



A controller for virtual fly locomotion

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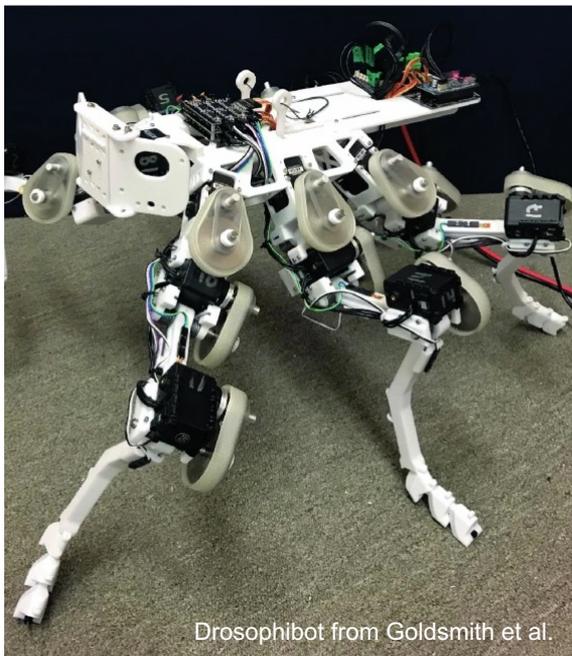
30 May 2023



NeuroMechFly model from Lobato-Rios et al.

Introduction

Understanding animal behavior is crucial in fields of **NEUROENGINEERING** and **ROBOTICS**



Drosophibot from Goldsmith et al.

- Extract information from simulation fails
- "Deconstruct" and artificially modulate behaviors
- Investigate biological underlying mechanisms
- Develop bio inspired robots



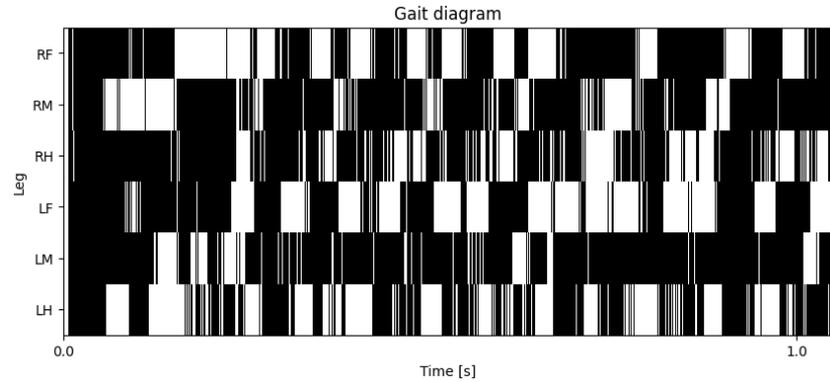
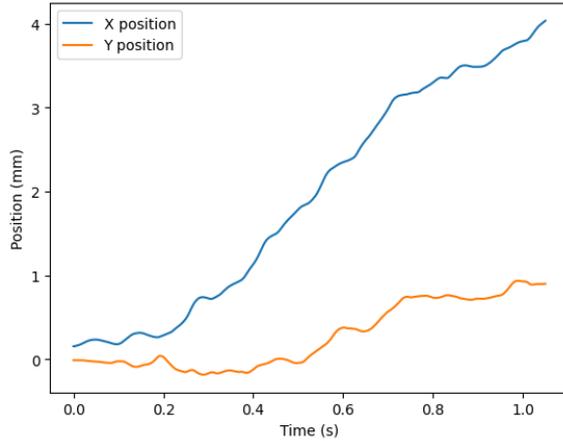
Rule-based controller

- Decentralized controller based on simple rules
- Results
- Possible improvements

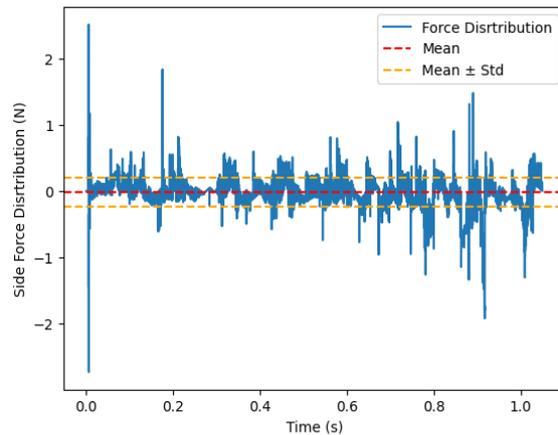
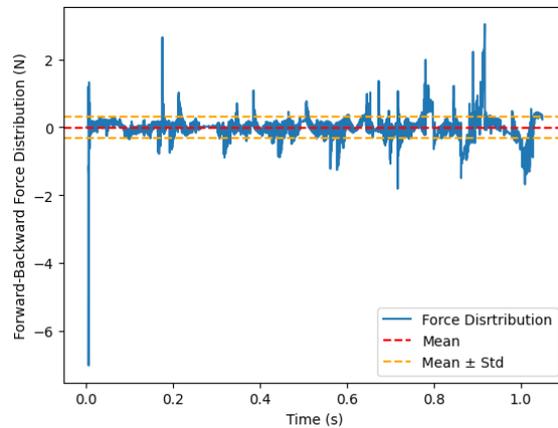
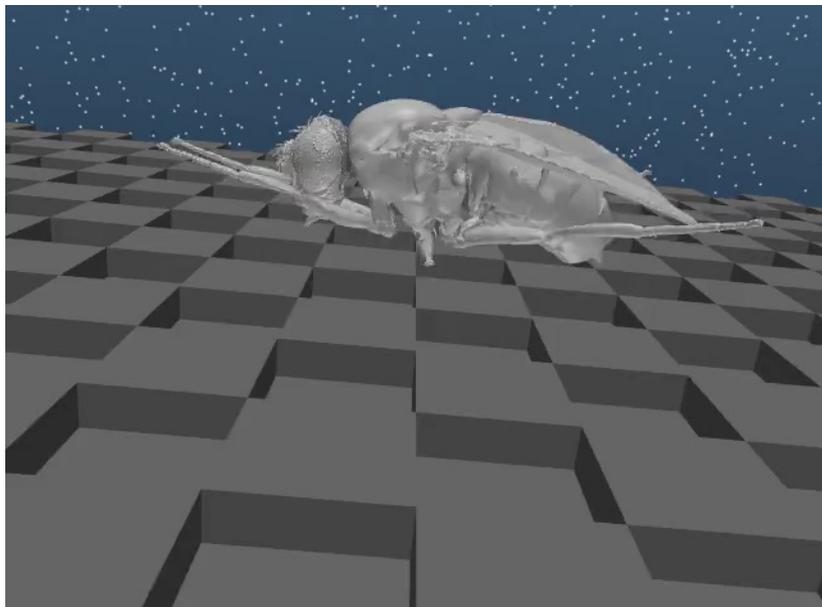
Decentralized controller based on simple rules

