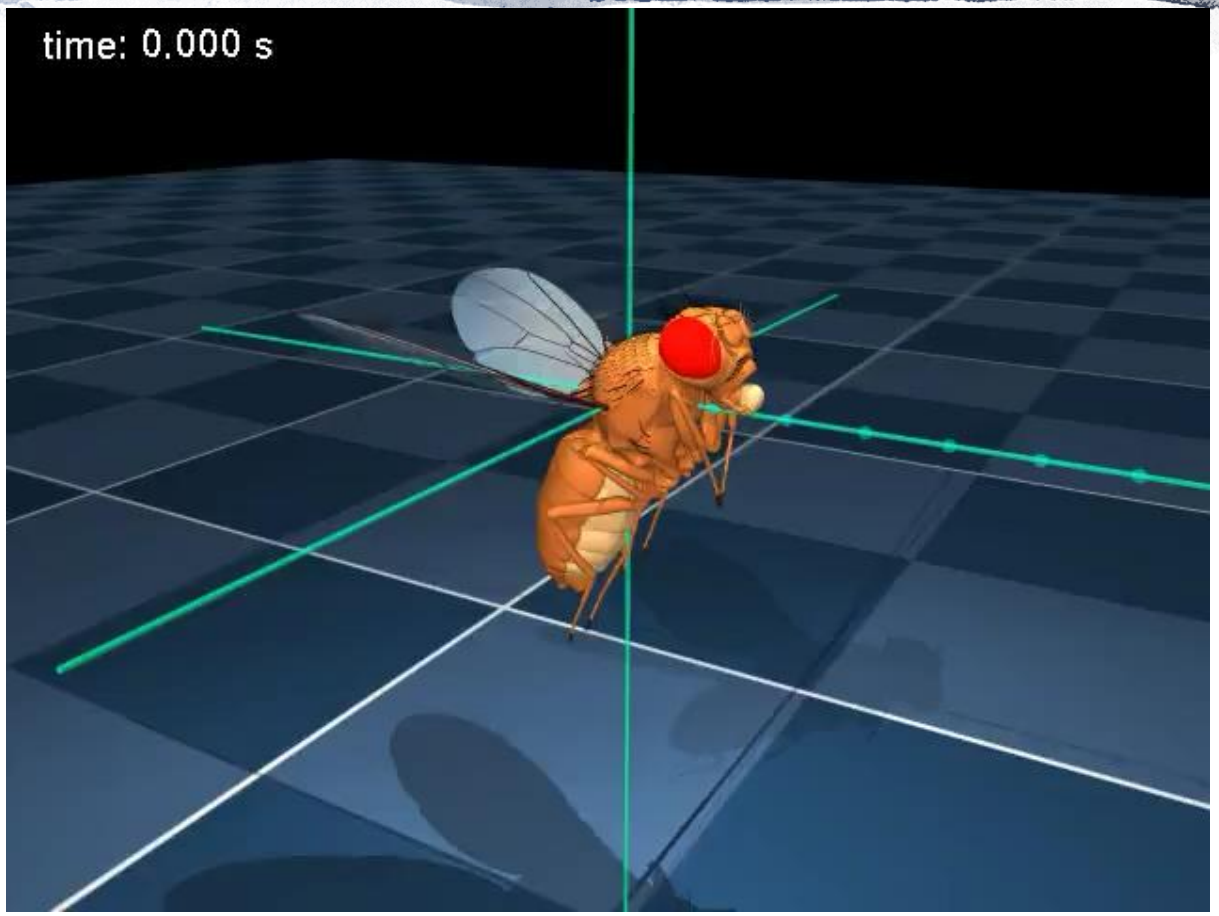
- Introduction to “Whole-body physics simulation of fruit fly locomotion”;
- Key researchers and Their Vision;
- Advancement in the Science Paradigm.

Whole-Body Physics Simulation of Fruit Fly Locomotion Introduction

Whole-body physics simulation of fruit fly locomotion

- This paper is accepted by Nature at April. 15, 2025 (submitted April 2 2024)
- Authors are from *HHMI Janelia Research Campus* and *Google DeepMind*;
- They simulated the locomotion of the fruit fly by a whole-body model and neural controller.

Simulation Results: Flying



Roman Vaxenburg, et.al, Whole-body Physics Simulation of Fruit Fly Locomotion, Nature, 2025

