TUTORIAL

Autonomous Driving with Neuromorphic Controllers

Elishai Ezra Tsur
The Open University of Israel

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Neuro-Inspired Computational Elements
NICE 2025

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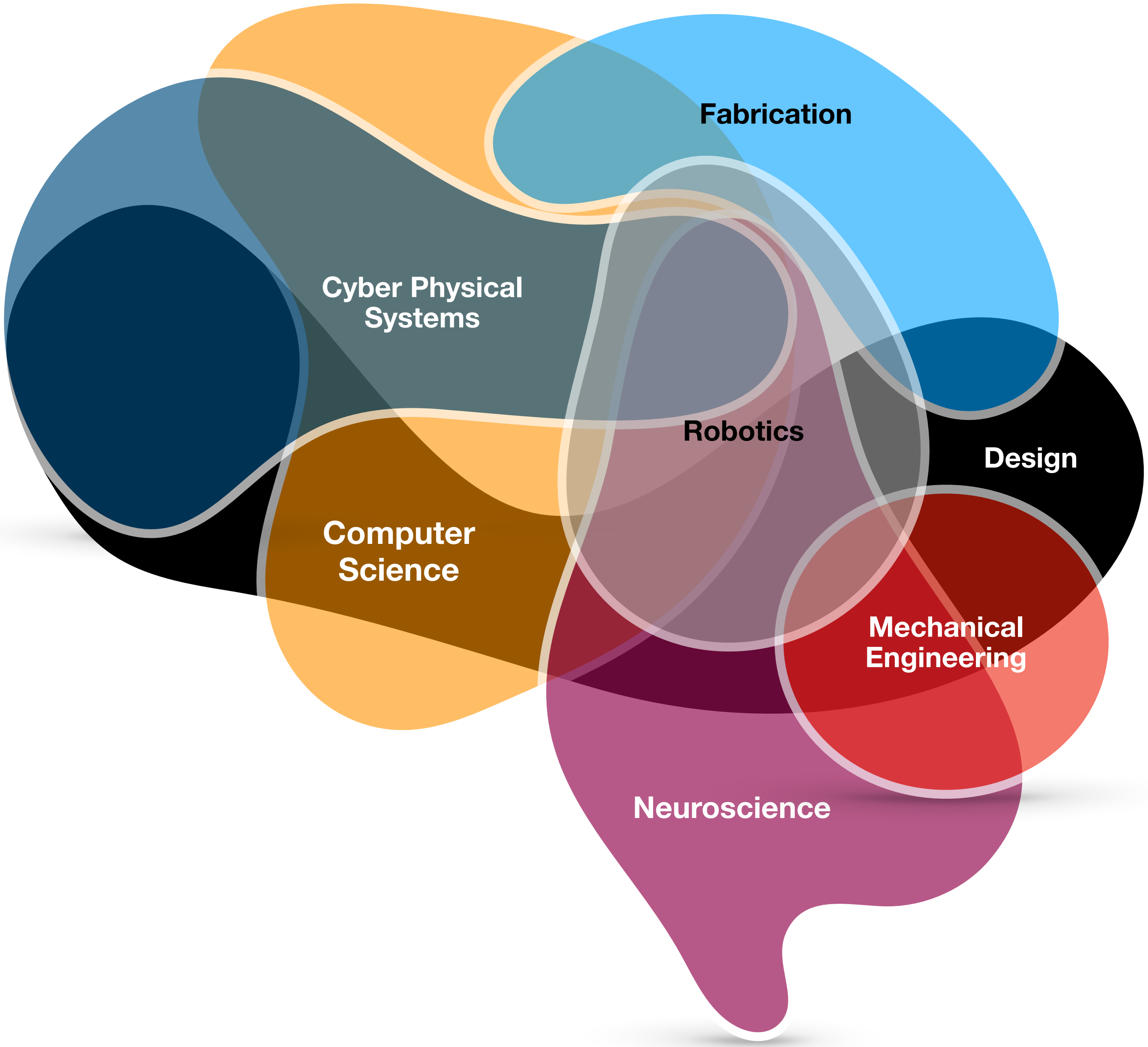

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- The largest university in Israel with more then 46,200 students
- 1 in every 5 students in Israel is a student of the Open University
- 60 learning centres across Israel. Main Campus in Raanana
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- Home for NBEL-lab.com

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Follow the code examples!

http://bit.ly/426swoN

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Tutorial Outline

Why Neuromorphic Control, Autonomous Behavior, Driving

What PID, Pure pursuit, Stanley Controller, MPC

How Neural Engineering Framework, Nengo, Airsim, Carla

Learn Resources

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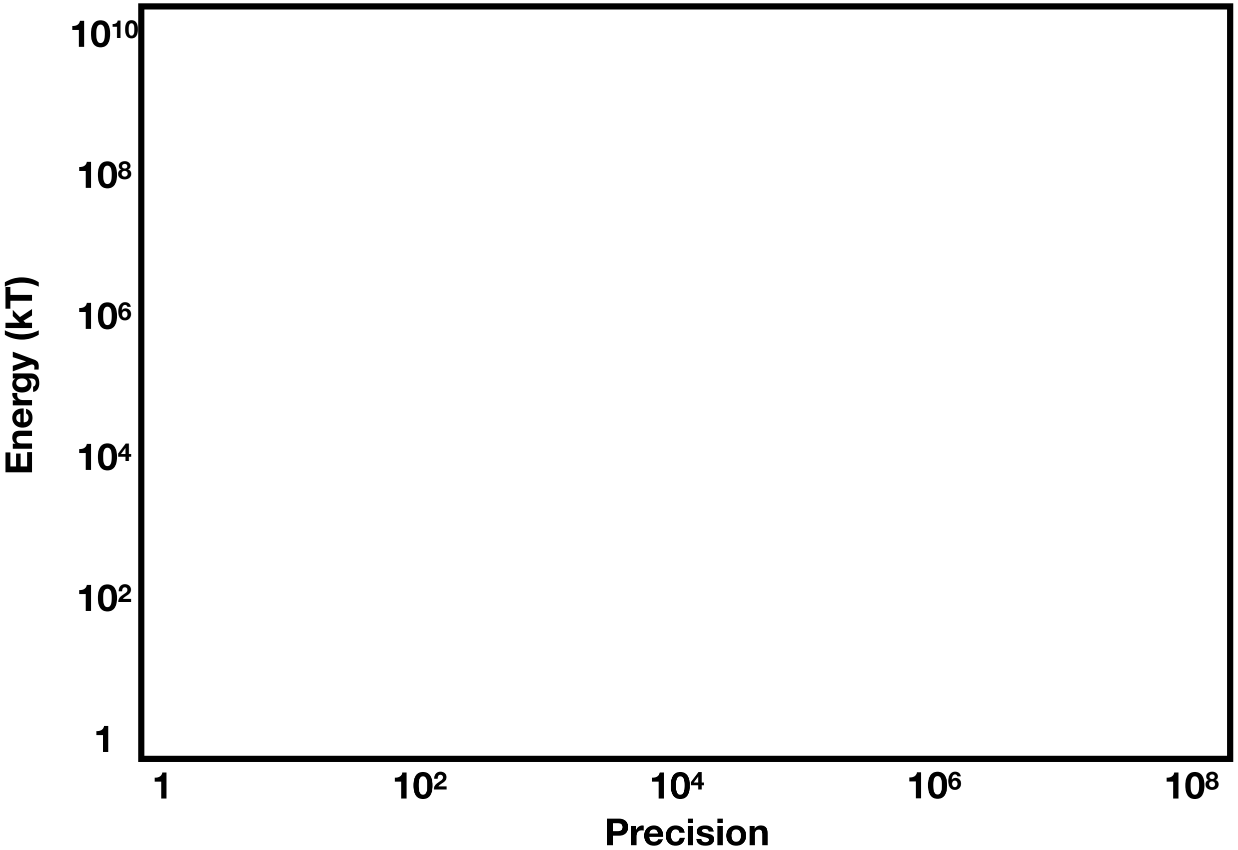
Where is Neuromorphic Computing is relevant?



A Neuromorph's Prospectus Kwabena Boahen, IEEE, 2018

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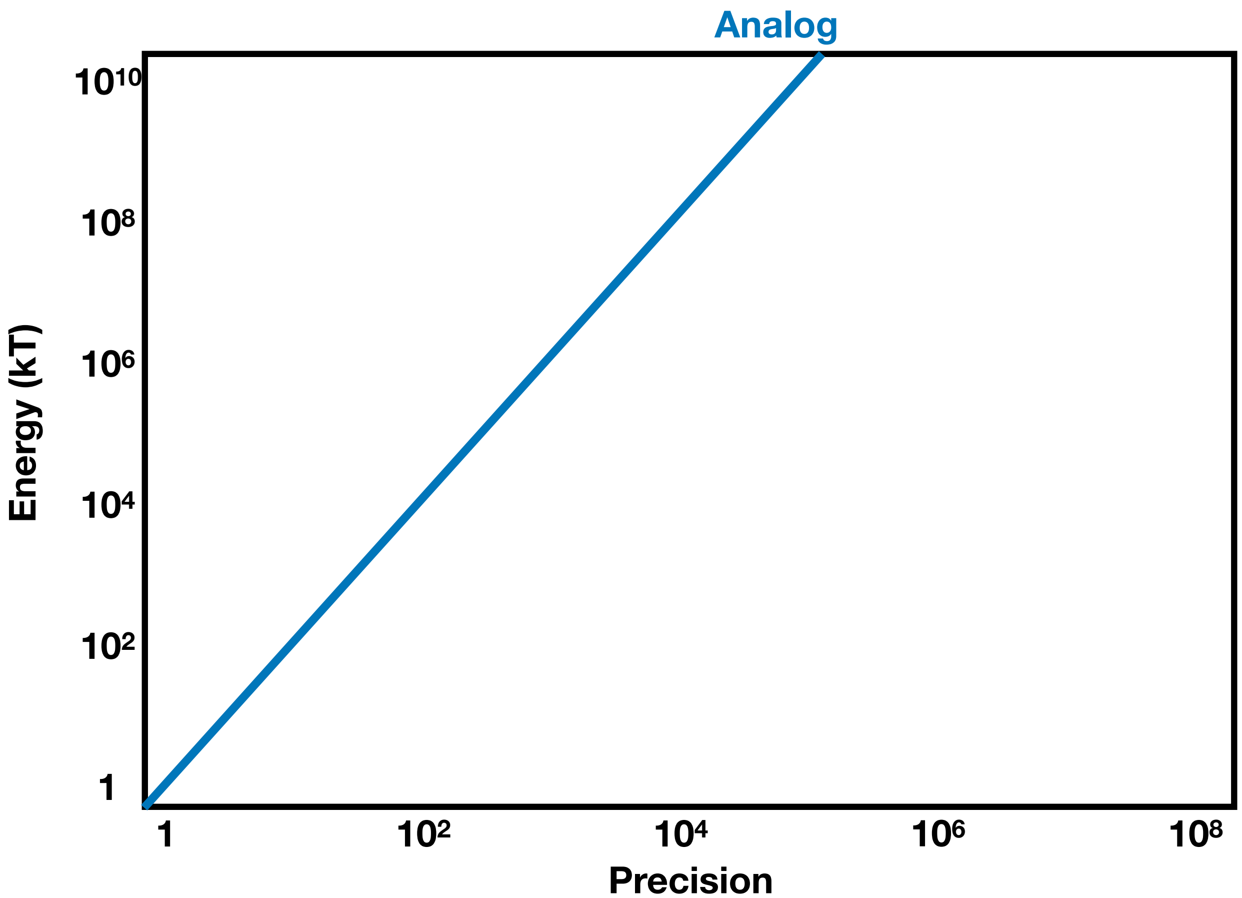

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- Energy consumed to generate an analog voltage signal scales quadratically with its amplitude.