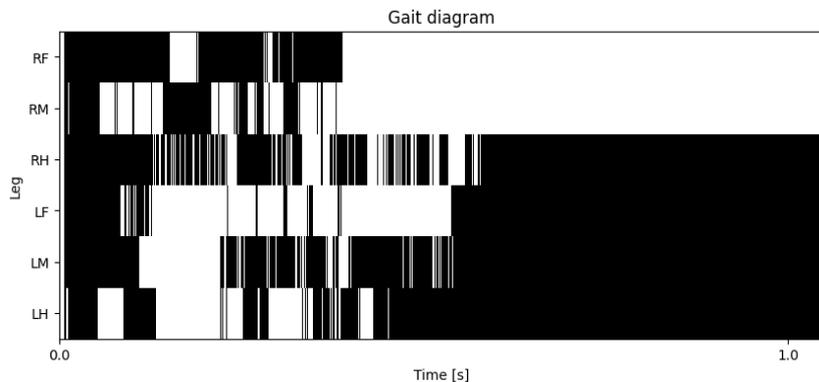
- Walking pattern controlled by rules presented in the Cruse et al.
 - 1st rule “suppress lift-off”
 - 2d rule “facilitate early protraction”
 - 3rd rule “enforce late protraction”
 - 5th rule “distribute propulsive force”

- New rule: "leg gap extraction"



- Forward motion
- Irregular gait pattern with unbalanced swing and stance phases





- Despite the additional rule the fly get stuck
- Find a rules which can extract the fly when multiple legs are trapped

Possible improvements

- Essential to tune the different rules weight with Reinforcement Learning
- Implement specific swing and stance movements
- Improve force signal detected by sensors
- Implement new experimental rules



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CPG-based controller

- Introduction
- From open-loop to closed-loop
- Tripod gait VS Caterpillar gait
- Results

- **CPG-based controllers** have been extensively described in **literature**;
- One of the **main limitations** of the standard formulation of **CPG** is that it is **open-loop**;
- CPGs are well suited for **rapid, cyclical movements** that do not heavily rely on sensory feedback;
- We decided to employ **six CPGs**, one per leg.



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- **CPG-based controllers** have been extensively described in **literature**;
- One of the **main limitations** of the standard formulation of CPG is that it is **open-loop**:

$$\dot{\theta}_i = 2\pi\nu_i + \sum_j (r_j w_{ij} \sin(\theta_j - \theta_i - \phi_{ij}))$$

ν_i → Frequency of the i-th oscillator;

r_i → Amplitude of the i-th oscillator;

w_{ij} → Coupling strength between the i-th and the j-th oscillators;

θ_i → Phase of the i-th oscillator;

ϕ_{ij} → Phase bias between the i-th and the j-th oscillators;

- We therefore decided to introduce **sensory feedback** in different ways;
- **Strategy 1:** Adding a term related to the **force** in the **differential equation**:

$$\dot{\theta}_i = 2\pi\nu_i + \sum_j (r_j w_{ij} \sin(\theta_j - \theta_i - \phi_{ij})) - c(F_{i,t} - F_{i,t-1})$$

ν_i → Frequency of the i-th oscillator;

r_i → Amplitude of the i-th oscillator;

w_{ij} → Coupling strength between the i-th and the j-th oscillators;

θ_i → Phase of the i-th oscillator;

ϕ_{ij} → Phase bias between the i-th and the j-th oscillators;

$F_{i,t}$ → Force experienced by the i-th end effector at time step t;

$F_{i,t-1}$ → Force experienced by the i-th end effector at time step t – 1.

- We therefore decided to introduce **sensory feedback** in different ways;
- **Strategy 2: Scaling the frequencies** of the oscillators based on the **contact forces** experienced by the end effectors:

$$F_{max} \rightarrow c_{max F} < 1$$

$$F_{min} \rightarrow c_{min F} > 1$$

$$\Delta_F = F_{max} - F_{min}$$

$$S_i = c_{max F} + (c_{min F} - c_{max F}) * \frac{F_i - F_{min}}{\Delta_F}$$

**Linear
interpolation
approach**

From open-loop to closed-loop

- We therefore decided to introduce **sensory feedback** in different ways;
- **Strategy 3: Freezing a leg** (keeping the phase and amplitude of the oscillator constant) if the experienced **force** is **above a threshold**.



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Tripod gait VS Caterpillar gait

- One of the gait types described more in detail in literature is the **tripod gait**:
 - **Three legs move simultaneously**, the others keep contact with the ground;
 - Good compromise between **speed** and **stability**.



$$\phi_{ij} = \begin{bmatrix} 0 & 0.5 & 1.0 & 0.5 & 0 & 0 \\ 0.5 & 0 & 0.5 & 0 & 0.5 & 0 \\ 1.0 & 0.5 & 0 & 0 & 0 & 0.5 \\ 0.5 & 0 & 0 & 0 & 0.5 & 1.0 \\ 0 & 0.5 & 0 & 0.5 & 0 & 0.5 \\ 0 & 0 & 0.5 & 1.0 & 0.5 & 0 \end{bmatrix}$$

Phase bias matrix for the tripod gait

Tripod gait VS Caterpillar gait



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Tripod gait VS Caterpillar gait

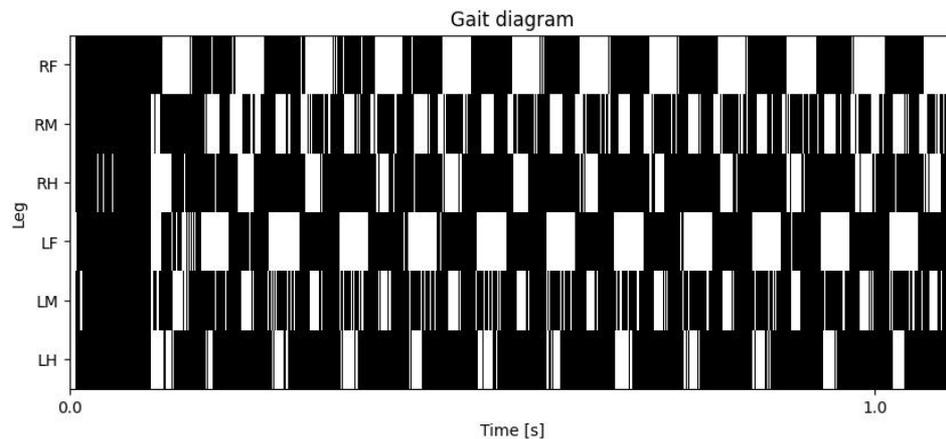
- We investigated a different type of gait, the **caterpillar gait**:
 - **Wave motion**, two front/mid/back legs are in the swing phase at the same time while the other four are in the stance phase;
 - **Very stable** motion without sacrificing speed.