Simulation Results: Walking



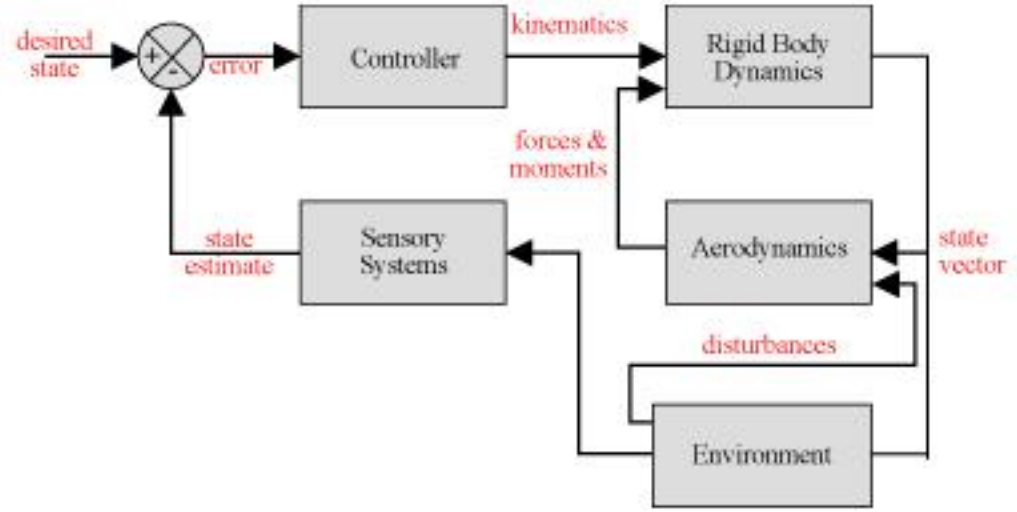
Roman Vaxenburg, et.al, Whole-body Physics Simulation of Fruit Fly Locomotion, Nature, 2025

Simulation Results: Jump



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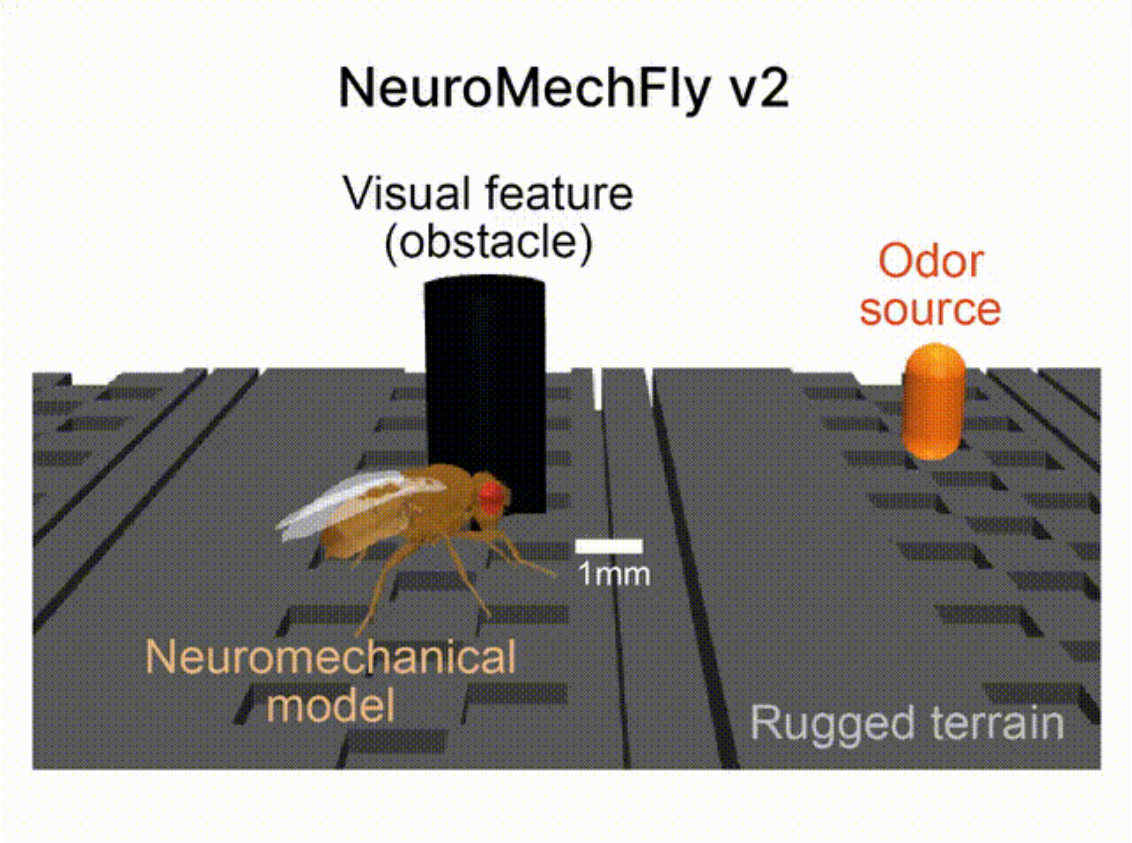
Previous Works: Grand Unified Fly (William B. Dickson, et. al, 2008)





https://strawlab.org/2011/03/23/grand-unified-fly/

Previous Works: NeuroMechFly v2 (Sibo Wang-Chen, et. al, 2024)