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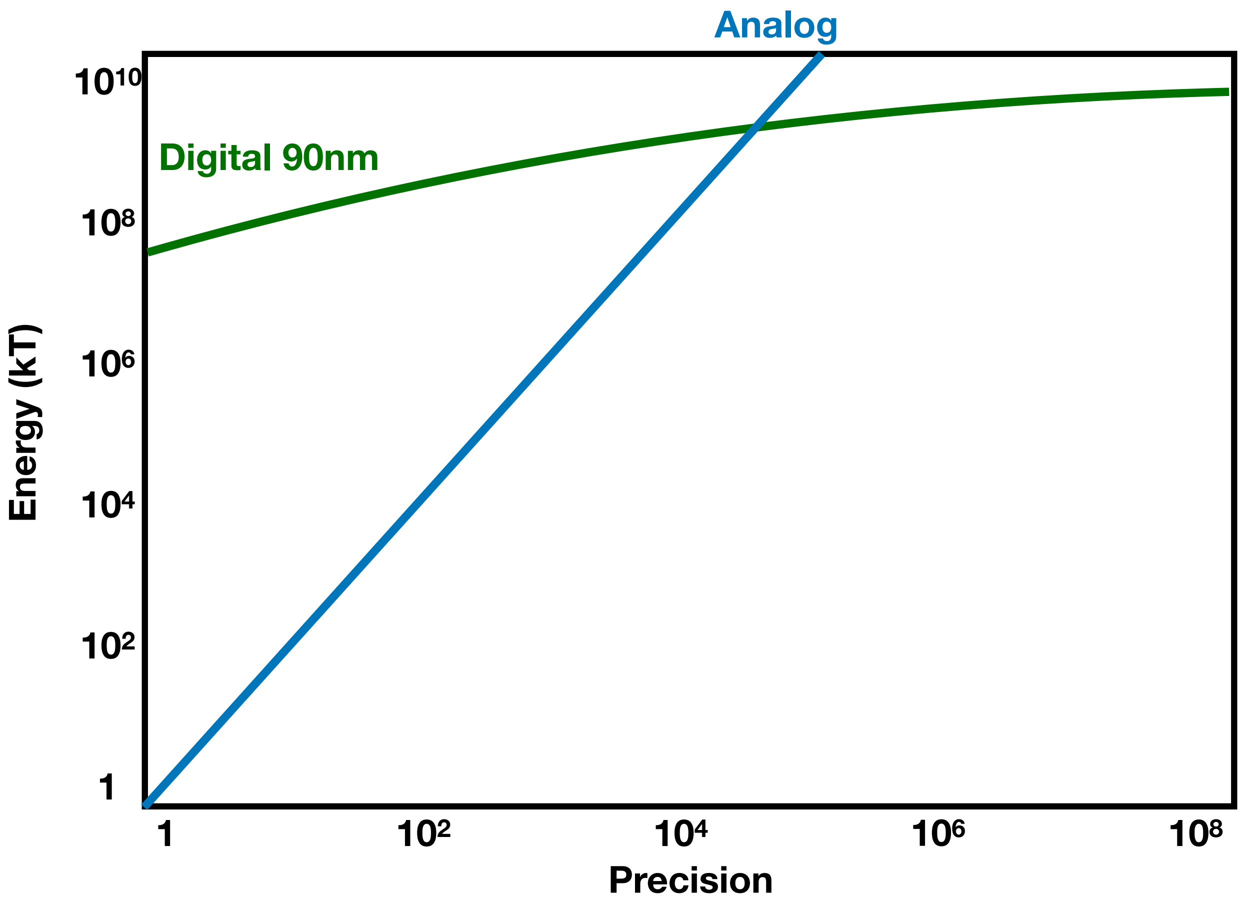

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- Energy consumed to generate an analog voltage signal scales quadratically with its amplitude.
- Digital signals scales logarithmically

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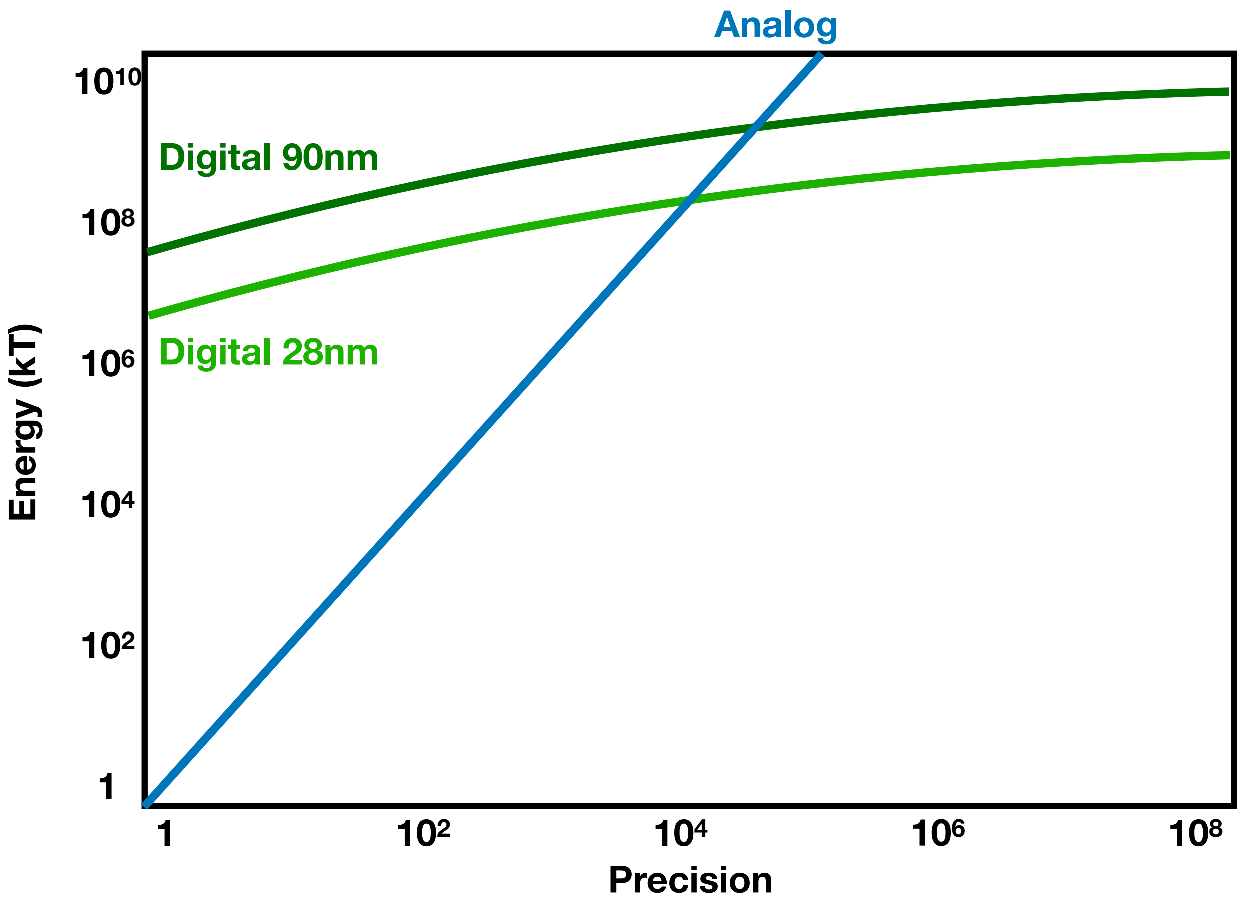

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- Energy consumed to generate an analog voltage signal scales quadratically with its amplitude.
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- The crossover point has migrated to the left over the years (with miniaturization) - favoring digital over analog computation for more and more applications

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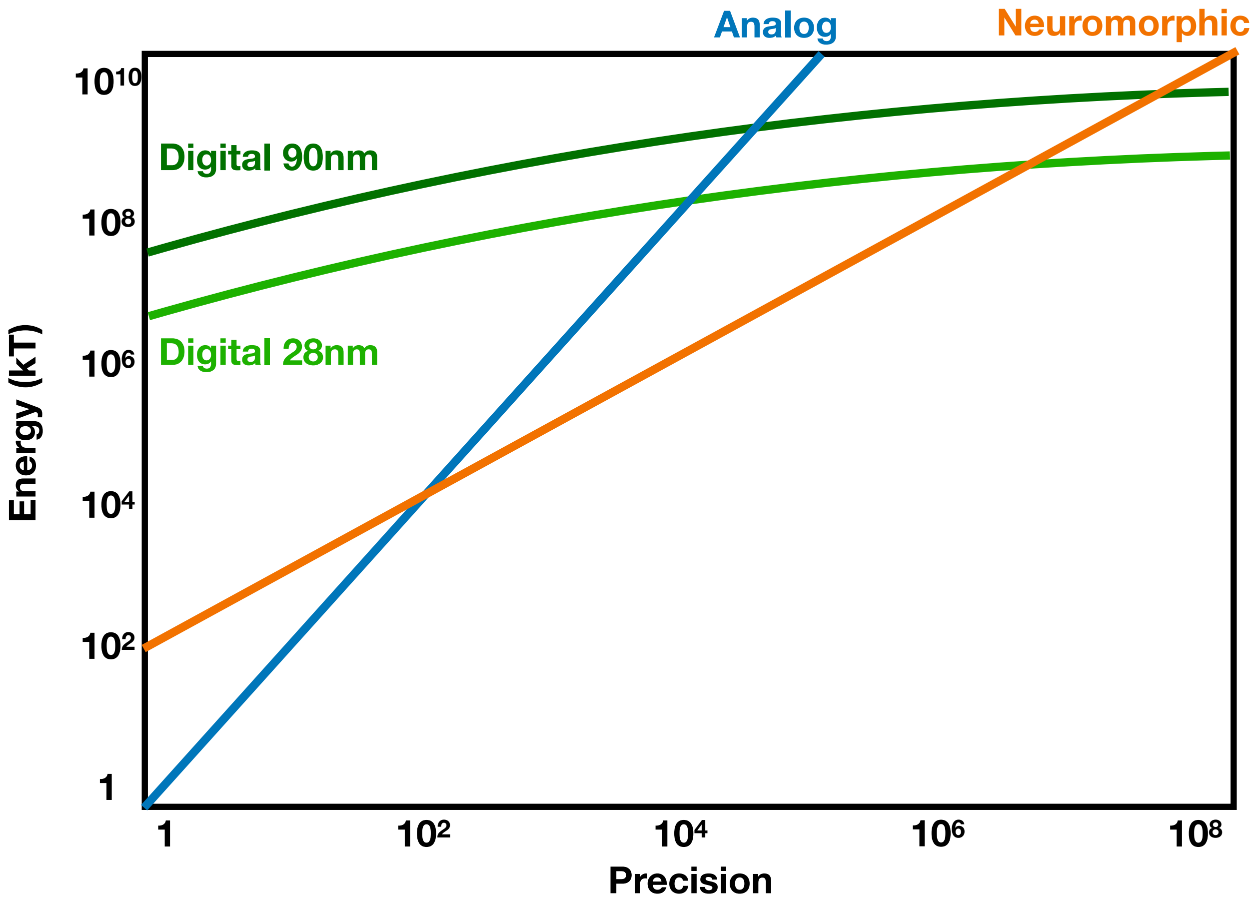

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- Most neuromorphic architectures aim to **mix analog-digital design**