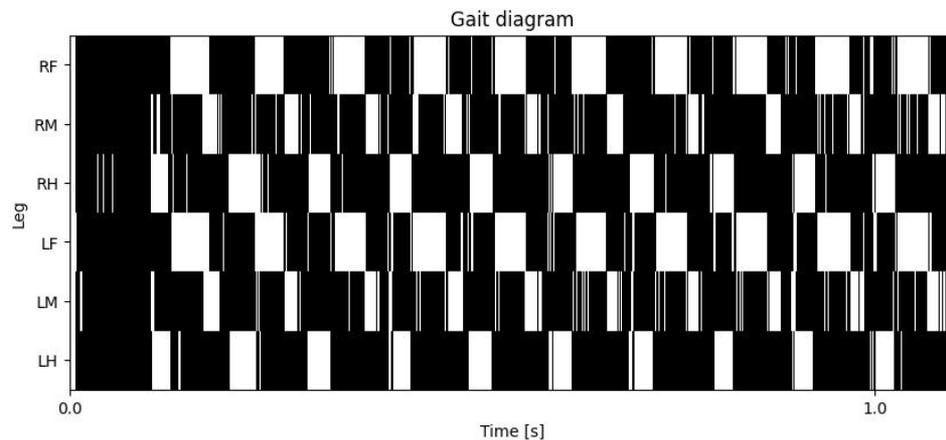
$$\phi_{ij} = \begin{bmatrix} 0 & 2 & 1 & 0 & 2 & 1 \\ 1 & 3 & 0 & 3 & 1 & 0 \\ 2 & 0 & 3 & 0 & 3 & 0 \\ 3 & 1 & 0 & 3 & 2 & 3 \\ 0 & 3 & 2 & 0 & 3 & 3 \\ 1 & 0 & 3 & 1 & 0 & 3 \\ 2 & 0 & 3 & 2 & 1 & 0 \\ 3 & 1 & 0 & 3 & 2 & 1 \\ 0 & 3 & 2 & 0 & 3 & 1 \end{bmatrix}$$

Phase bias matrix for the caterpillar gait

Tripod gait VS Caterpillar gait

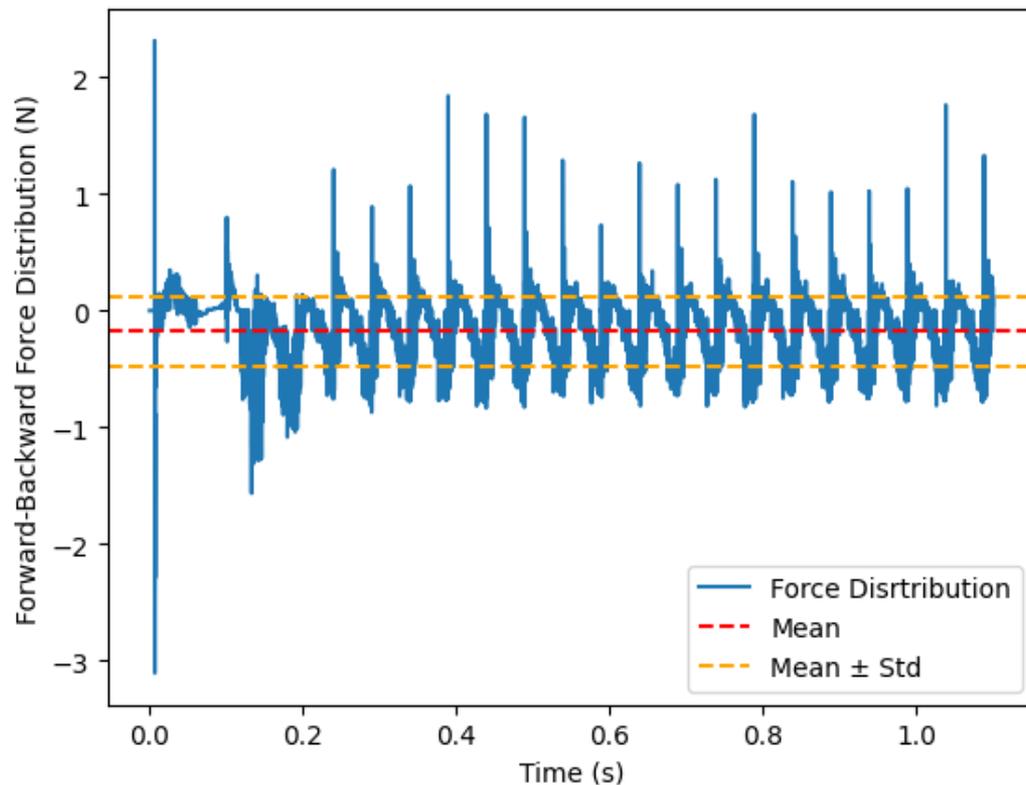


**Tripod
gait**



**Caterpillar
gait**

Tripod gait VS Caterpillar gait



Forward-backward force distribution for the caterpillar gait on flat terrain

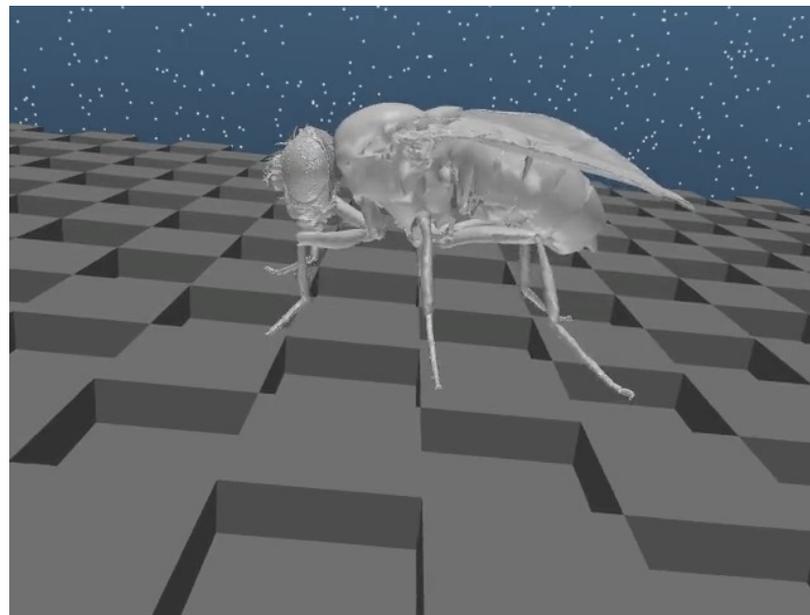
- The **fly** is quite **fast** and **stable**, the distance travelled with the caterpillar gait is larger than the one travelled with the tripod gait;
- The **terrain** is **easy** to be traversed.