https://neuromechfly.org/

Contribution of this Work

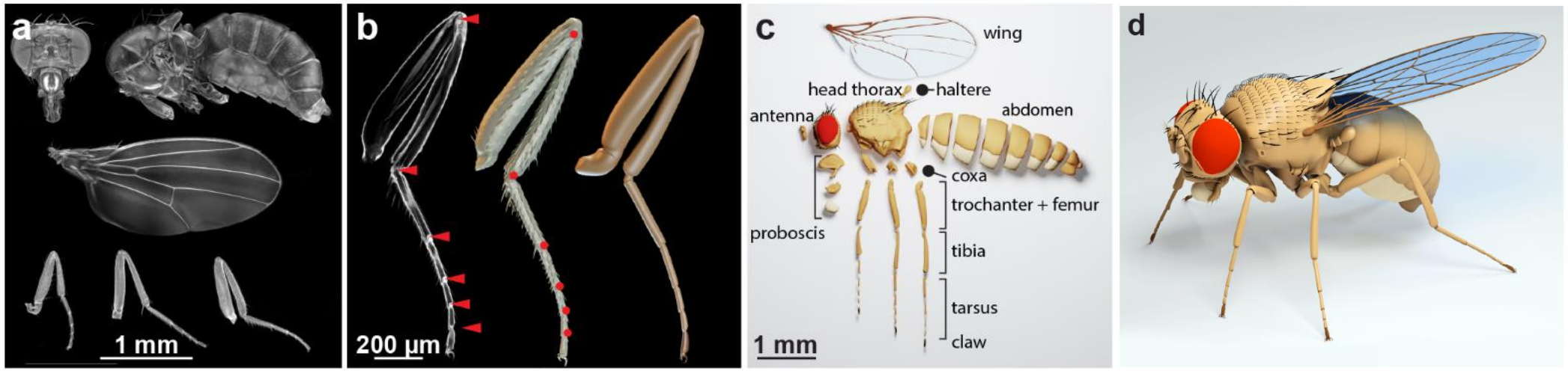
- Unified Simulation of Flight and Walking
- Enhanced Physical Realism
- Fully Data-Driven Control Method
- Hierarchical Visual-Guided Flight
- Open-Source Platform Released

Whole-Body Physics Simulation of Fruit Fly Locomotion System Construction

Construction of the System

- Building the Fruit Fly Body Model Geometry
- Building the Physical Model of the Body
- Modeling Body-Environment Interaction
- Integrating the Sensory System
- Training Motion Controllers through Imitation Learning
- Implementing Hierarchical Visual-Guided Flight

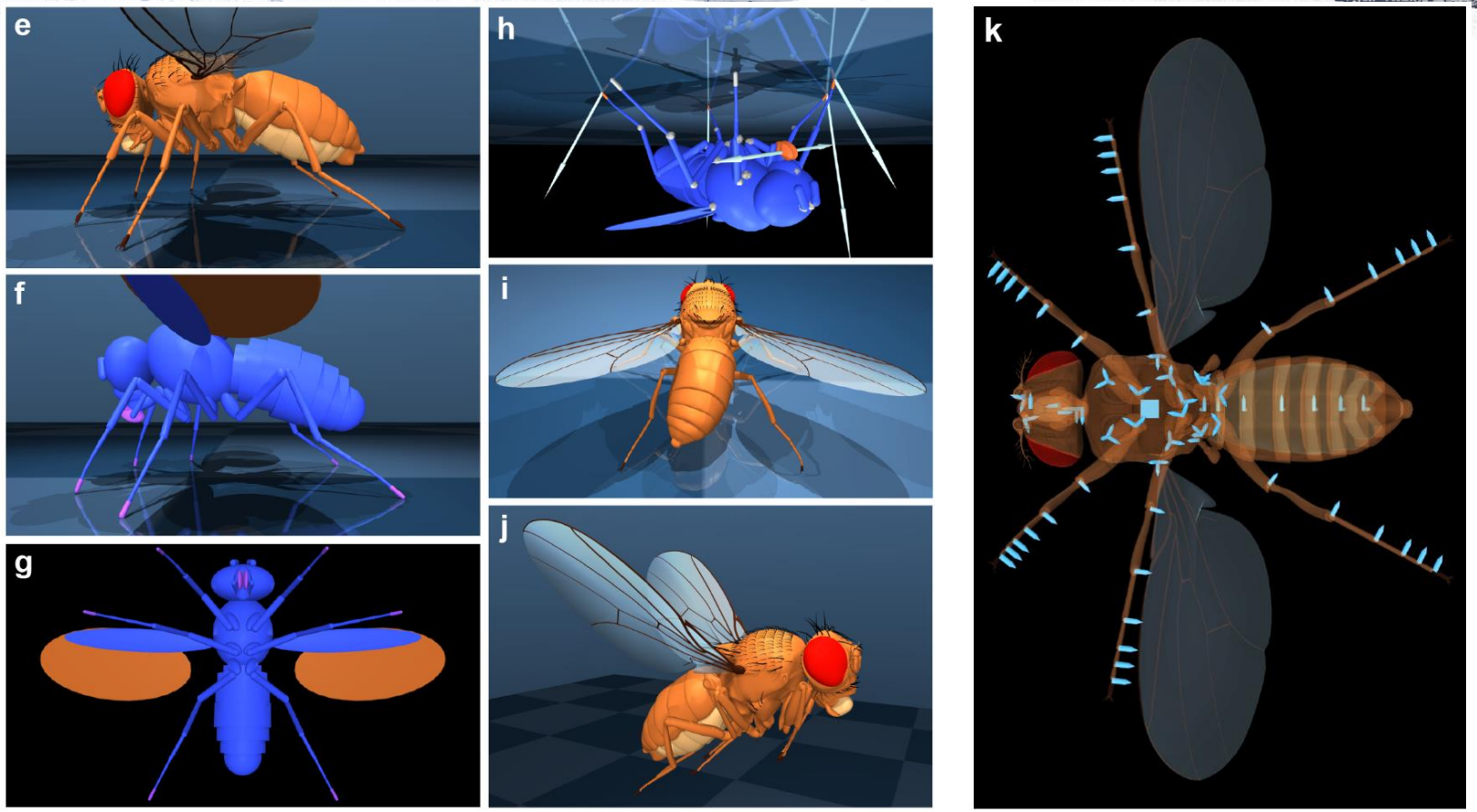
Building the Fruit Fly Body Model Geometry