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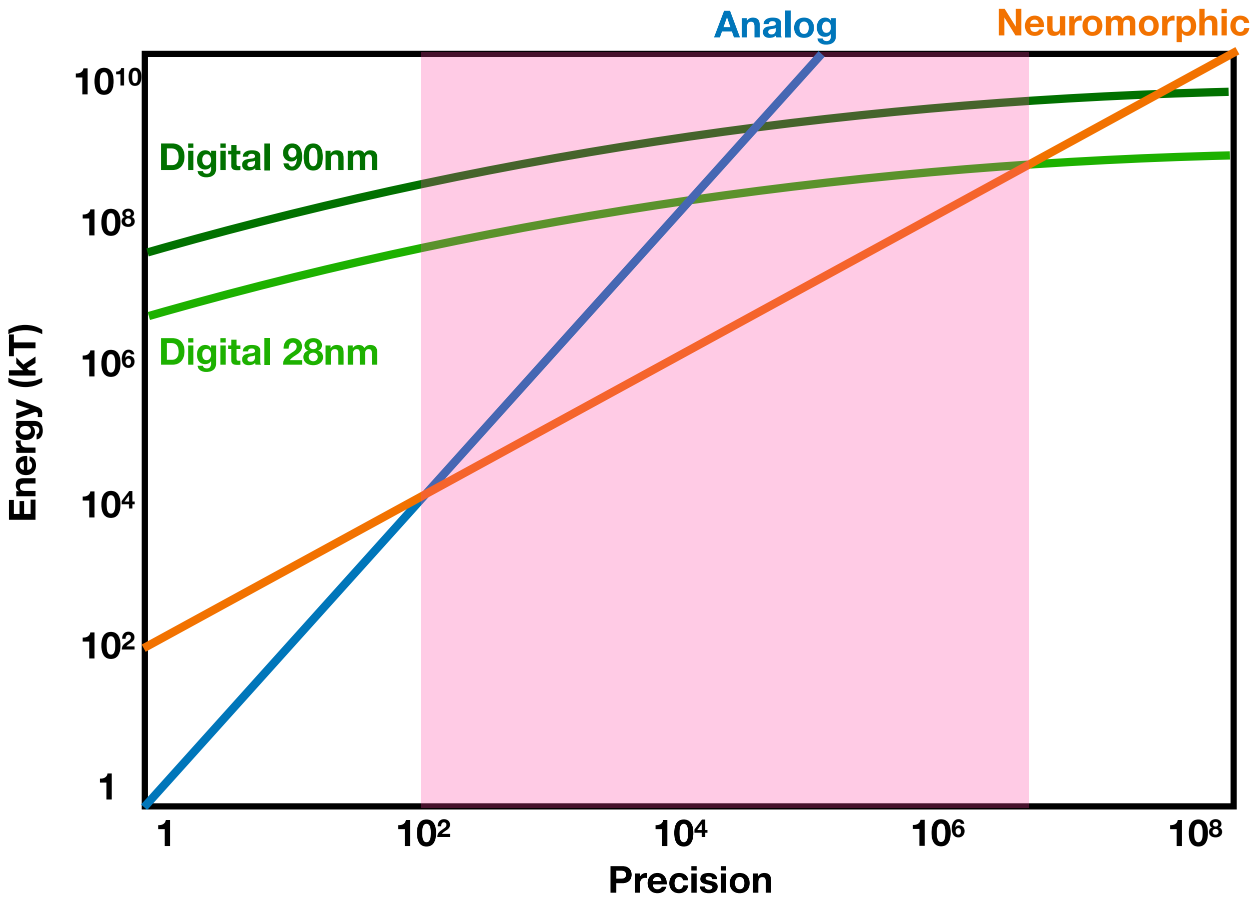

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- Energy consumed to generate an analog voltage signal scales quadratically with its amplitude.
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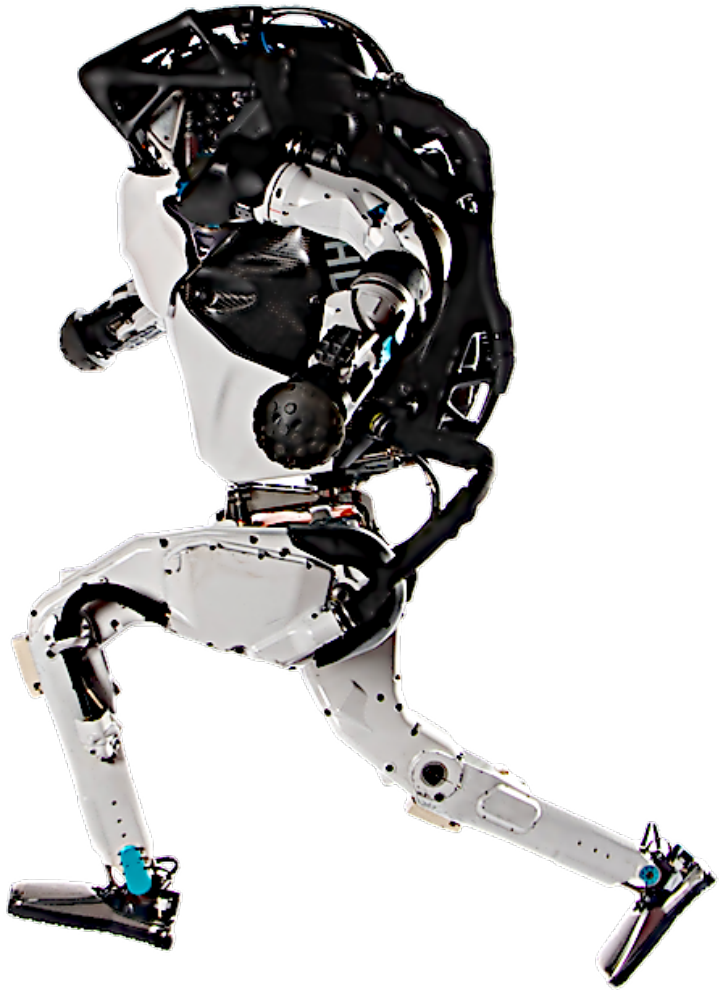
- Most neuromorphic architectures aim to **mix analog-digital design** to achieve best performance across five-decade precision range.



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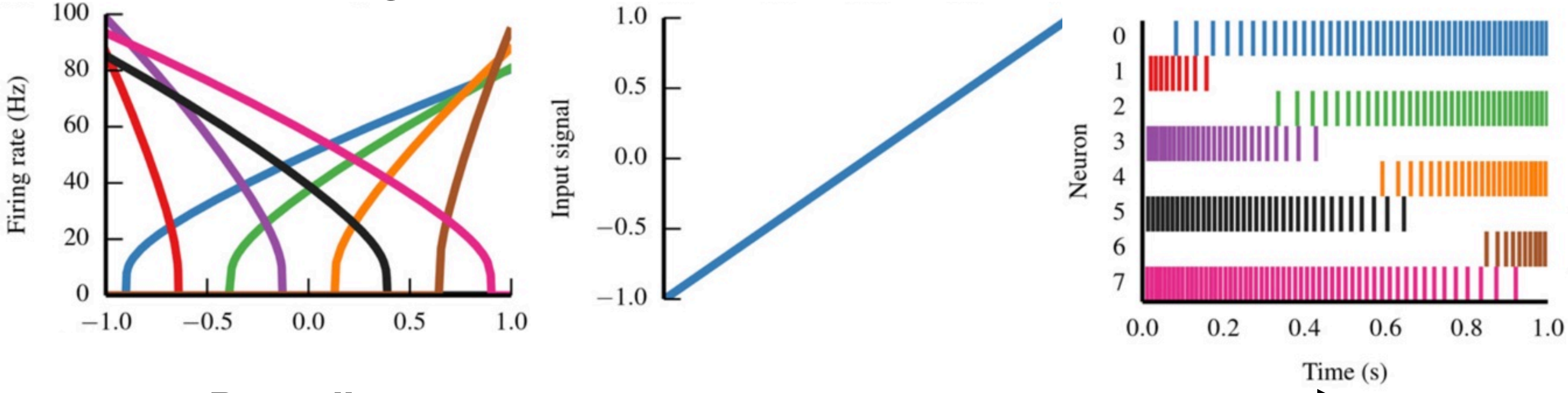
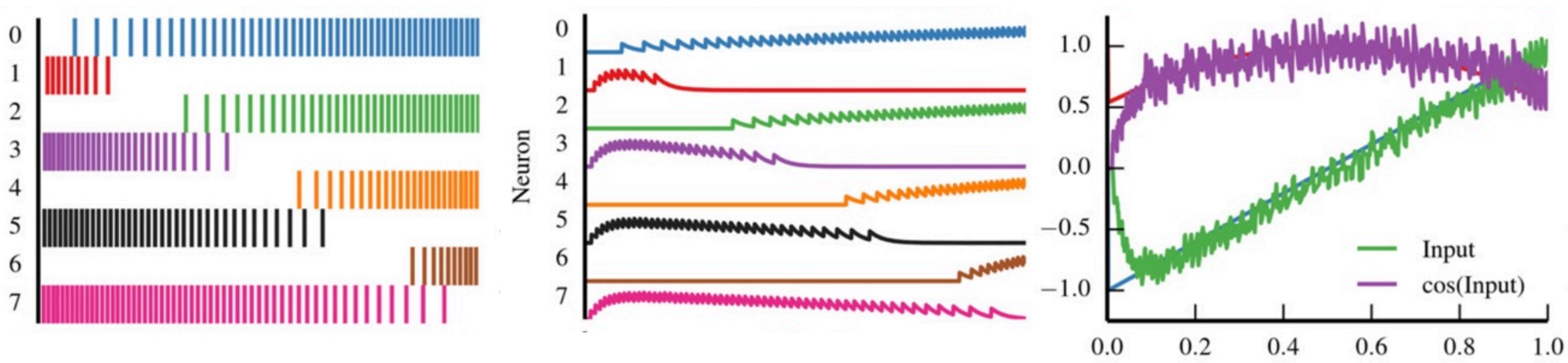
In the Neural Engineering Framework

Encoding



Decoding



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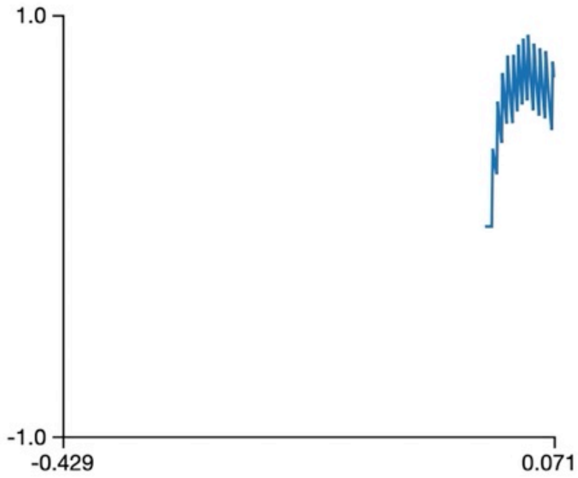
Computing with Spiking Neural Networks
Representation

Encoding-Decoding with 1 neuron:

Computing with Spiking Neural Networks
Representation

Encoding-Decoding with 2 neurons:



Computing with Spiking Neural Networks
Representation

Encoding-Decoding with 20 neurons:

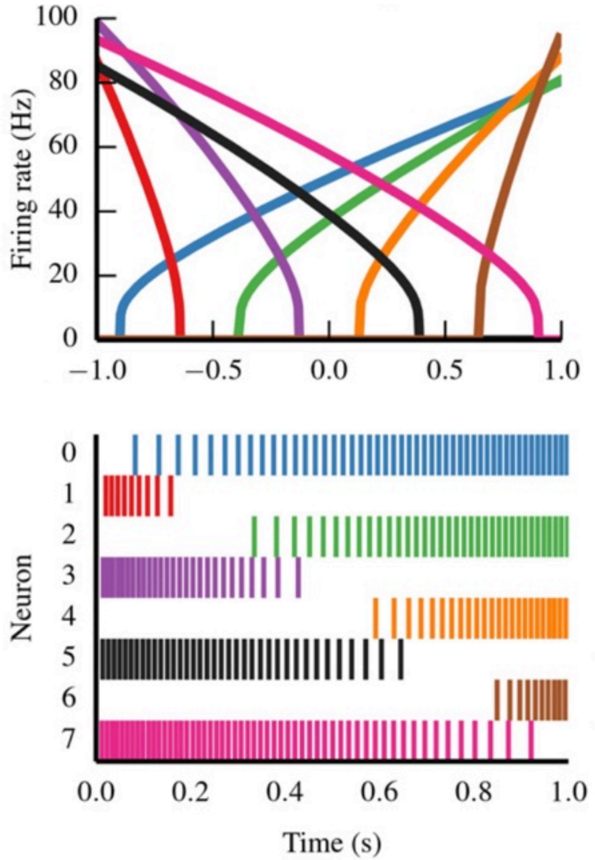
Live Examples

Representation, transformation and integration

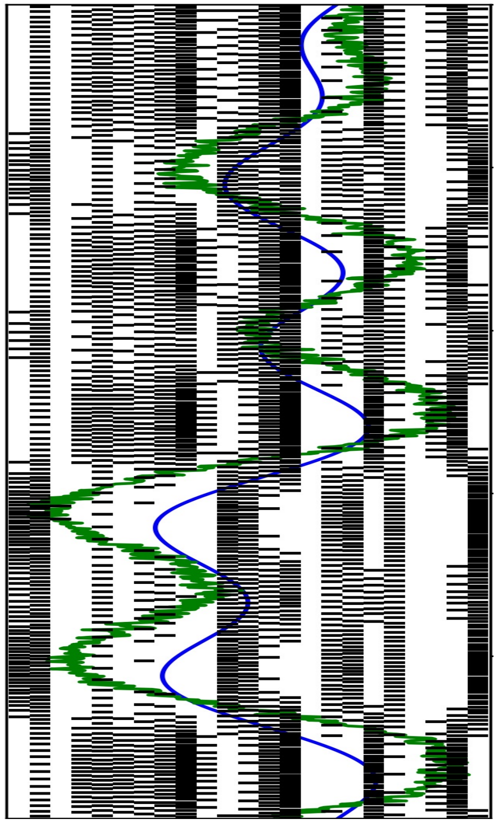
Neural Engineering Framework

Computing with Spiking Neural Networks

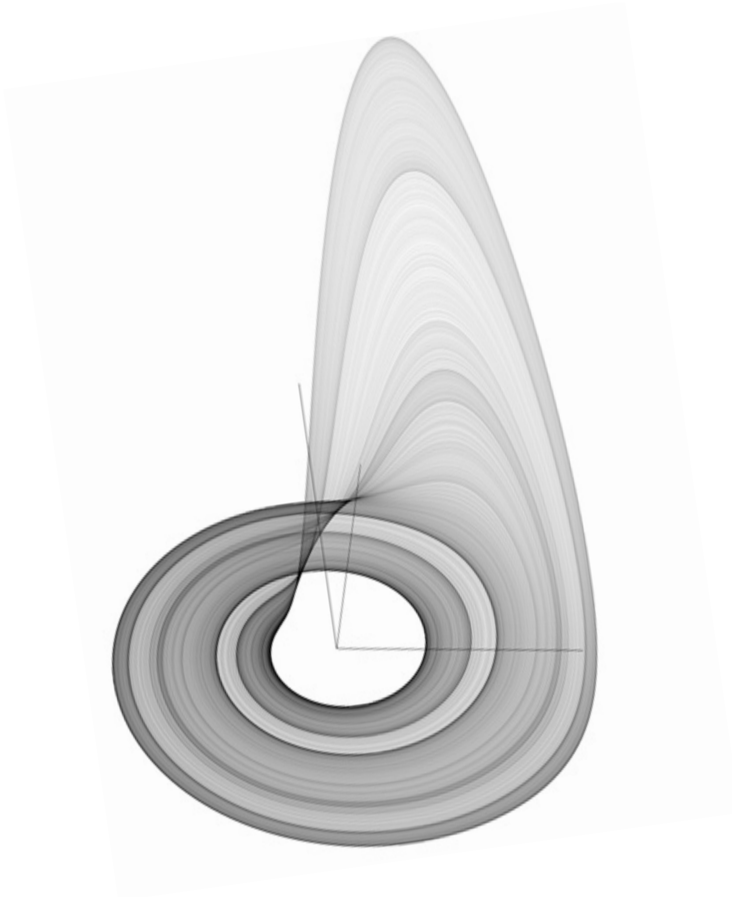
Representation



Transformation



Dynamics



To learn more…

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The Scientist's, Algorithms Designer's and Computer Architect's Perspectives on Brain-Inspired Computing

The brain is not a glorified digital computer. It does not store information in registers, and it does not mathematically transform mental representations to establish perception or behavior. The brain cannot be downloaded to a computer to provide immortality, nor can it destroy the world by having its emerged consciousness traveling in cyberspace. However, studying the brain's core computation architecture can inspire scientists, computer architects, and algorithm designers to think fundamentally differently about their craft.

Neuromorphic engineers have the ultimate goal of realizing machines with some aspects of cognitive intelligence. They aspire to design computing architectures that could surpass existing digital von Neumann-based computing architectures' performance. In that sense, brain research bears the promise of a new computing paradigm. As part of a complete cognitive hardware and software ecosystem, neuromorphic engineering opens new frontiers for neuro-robotics, artificial intelligence, and supercomputing applications.

The book presents neuromorphic engineering from three perspectives: the scientist, the computer architect, and the algorithm designer. It zooms in and out of the different disciplines, allowing readers with diverse backgrounds to understand and appreciate the field. Overall, the book covers the basics of neuronal modeling, neuromorphic circuits, neural architectures, event-based communication, and the neural engineering framework.

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The Scientist's, Algorithms Designer's and Computer Architect's Perspectives on Brain-Inspired Computing

Elishai Ezra Tsur

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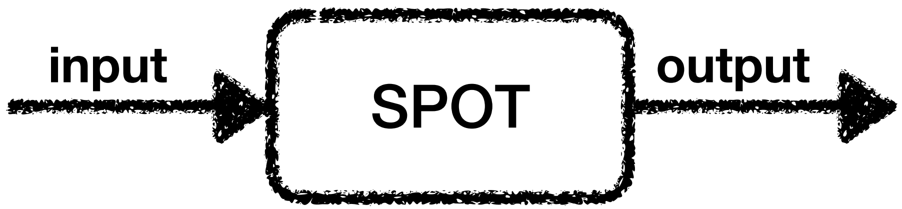
Control System / Feedback Loops

Control System / Feedback Loops

Calculate time based on movement velocity and distance from goal



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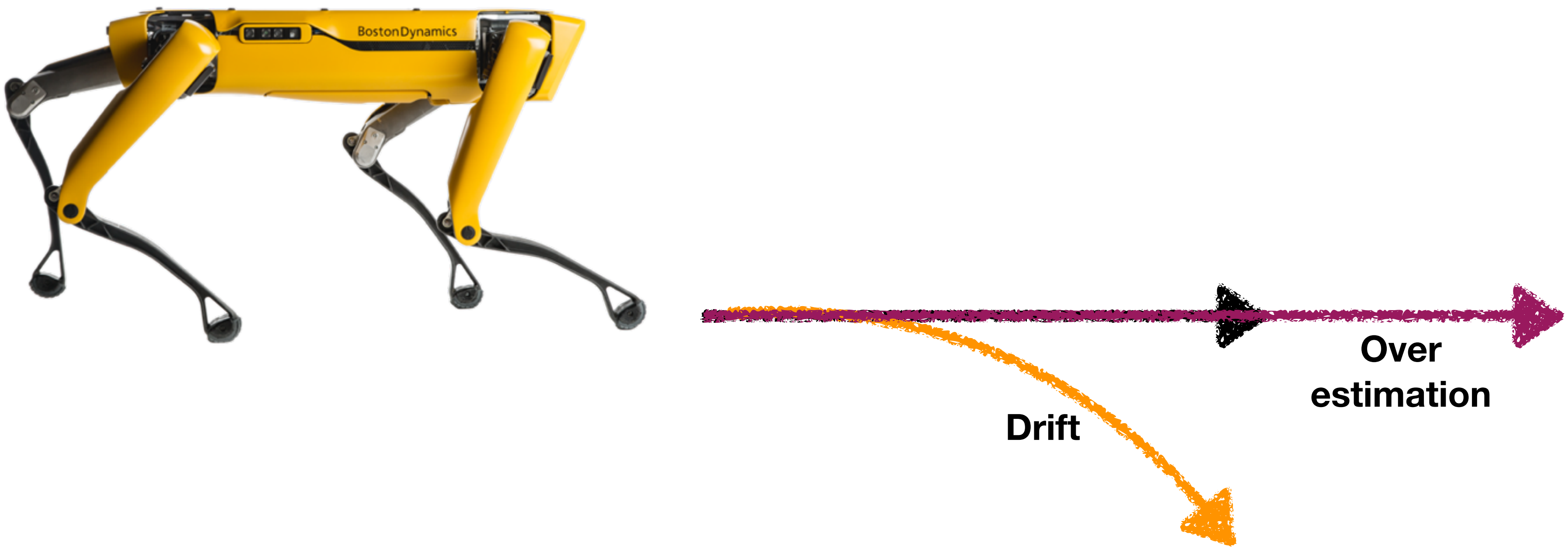

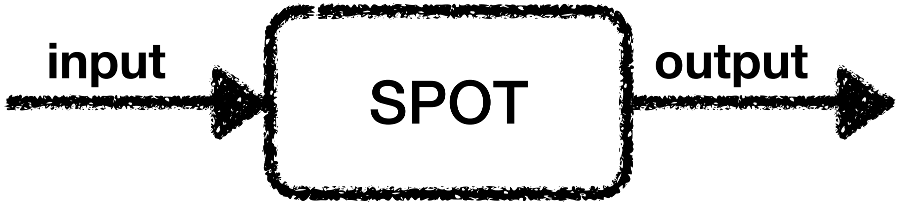

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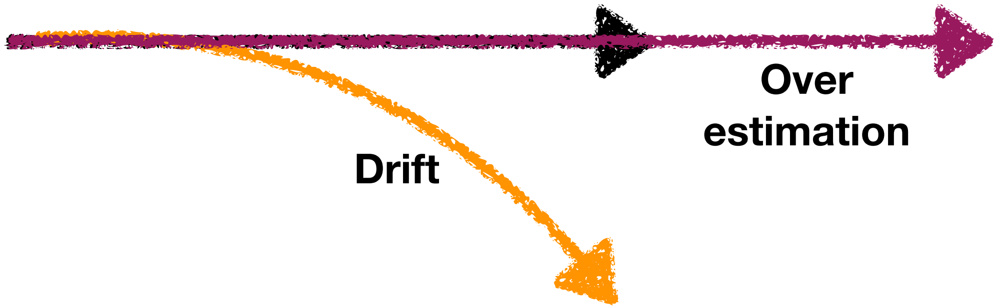

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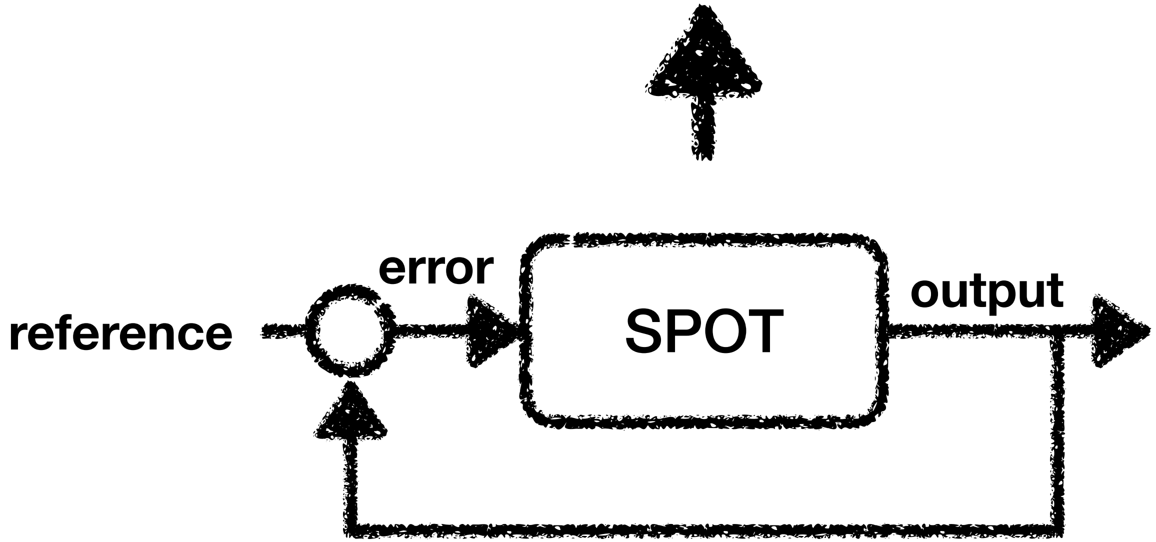
Control System / Feedback Loops