Terrain	Final X distance	Final Y distance
Flat	18.65 mm	1.71 mm
Blocks	3.47 mm	0.65 mm
Gapped	4.55 mm	0.16 mm



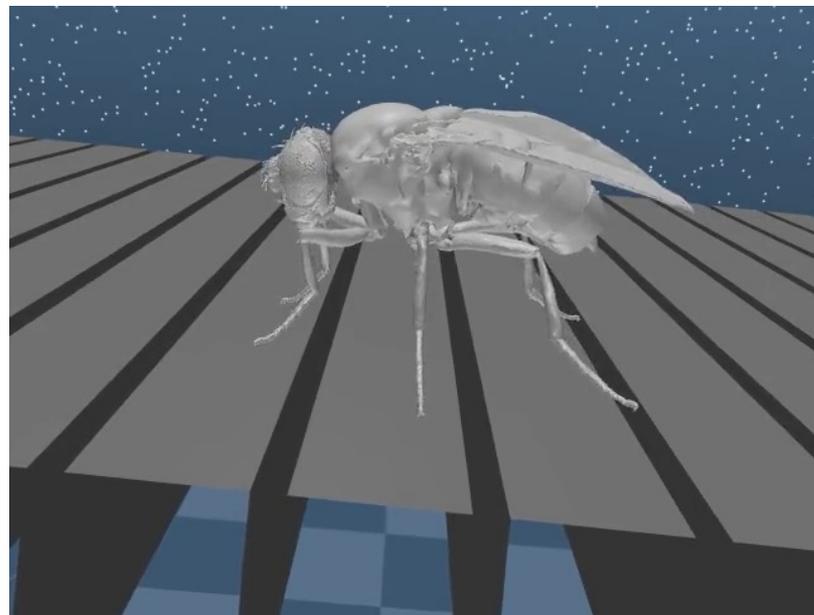
- The **controller has trouble keeping stability** in all situations, but the **caterpillar gait** seems to be **beneficial** in this regard;
- Sometimes, the fly tips over.

Terrain	Final X distance	Final Y distance
Flat	18.65 mm	1.71 mm
Blocks	3.47 mm	0.65 mm
Gapped	4.55 mm	0.16 mm



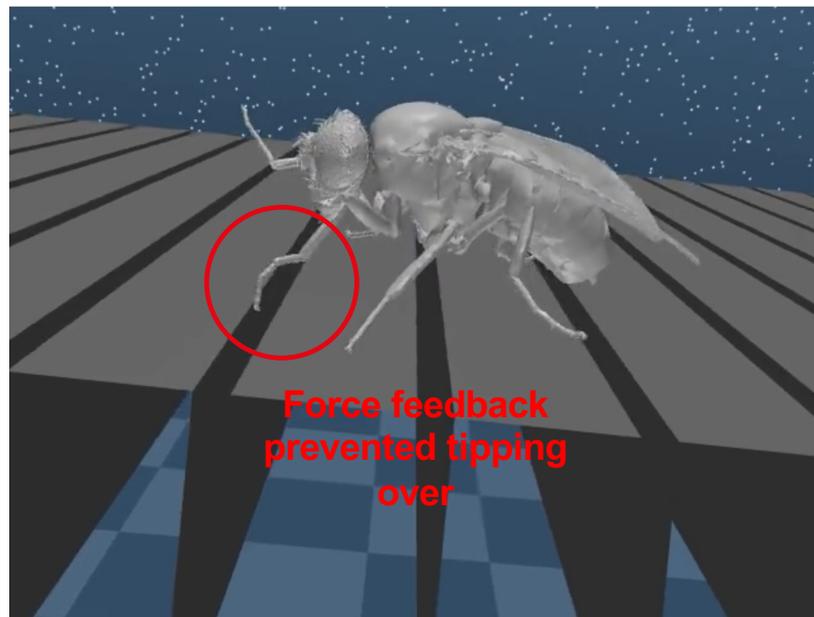
- The **fly** can free the legs from the gaps most of the time;
- The **caterpillar gait seems beneficial**, but sometimes two legs get stuck at the same time.