Roman Vaxenburg, et.al, Whole-body Physics Simulation of Fruit Fly Locomotion, Nature, 2025

Acquire High-Resolution Biological Imaging Data, build the Mesh Model, assemble and define the Kinematic Tree. 67 Components, 102 Degrees of Freedoms

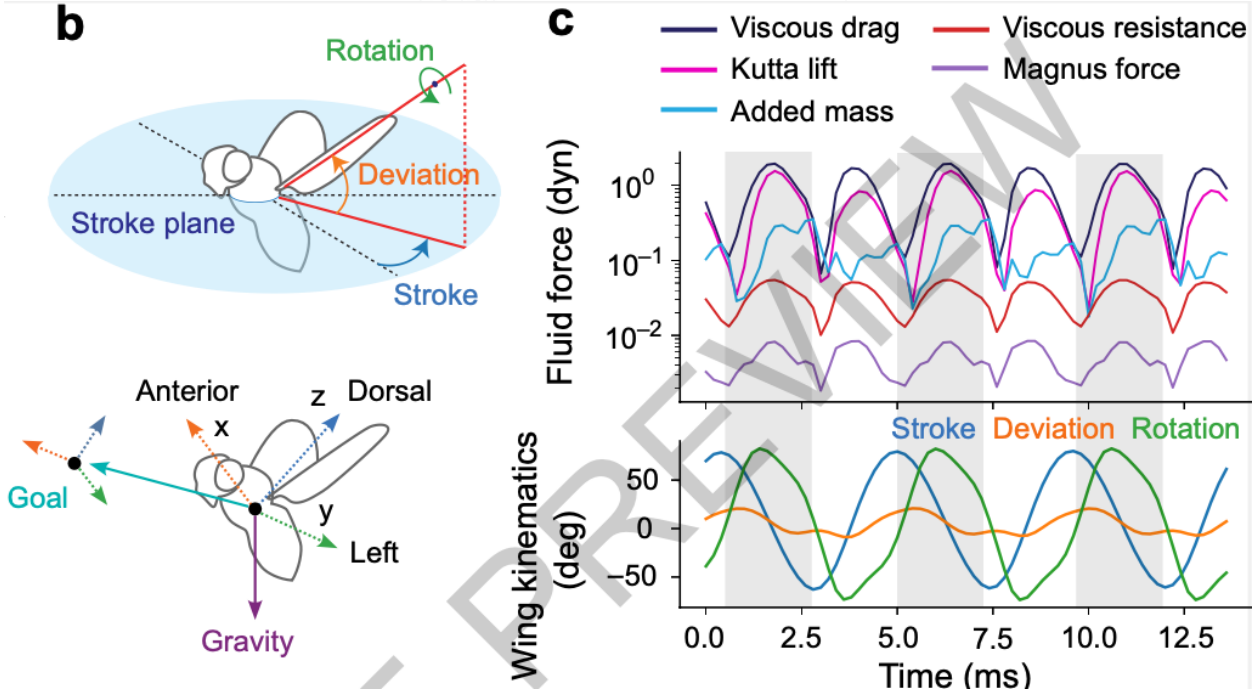
Building the Physical Model of the Body



Roman Vaxenburg, et.al, Whole-body Physics Simulation of Fruit Fly Locomotion, Nature, 2025

Modeling Body-Environment Interaction

- Mainly use the Mojoco‘s Physical Engine
- Developed a fluid dynamics model of the forces exerted onto a moving rigid body by the surrounding fluid, extends a previous approach to three dimensions.
- It approximates five fluid dynamics phenomena: added mass, viscous drag, viscous resistance, Magnus lift, and Kutta lift.



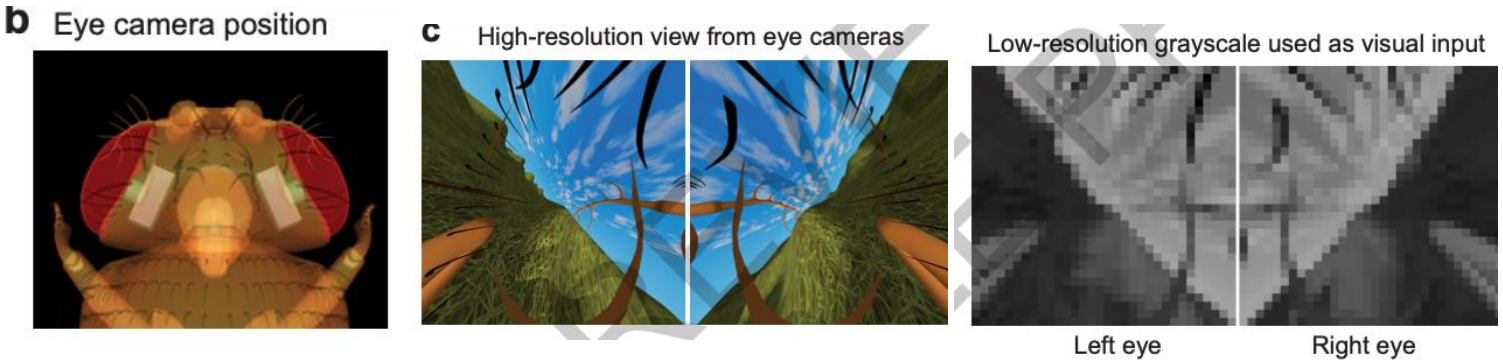
Roman Vaxenburg, et.al, Whole-body Physics Simulation of Fruit Fly Locomotion, Nature, 2025