Integration of **sensing** and **computation**



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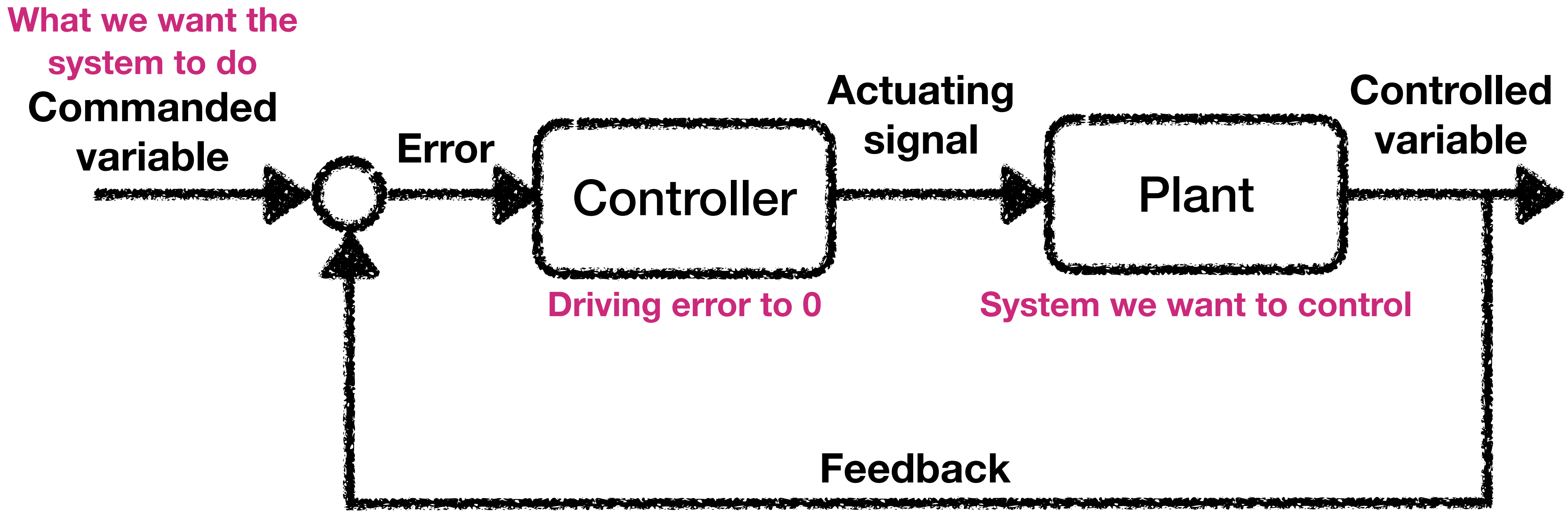

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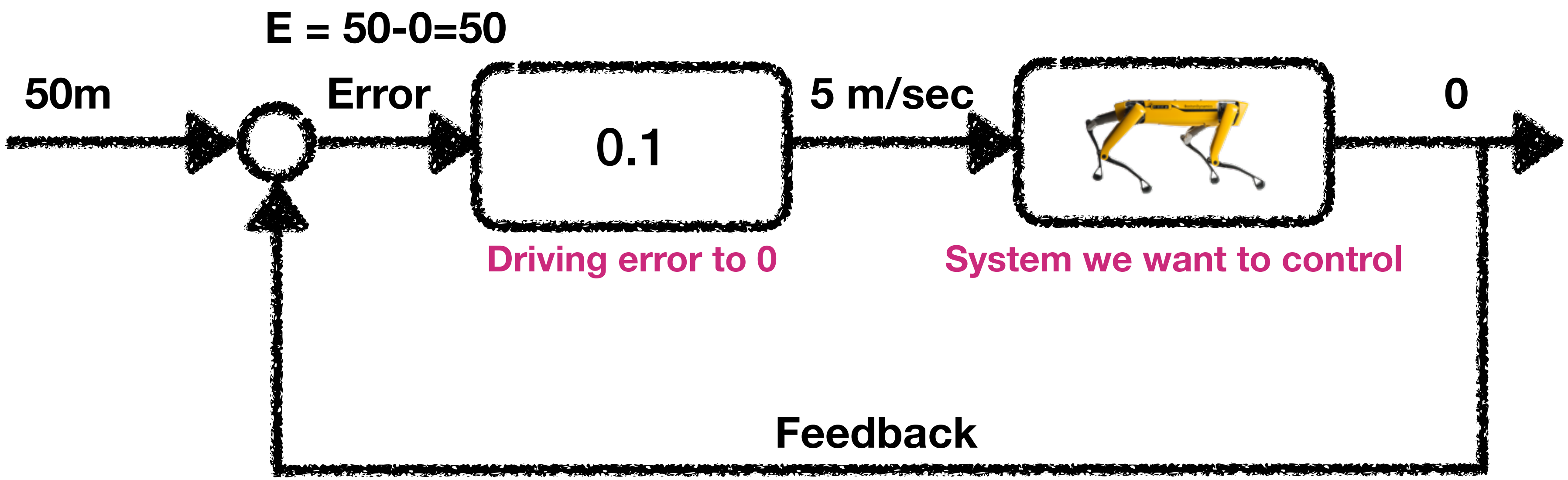

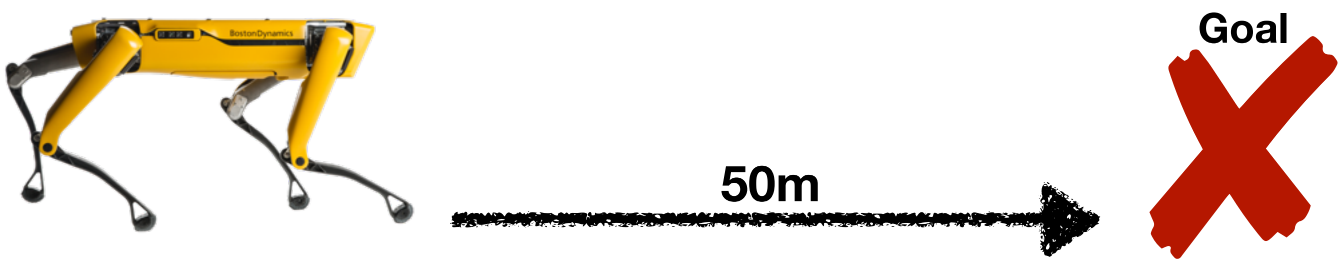

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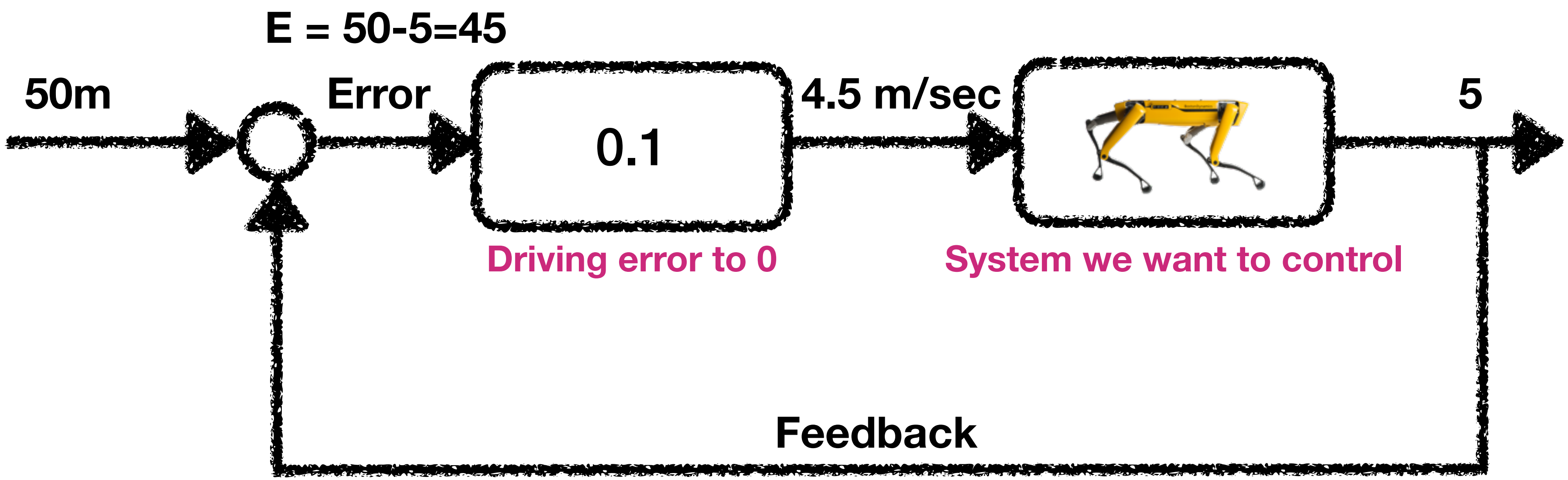

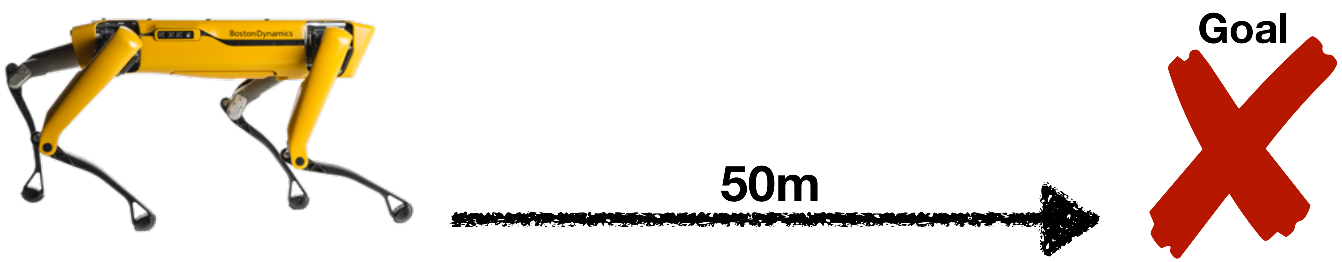

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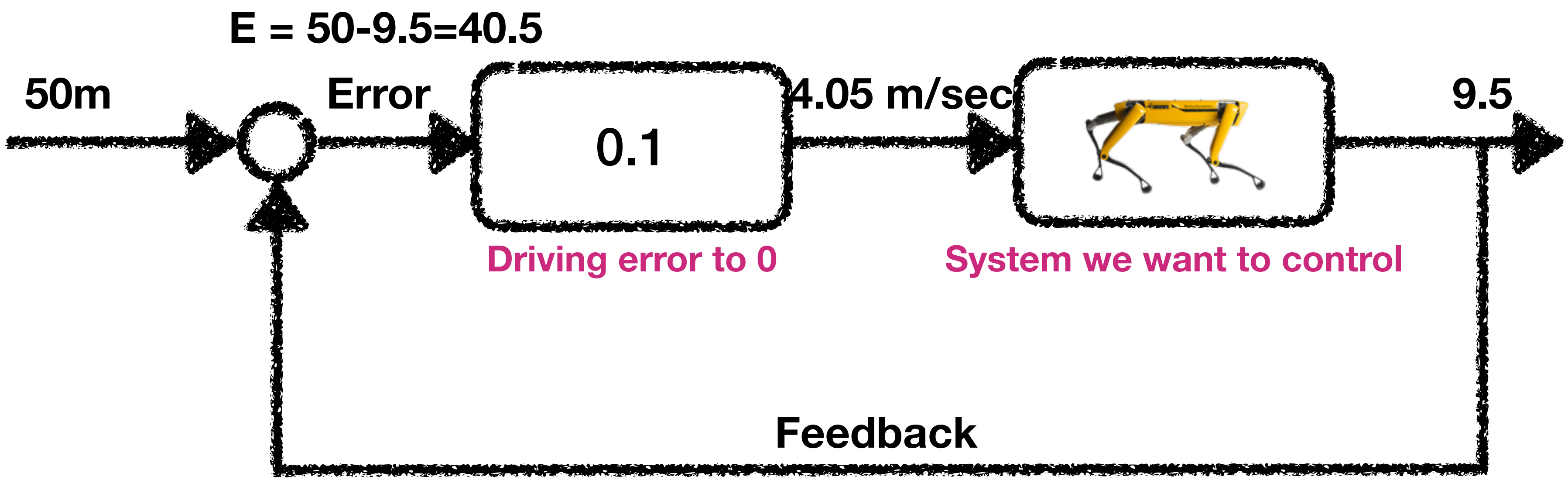