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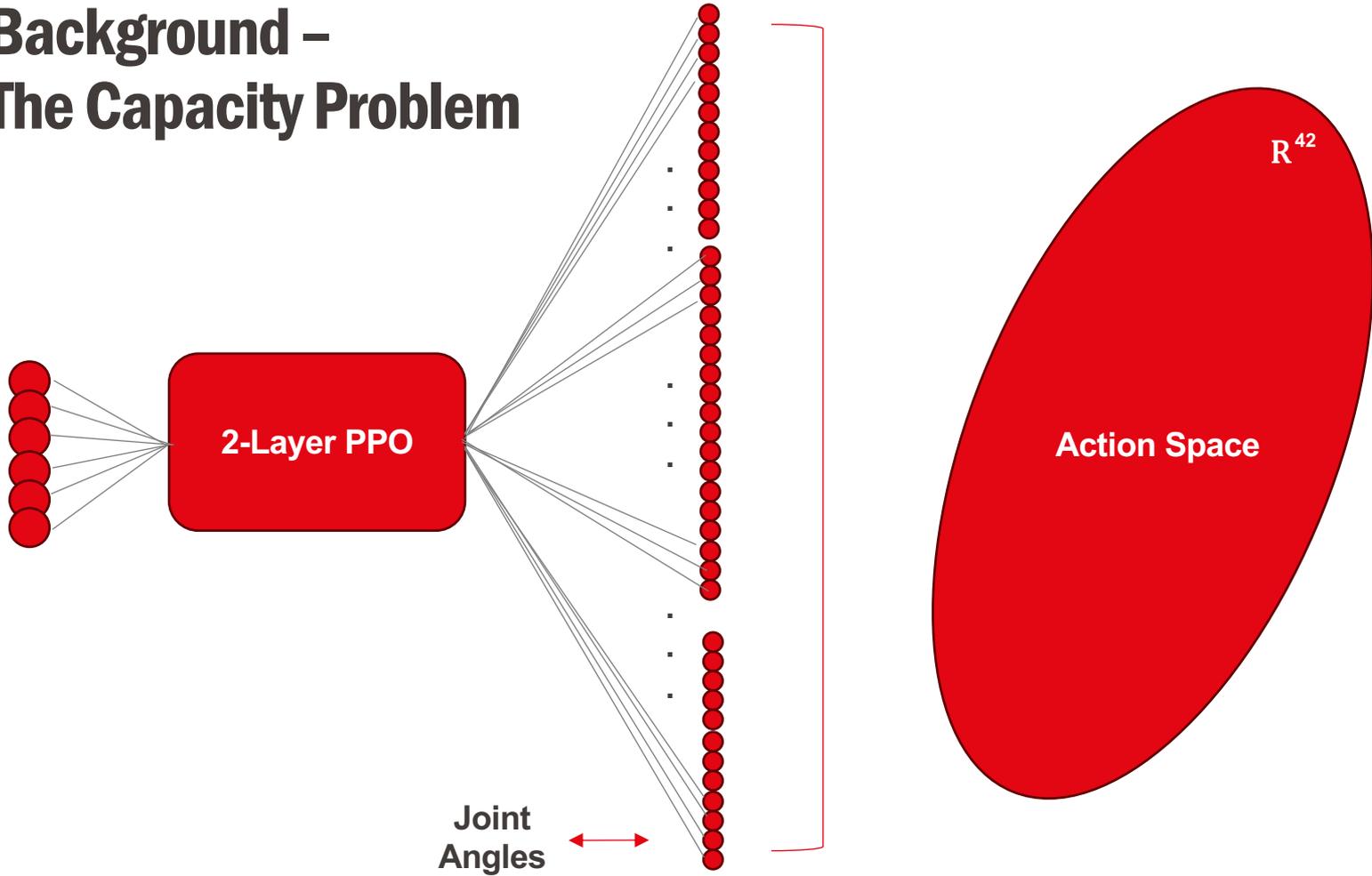
Rule-Based Reinforcement Learning Hybrid controller

Background

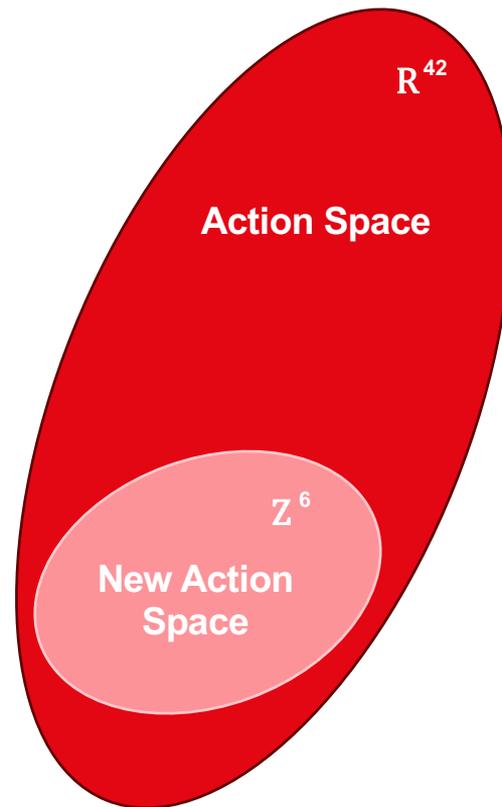
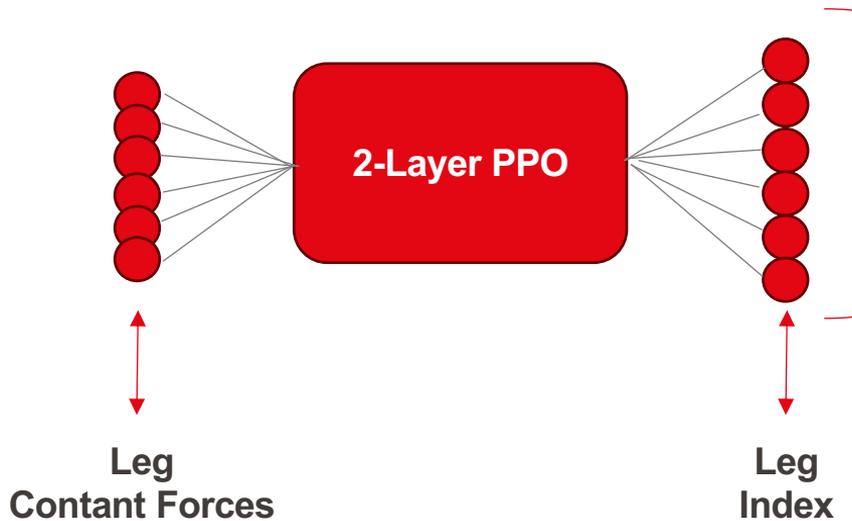
- The team trying to fine-tune Cruse rules.
- The team trying to fine-tune CPGs.
- The team trying to learn a 42-DoF continuous output using a 2-layer PPO Policy Network.