PREVIEW

Integrating the Sensory System

- The model is equipped with visual, vestibular, proprioceptive, and mechanosensory sensors.
- A camera sensor in MuJoCo simulates the eyes in visual-guided flight tasks.

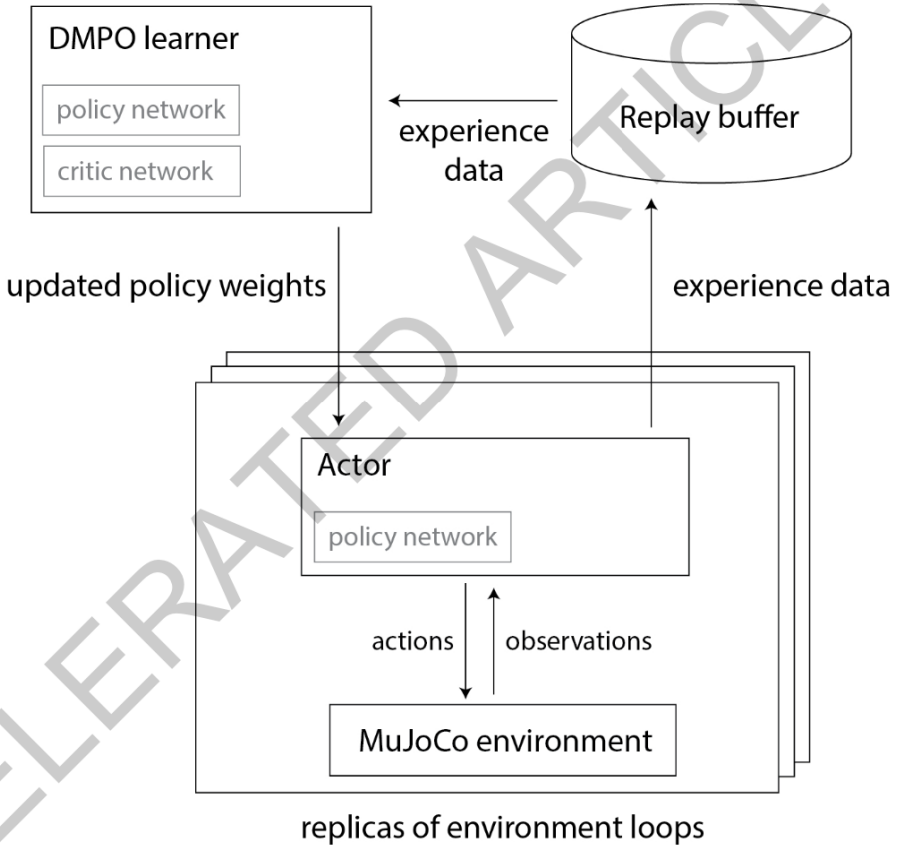
Category	Sensor	Units	Array shape
vision	right eye camera left eye camera	unitless RGB	(32, 32, 3) (32, 32, 3)
vestibular	velocimeter accelerometer gyro (rotational velocity) gravity direction	cm/s cm/s^2 rad/s cm	3 3 3 3
proprioception	joint angles joint velocities actuator activation state end-effector positions	rad rad/s same as control cm	102 102 78 (7, 3)
mechanoreception	leg force sensors leg touch sensors	dyn dyn	(6, 3) 6



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Training Motion Controllers through Imitation Learning: Overview

- A Standard Offline Refinforcement Learning Procedure
- Dataset: Offline collected Centroid (CoM) trajectories and body segment motion data;
- Inputs: Expected CoM position and orientation change and the perception.
- Output: the control signal to the simulated engine.
- Model: Simple MLP.