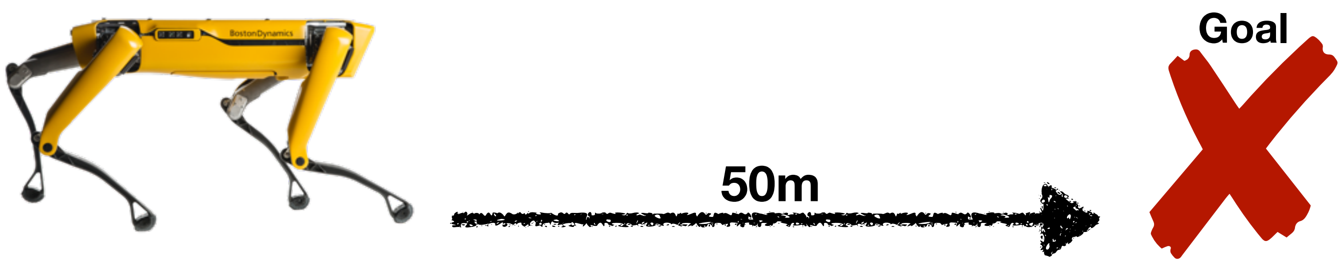

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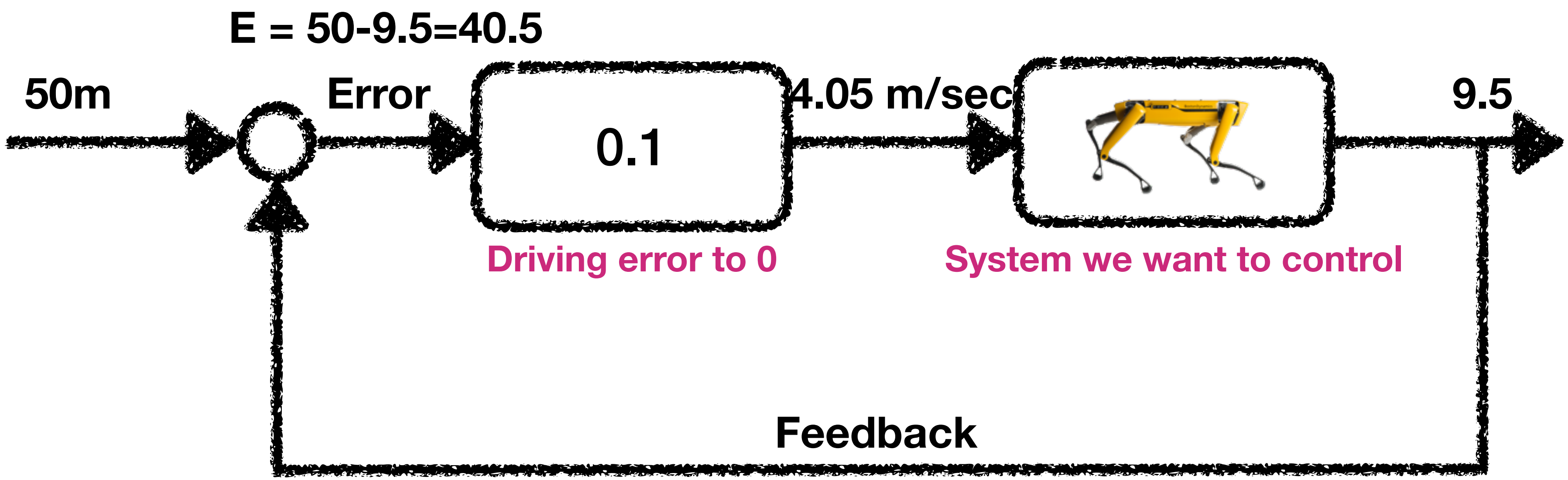

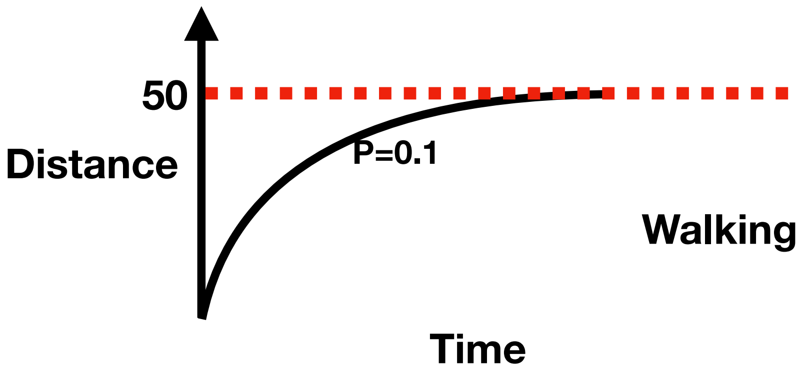

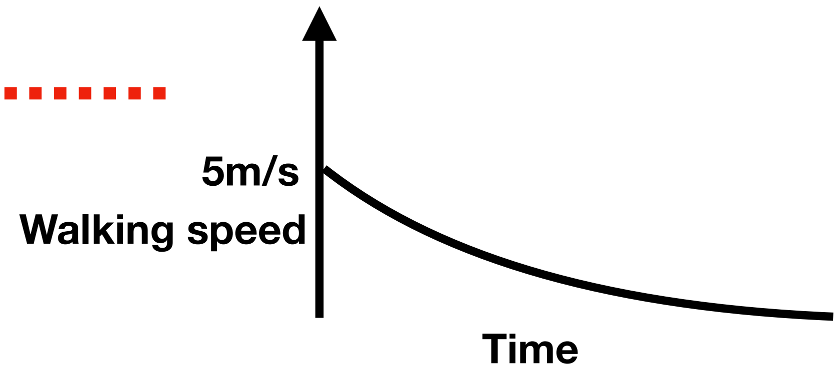

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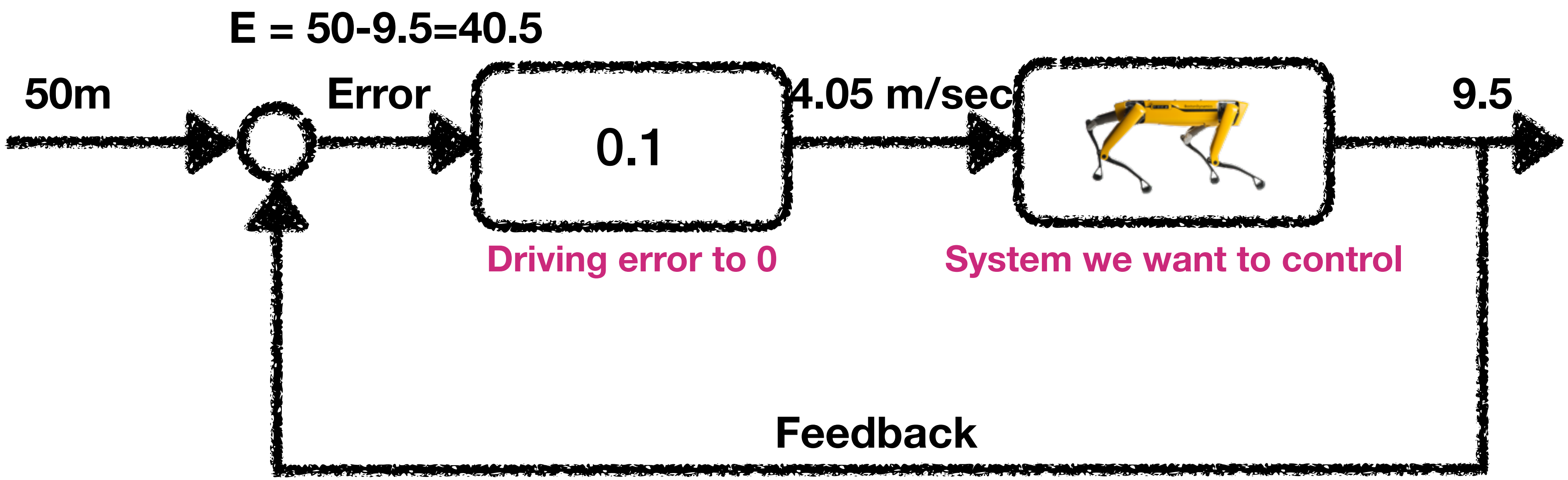

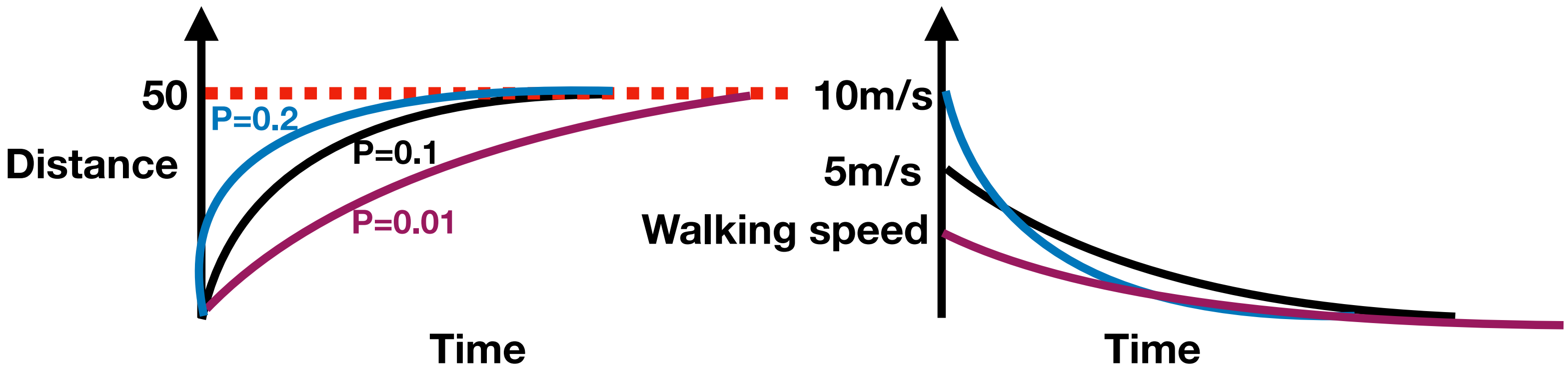

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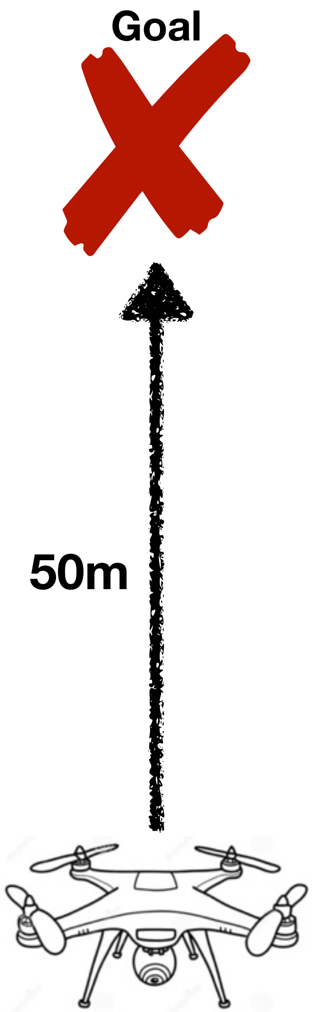