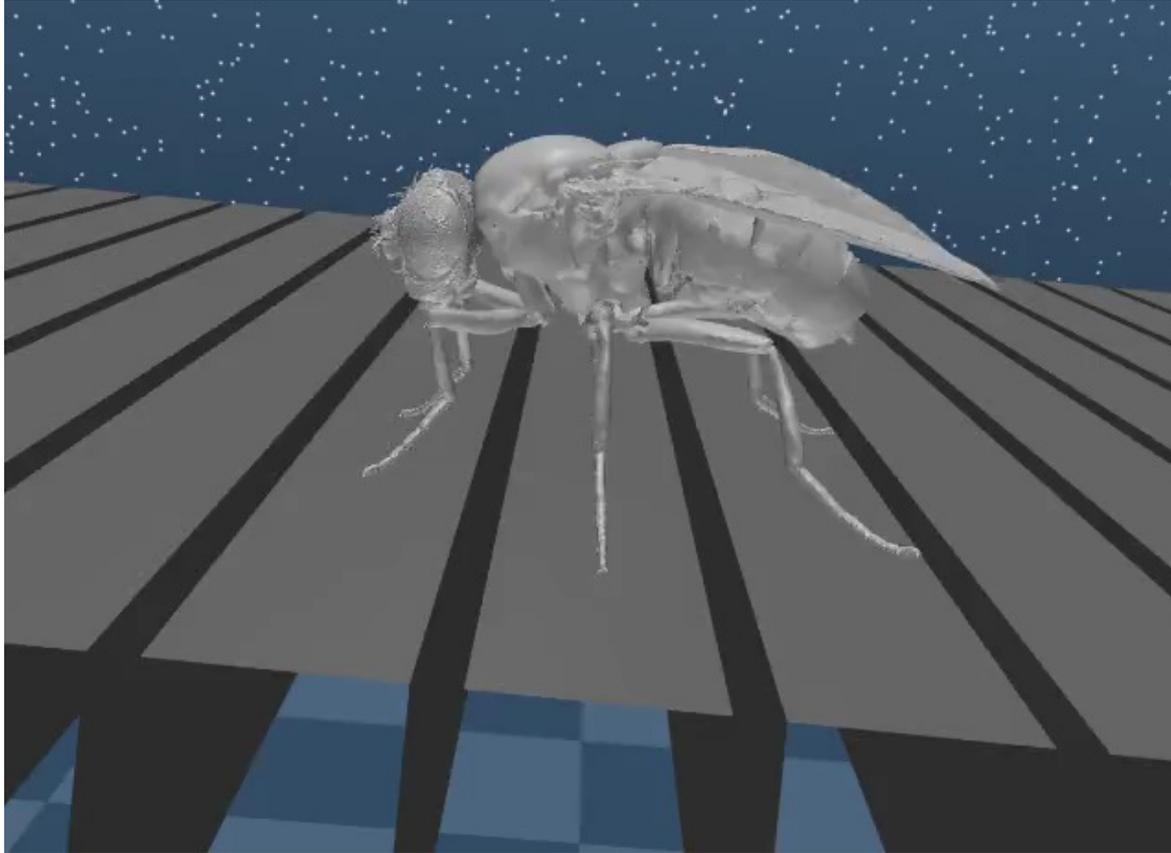


Background – The Capacity Problem

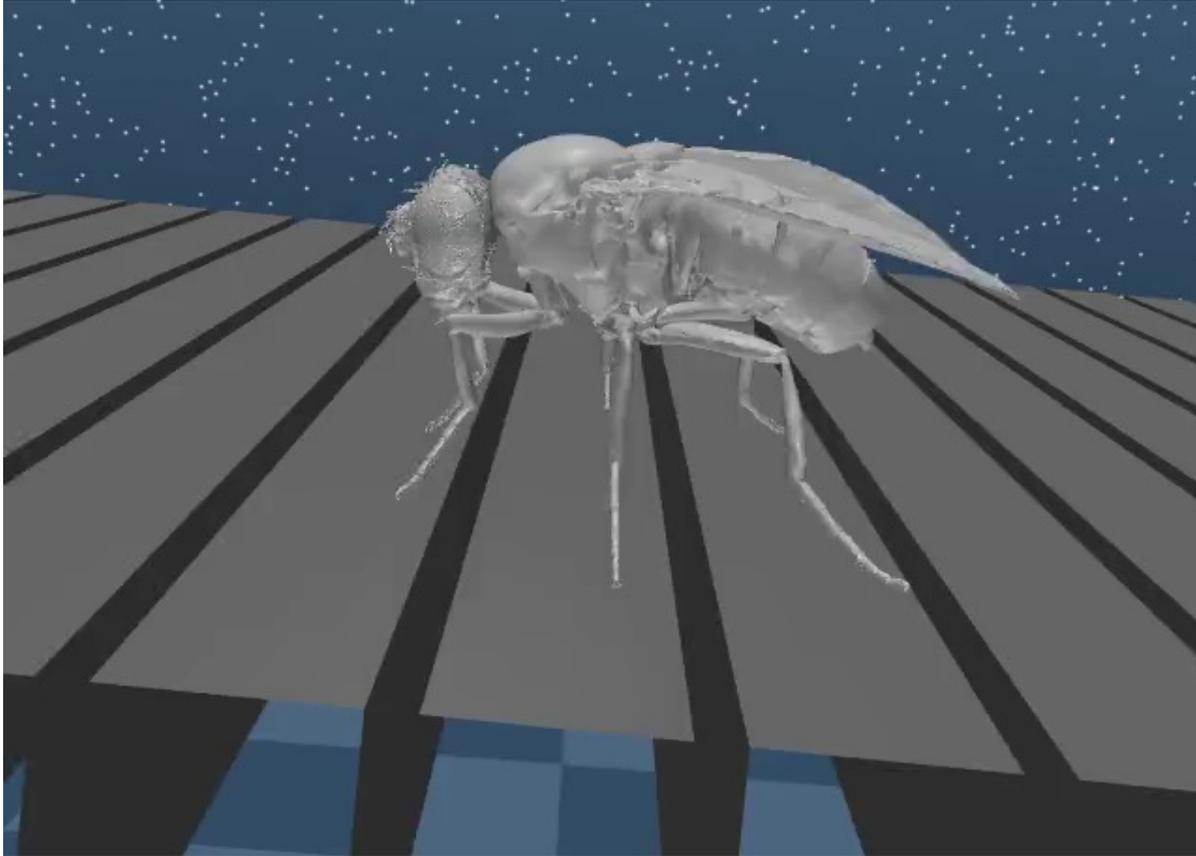


Background – Matching Capacities





Terrain	Final X	Final Y
Gapped	~16 mm	-

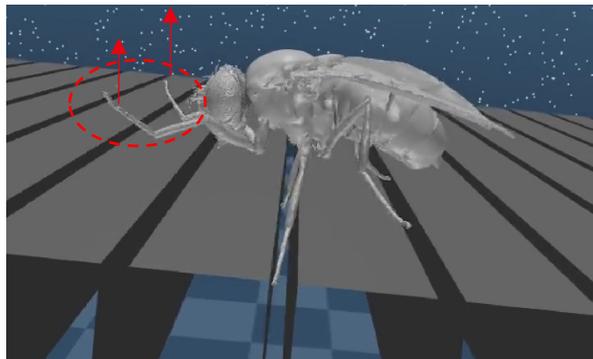


Terrain	Final X	Final Y
Gapped	10 mm	~ -5 mm

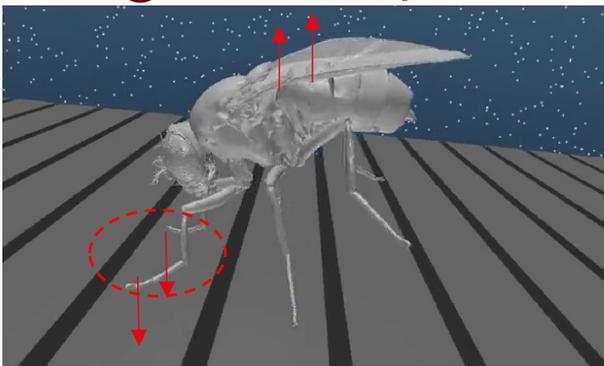
1 Gets Stuck



2 Thrusts with Front Legs