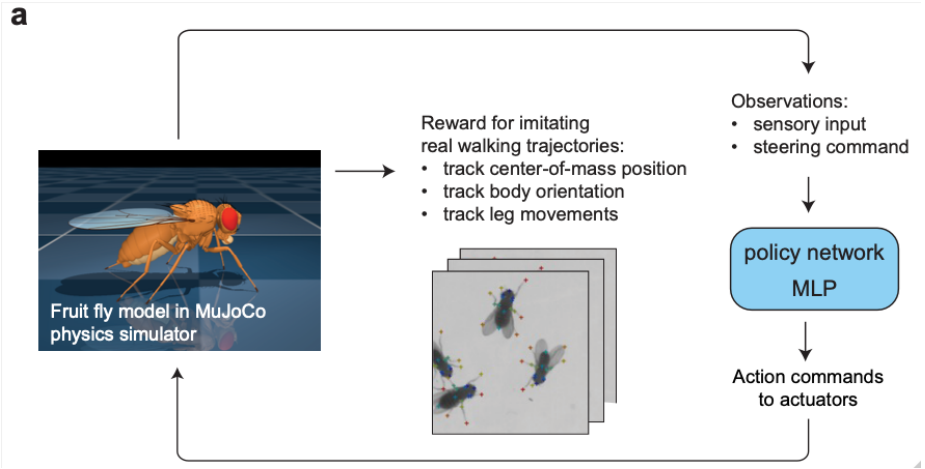


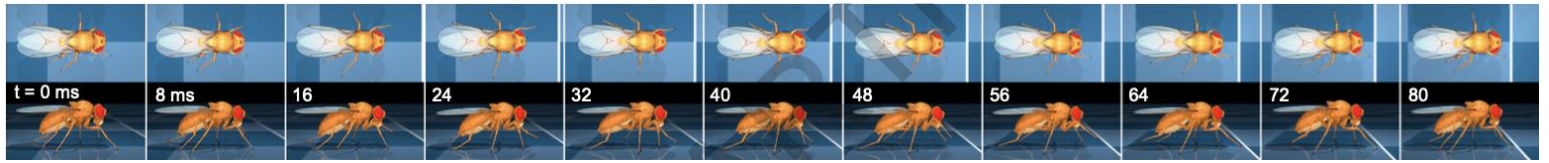
ELERATED ARTICLE

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Training Motion Controllers through Imitation Learning: Walk

- Environment: A physical simulation environment that includes a flat surface on which the model can walk. The model also has foot adhesion properties, which are modeled using adhesion actuators.
- Scenario: Mimicking the walking behavior of a real fruit fly, including walking at different speeds, turning, and standing.
- Training Data: 3D posture trajectories via regularized inverse kinematics from2D keypoint positions detected from 13,000 high-speed top-view video footage (60min).
- Controller: A fully connected MLP controller was trained with no predefined structure (4 layer, input dim 286, output dim 59 – the freedom of legs).
- Reward Function: The reward function encourages the model to replicate real leg movements and track the CoM trajectory.

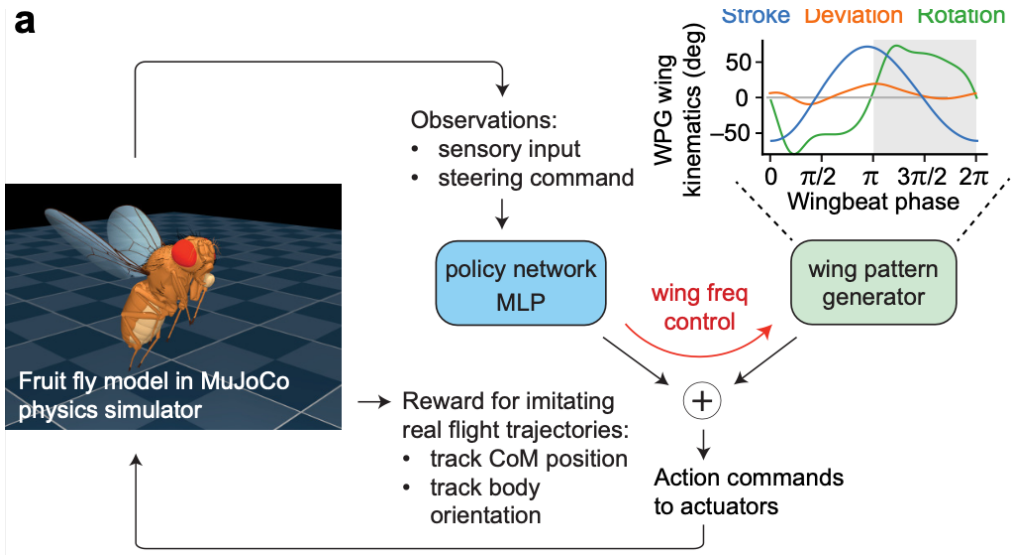


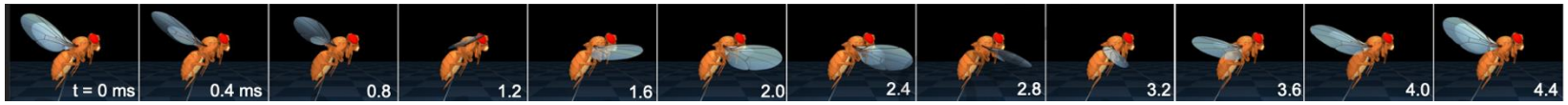


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Training Motion Controllers through Imitation Learning: Fly

- Environment: A 3D physical simulation environment with a fluid dynamics model
- Scenario: Mimicking the flight trajectory of a real fruit fly, including spontaneous saccadic turns and evasive maneuvers.
- Training Data: High-speed video footage was used to obtain centroid (CoM) position and body orientation trajectory data (272 trajectories, 53s)
- Controller: A flight controller was trained consisting of a wingbeat pattern generator (WPG) and a trainable fully connected multi-layer perceptron (MLP) (3 layer, input dim 62, output dim 12 – the freedom of flying).
- Reward Function: The reward function was designed to encourage the model to match the real CoM trajectory and body orientation.