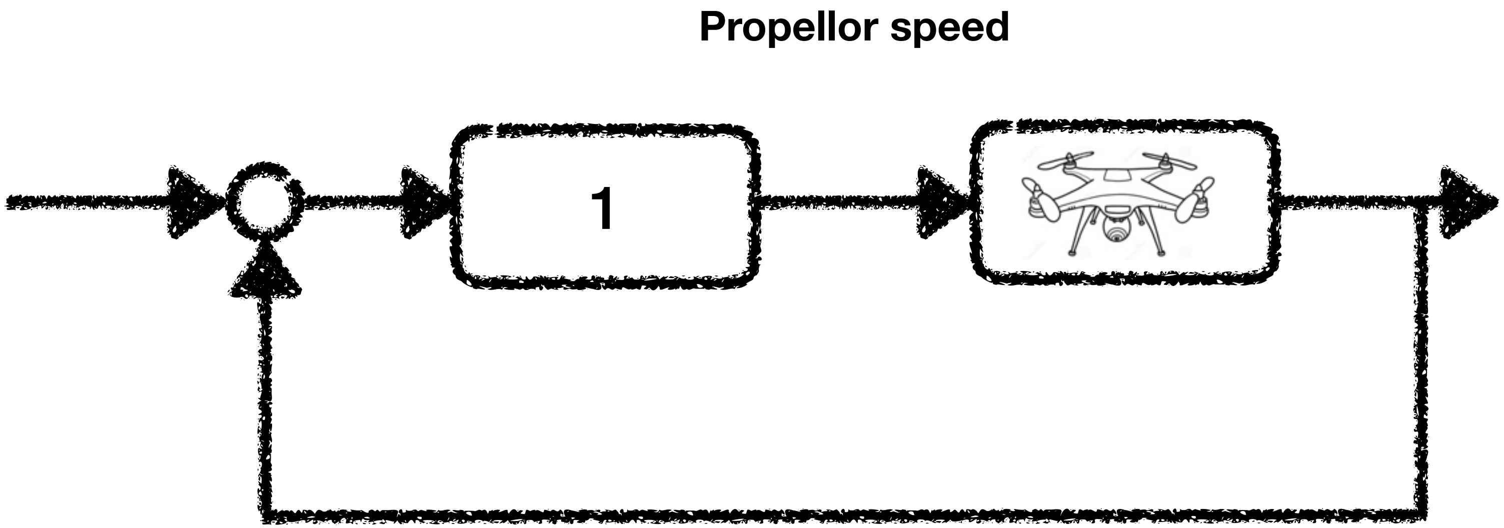

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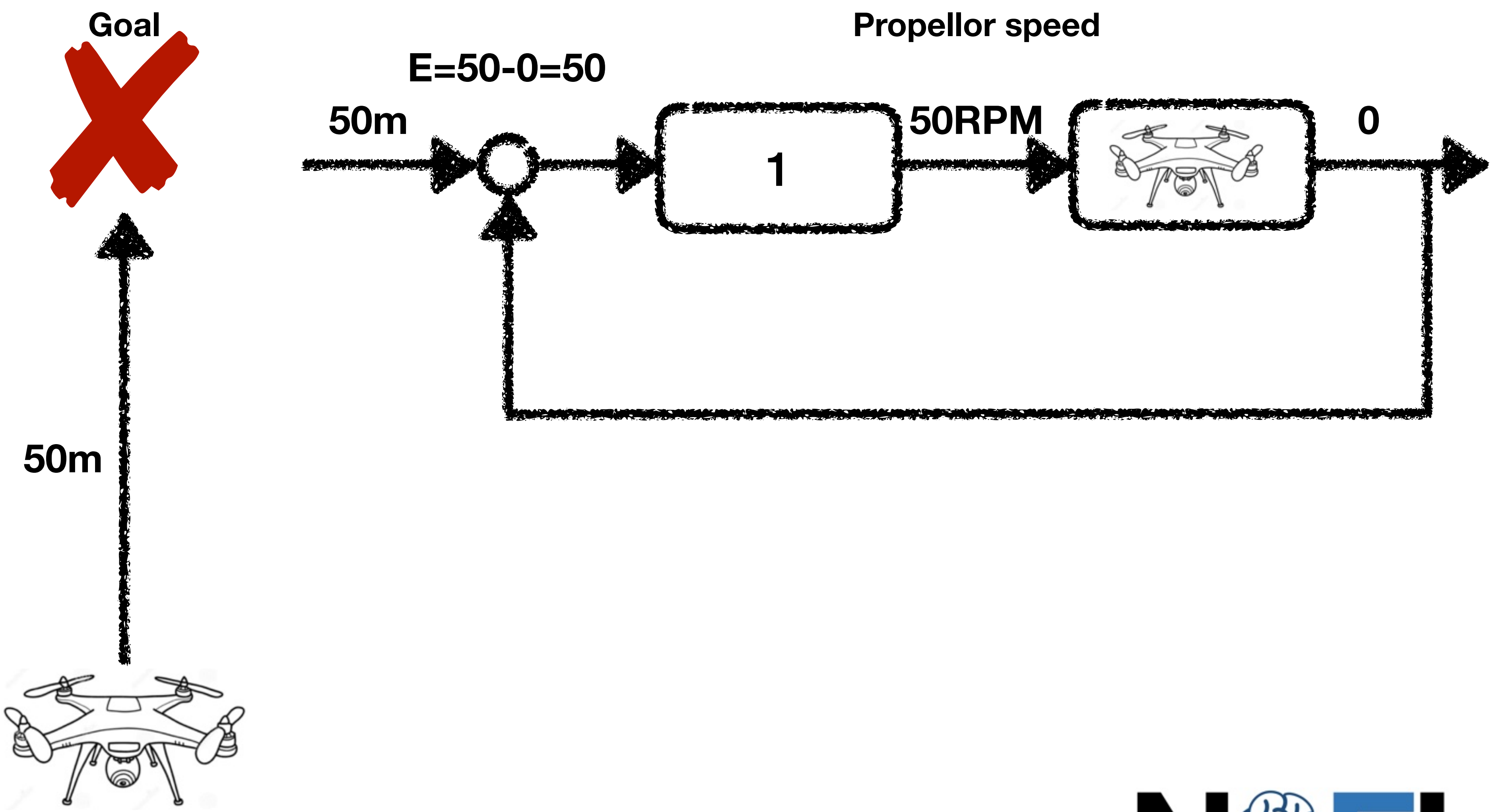

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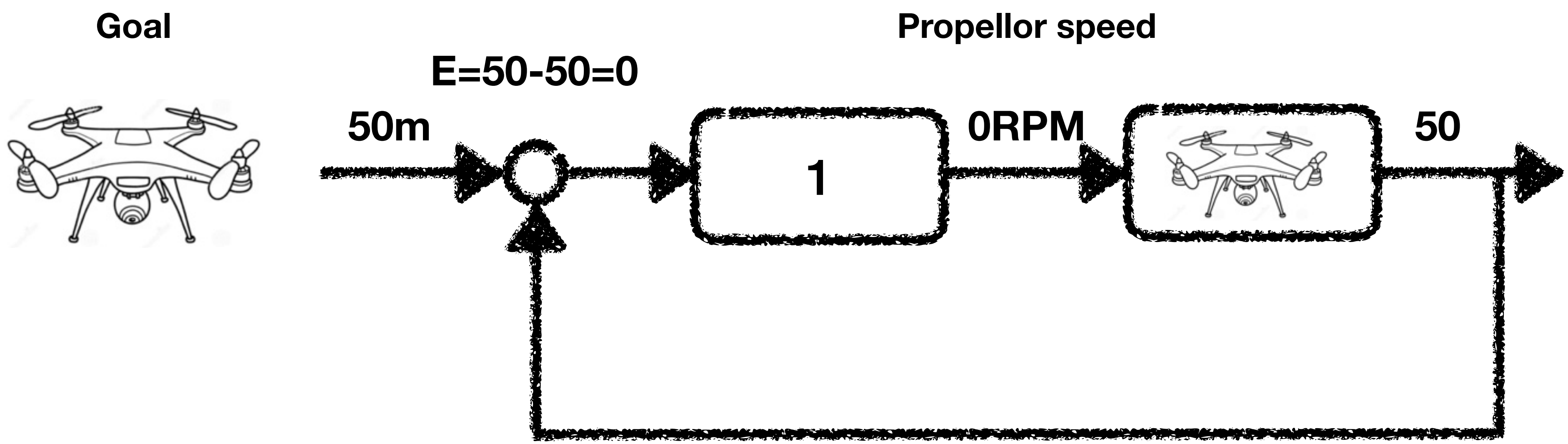

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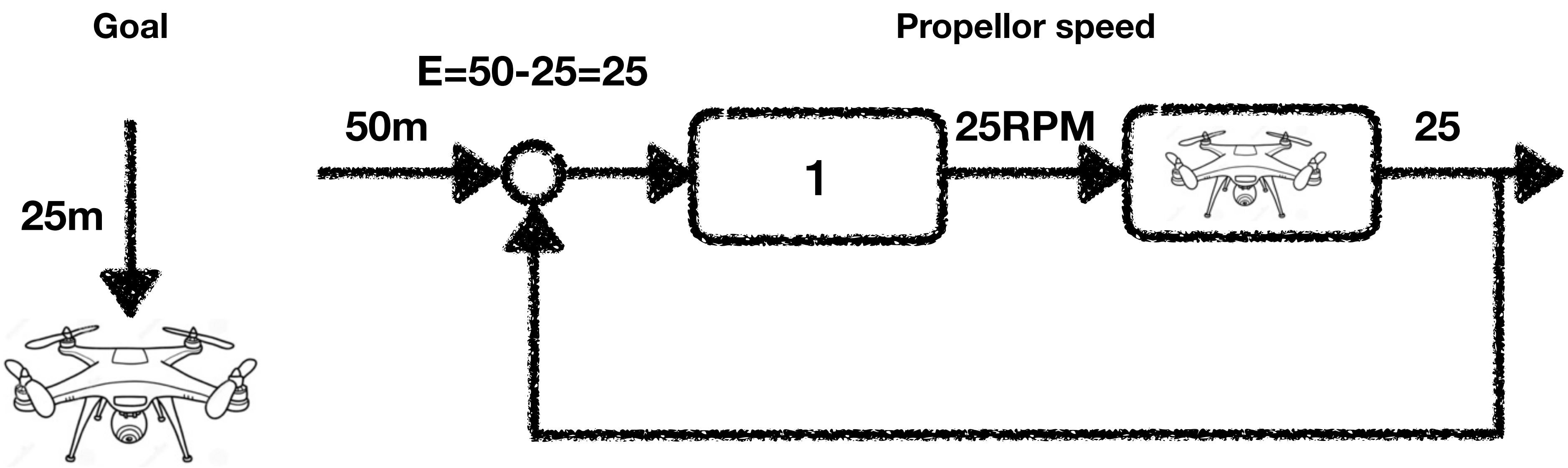