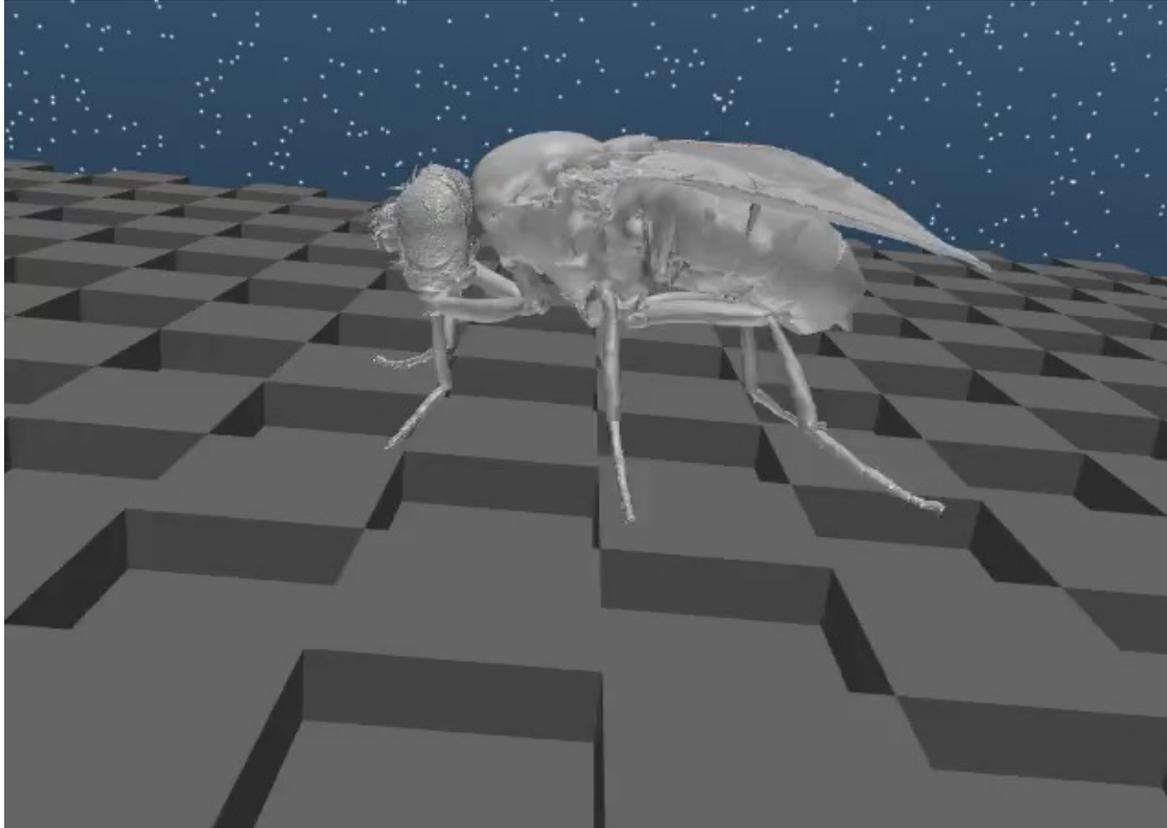


3 Pulls Itself Up



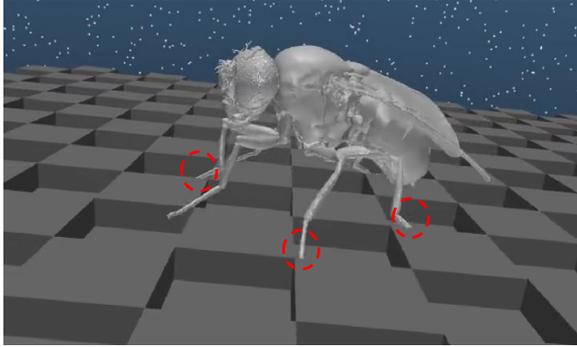
4 Locomotes to the Edge of the World



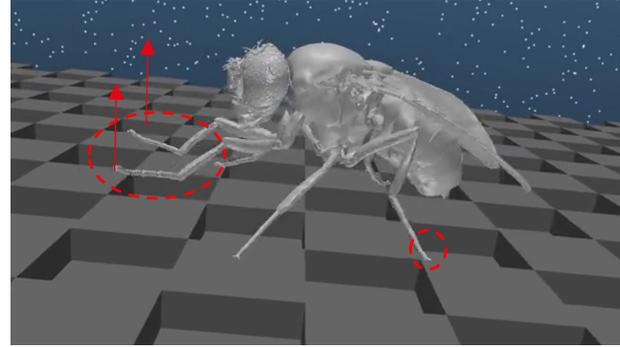


Terrain	Final X	Final Y
Blocks	7 mm	~2 mm

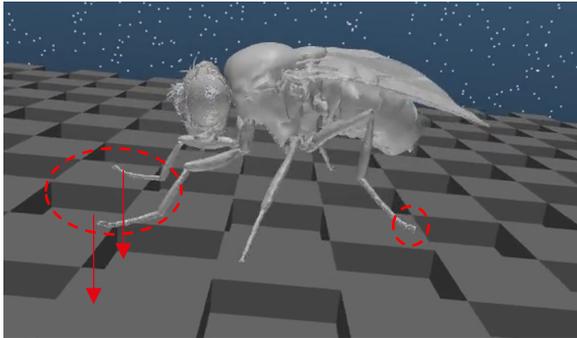
1 Legs in Cavities



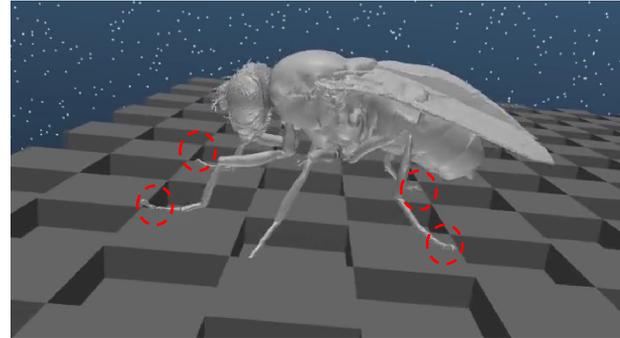
2 Swings Front Legs – Supports with Hind Legs