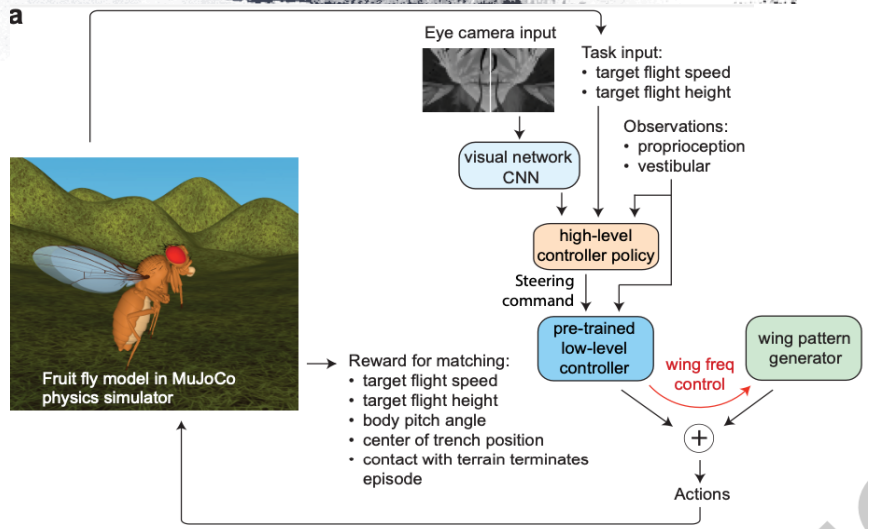




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Implementing Hierarchical Visual-Guided Flight

- Environment: Flying environment with visual input;
- Scenario: Includes two tasks:
  - “Bumps” Task: Mmaintain a constant target altitude above the ground and fly in a straight line at a constant target speed.
  - “Trench” Task: Maintain a constant forward speed and altitude while avoiding the trench’s side walls.
- Controller: A hierarchical controller consisting of a pre-trained low-level flight strategy from the flight imitation task and a high-level navigation strategy. The high-level controller receives visual features, along with proprioceptive and vestibular sensory signals, and issues steering commands to the low-level controller.
- Reward Function: Keep flight speed and altitude, while avoiding collisions with the trench walls.





Roman Vaxenburg, et.al, Whole-body Physics Simulation of Fruit Fly Locomotion, Nature, 2025

Whole-Body Physics Simulation of Fruit Fly Locomotion Evaluation and Performance

Walking

- Evaluation Method: The trained walking controller was evaluated on a test set containing 3,200 trajectory samples.
- Evaluation Results:
  - The model accurately tracked the desired CoM trajectory, with a median position error of 0.4 cm and a median direction error of 4°.
  - At various speeds, the duration of standing and swinging phases in the model closely matched that of real fruit flies. The model maintained at least three legs in the standing position at all times, and the number of legs on the ground at different speeds was very close to that of real fruit flies.
  - By calculating the phase delay of the swing start relative to the left front leg (L1), it was found that the model's leg coordination closely matched real fruit flies.
  - When instructed to turn at a speed of 1-3 cm/s and a 1 cm turning radius, the model reduced the step length on the turning side while increasing it on the other side, consistent with real fruit fly behavior.
  - The adhesion actuators enabled the model to perform realistic movements on steep surfaces, and the model learned to dynamically adjust adhesion force based on terrain slope.

Flying

- Evaluation Method: The trained flight controller was evaluated on a test set consisting of 56 CoM trajectory samples.
- Evaluation Results:
  - The model accurately tracked the target CoM trajectory, with a median position error of 0.25 mm and a median direction error of less than 5°.
  - The wing motion trajectory generated by the model was qualitatively similar to that of real fruit flies, although there were minor differences in flapping frequency.
  - The model also reproduced key features of real fruit flies during rapid turns (saccades), such as generating larger accelerations through slight left-right wing asymmetry.
  - Analysis of stable and unstable flight trajectories indicated that the model only needed slight adjustments to the median wingbeat pattern to achieve significant body acceleration changes.
  - The model also replicated key characteristics of real fruit fly turning maneuvers, including typical changes in angular velocity, orientation, and speed.

Hierarchical Visual-Guided Flight

- “Bumps” Task Evaluation Method and Results: The model flew on randomly generated sinusoidal terrain, with rewards set for maintaining a constant target speed and stable altitude relative to the ground. After training, the model successfully adjusted altitude using visual input, achieving a median height error of 0.045 cm and a median speed error of 2.2 cm/s after the initial acceleration phase.
- “Trench” Task Evaluation Method and Results: The model flew through a narrow virtual trench with a sinusoidal profile, with rewards set for maintaining a constant forward speed and altitude. Collisions caused early termination. After training, the model reliably navigated the entire trench while maintaining the target height and speed, achieving a median height error of 0.032 cm and a median speed error of 0.16 cm/s after the initial acceleration phase.

Key Researchers and Their Vision

HHMI Janelia Research Campus

- 15-year research model: develop a given research area for roughly 15 years to gain traction and attract outside interest, at which point they'll cycle to a new area of focus.
- Mechanistic Cognitive Neuroscience (2019)
  - To understand how animals infer and use internal models to produce adaptive, flexible behavior in dynamic, uncertain settings.
  - To discover the circuit dynamics, network architectures, neuronal biophysics, synaptic rules, and molecular pathways that make cognition possible.
- 4D Cellular Physiology (2022)
  - To understand the function, structure, and modes of communication of cells in organs and tissues with an aim of expanding our understanding of cells and how they collectively give rise to the physiological functions of the body.

DeepMind

- Pioneer in AI Field (OpenAI was established because DeepMind was be acquired by Google)
- This work is a typical DeepMind's Artwork:
  - Field with little Exploration or filled with Failures;
  - Interdisciplinary Research Approach
  - Data Driven Deep Learning (maybe no New Deep Theory)
  - Reinforcement Learning with Simulated Environments
  - Strong Engineering Ability to Build Highly Effective Systems
  - Long term preparing (In 2021, they acquired MuJoCo)

Advancement in the Science Paradigm

Fourth Paradigm (Jim Gray, 2009)

- Empirical Science (First Paradigm)
- Theoretical Science (Second Paradigm)
- Computational Science (Third Paradigm)
- Data-Intensive Science (Fourth Paradigm)

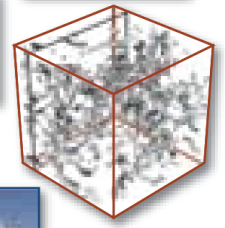
AI for Science (The Fifth Paradigm?)

Science Paradigms

- Thousand years ago:
  science was **empirical**
  describing natural phenomena
- Last few hundred years:
  theoretical branch
  using models, generalizations
- Last few decades:
  a **computational** branch
  simulating complex phenomena
- Today: **data exploration** (eScience)
  unify theory, experiment, and simulation
  - Data captured by instruments or generated by simulator
  - Processed by software
  - Information/knowledge stored in computer
  - Scientist analyzes database/files using data management and statistics



$$\left(\frac{\dot{a}}{a}\right)^2 = \frac{4\pi G p}{3} - \mathrm{K}\frac{c^2}{a^2}$$





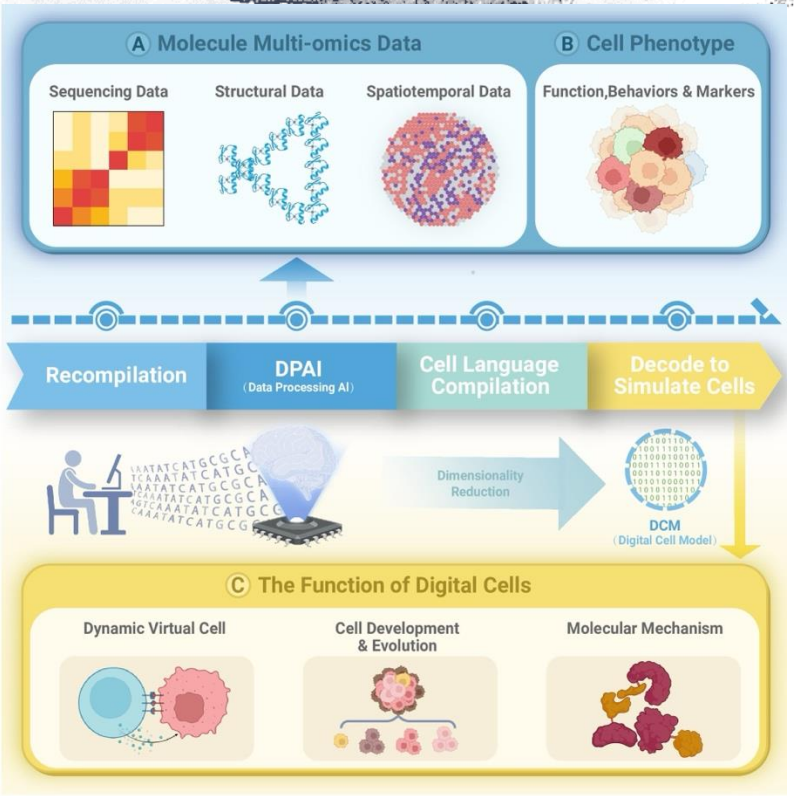


The Fourth Paradigm: Data-Intensive Scientific Discovery

Simulating Complex System: A New Phase

- Digital Cell
- Digital Fly
- Digital Human Mind (AGI LLM)
- Digital Economic System/Society

AGI and AI4Science is Unified in this Framework.



https://www.the-innovation.org/article/doi/10.59717/j.xinn-life.2024.100102

AI in New Phase: Delegate to Real Complex System

- Alpha Fold: Solve a single problem (protein folding problem)
- AI in New Phase: Simulating an entire complex system and act as the delegate of it.
- Why? Of course we can use the simulation model to do a lot of things. But more importantly:
  - What I cannot create, I do not understand. -- Richard Feynman
  - What an AI cannot create, it does not understand. -- Ian Goodfellow
- Simulating complex systems using AI is a major direction in next decade.
- We should be part of it.

Problems of Simulating A Complex System

- How to evaluate the realism of the simulation model?
- Does the reality improvement of the system depends on the reality improvement of the environment?
- Are we simulating the behavior or the mechanism (so the behavior)?
- Under what principle, the accurate simulating of the behavior results in the honest simulation of mechanism? (Maybe the Energy Minimization Principle?)
- How can we understand the complex simulated system? (sparsity? counterfactual experiments? IdopNetwork ?)
- Can the symbolism structure emerges from connectionism activities for more deeper understanding?

Thank You!