3 Pulls Itself Up

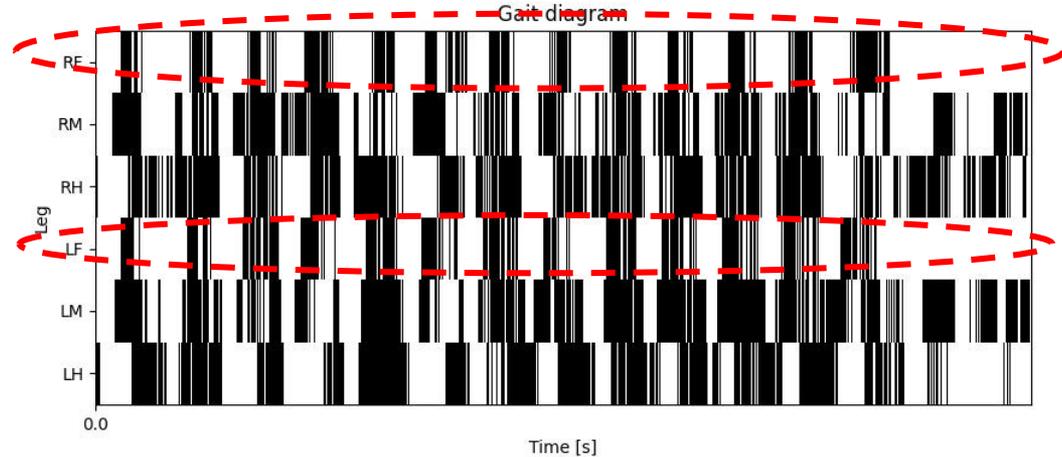


4 Good Placement



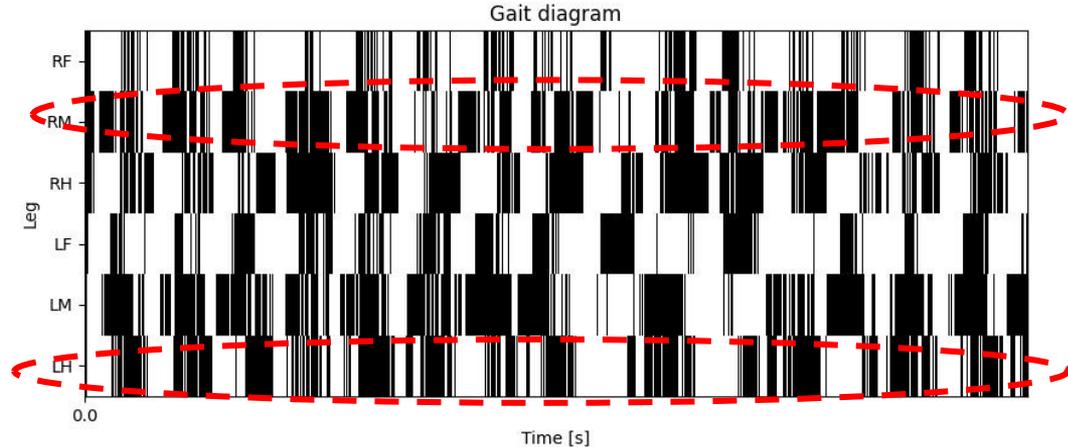
LF & RF exhibit a shorter stance phase:

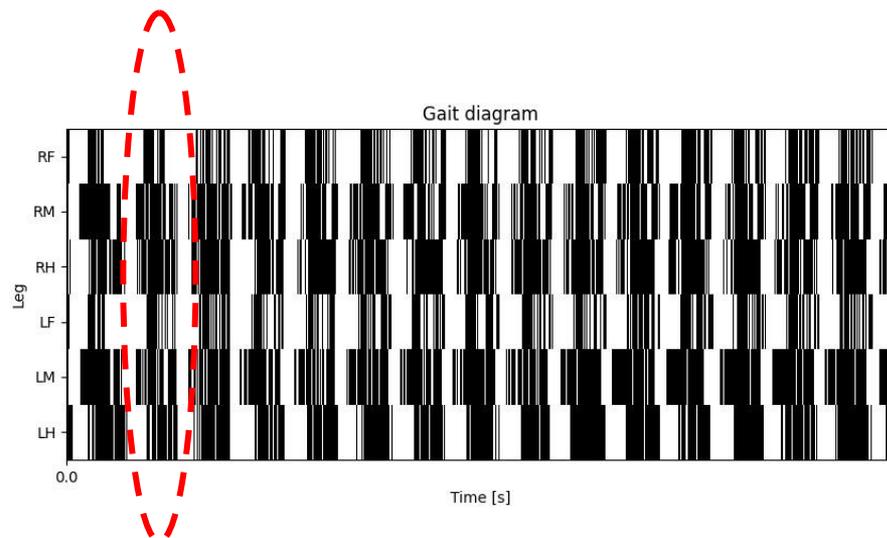
- More reactive
- Contribute less to stabilization
- Contribute more to locomoting



Middle & Hind Legs exhibit a Longer stance phase:

- Contribute more to stabilization





Terrain	Final X	Final Y
Flat	13 mm	~ 1 mm

Near-Synchronized Gait:

- Hop-like locomotion



Summary

- Summary – Rule-based controller
- Summary – CPG-based controller
- Summary – RL-based controller

- Rule-based controller shows some unsatisfactory results, but some improvements could be done to increase its robustness.



Summary – CPG-based controller

- Controllers purely based on CPG are very effective on flat terrain, while sensory feedback is needed to improve performance on complex terrain;
- Even with force feedback, CPG-based controllers are not entirely robust on complex terrains.



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- Pure RL lacks capacity to learn a 42-DOF continuous action space;
- Rule-based RL allows for a narrow action space and a more efficient optimization process, adapting well to all 3 terrains.



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Critique

- We were given a single dataset for the fly step, having more data could have allowed for more variability in the stepping pattern;
- The mechanical model of the fly seemed quite realistic and well realized;
- Integrating vision and olfaction could be valuable to realize a more robust controller.

- These three controller could be merged:

- ① Rule-based as a baseline \longrightarrow simplicity
- ② CPG-based for enhancement \longrightarrow regularity
- ③ Reinforcement learning for fine-tuning \longrightarrow optimization

- We obtained some non-realistic gait patterns with some controllers;
- Combine neurophysiological experiments with controller development to get more biologically relevant gait patterns.

Thanks for your attention!