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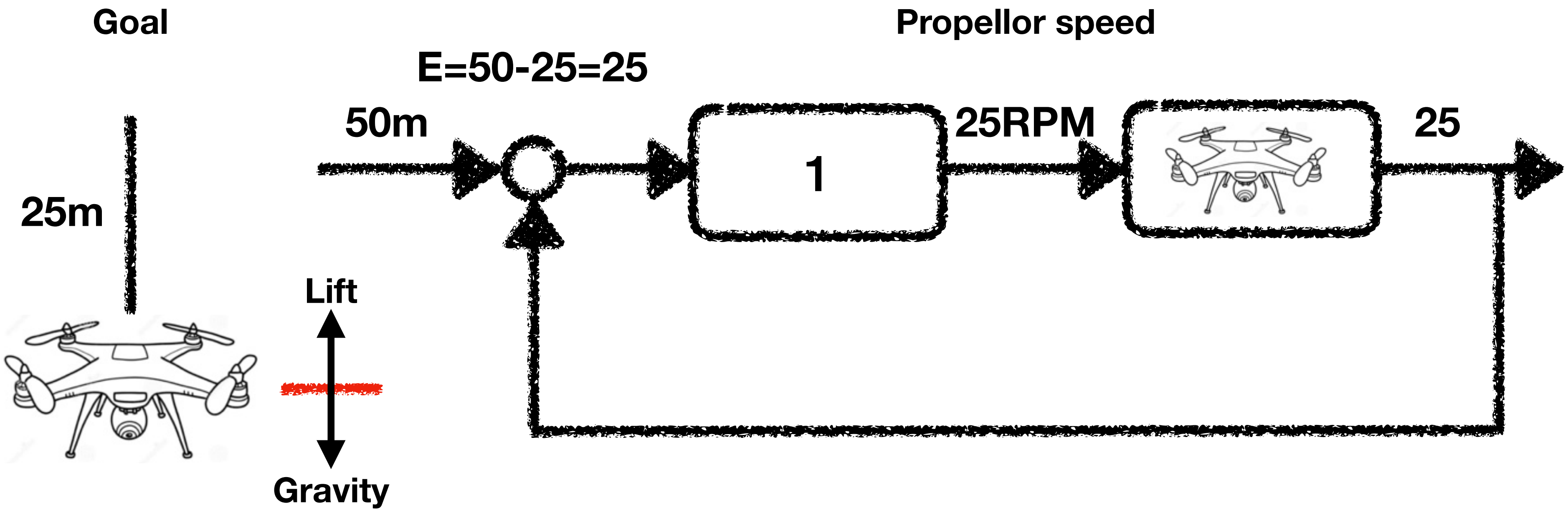

Stable state Error

Hover speed = 25RPM

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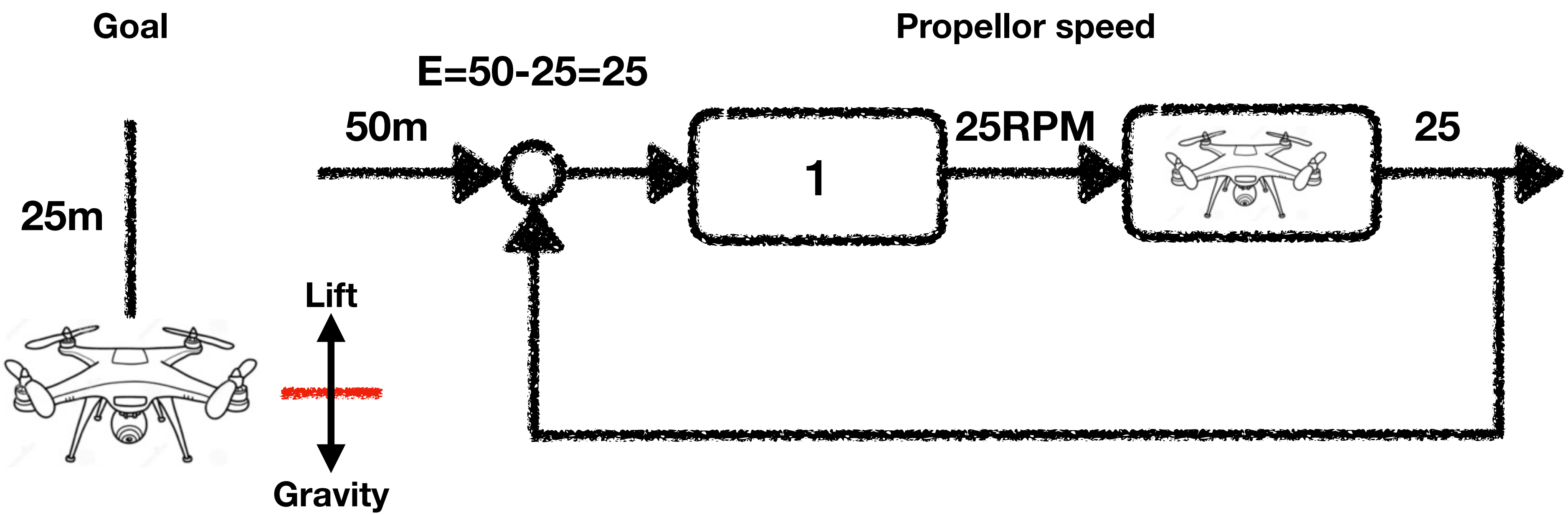
Control System / Feedback Loops



Stable state Error

Hover speed = 25RPM

P=0.5, 50.   * 0.5=25 RPM -> hover at 50.   = Error
P=0.6, 41.6 * 0.6=25 RPM -> hover at 41.6 = Error
P=1. , 25.   * 1. =25 RPM -> hover at 25   = Error
P=2. , 12.5.* 2. =25 RPM -> hover at 12.5 = Error
P=10 , 2.5.* 10. =25 RPM -> hover at 2.5   = Error

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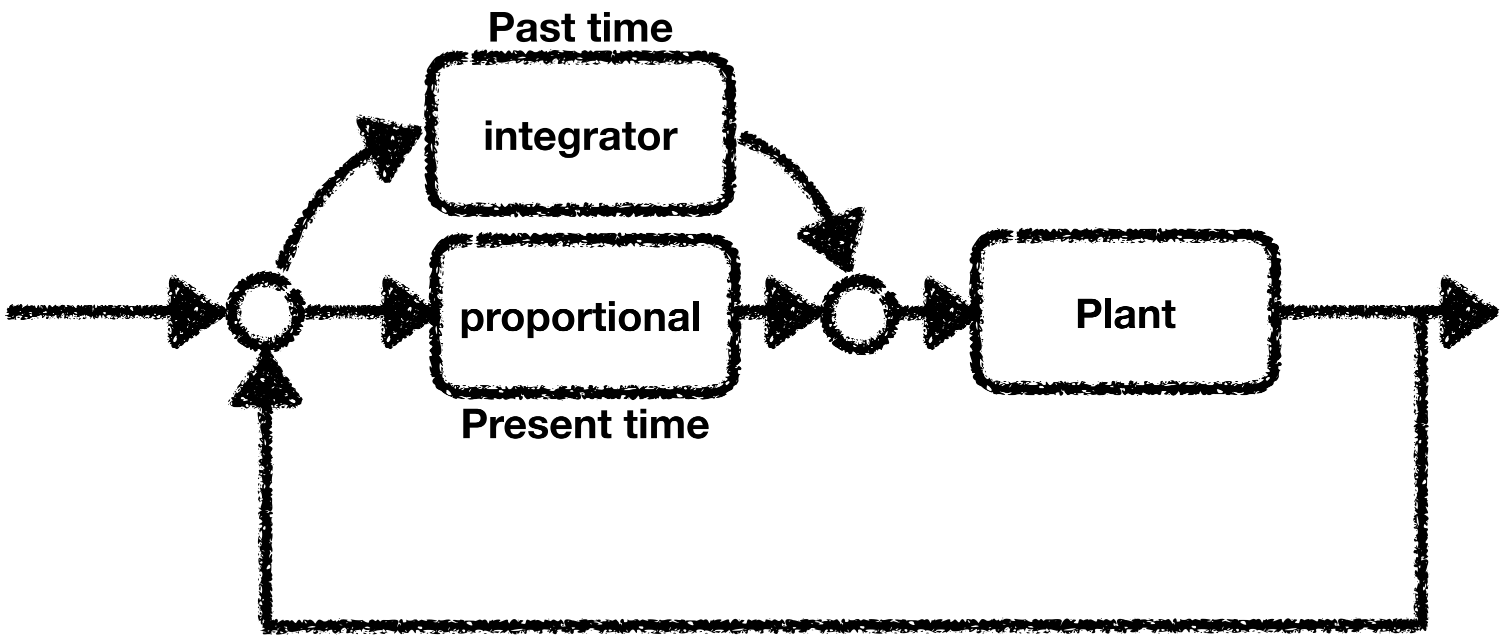
Control System / Feedback Loops



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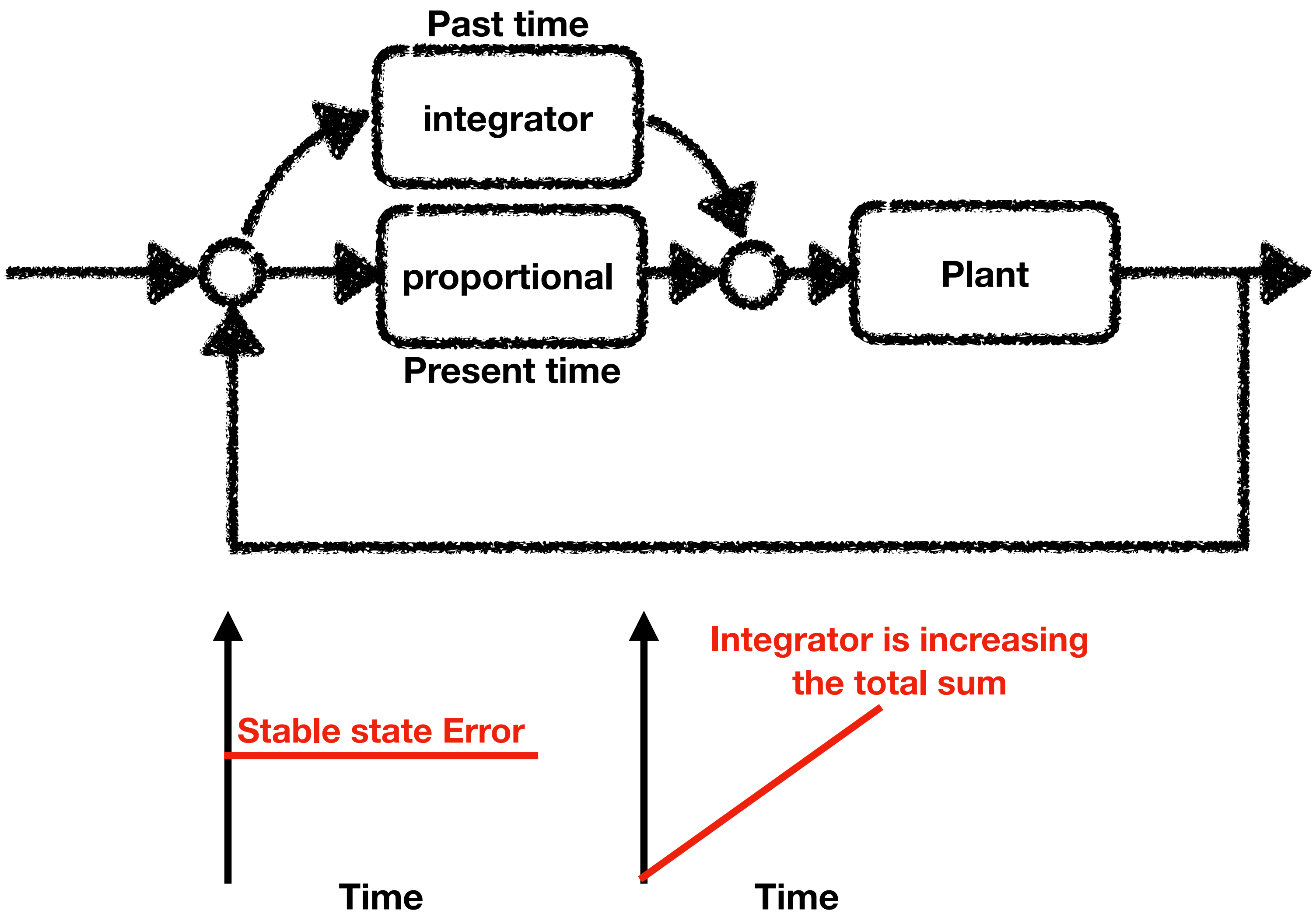

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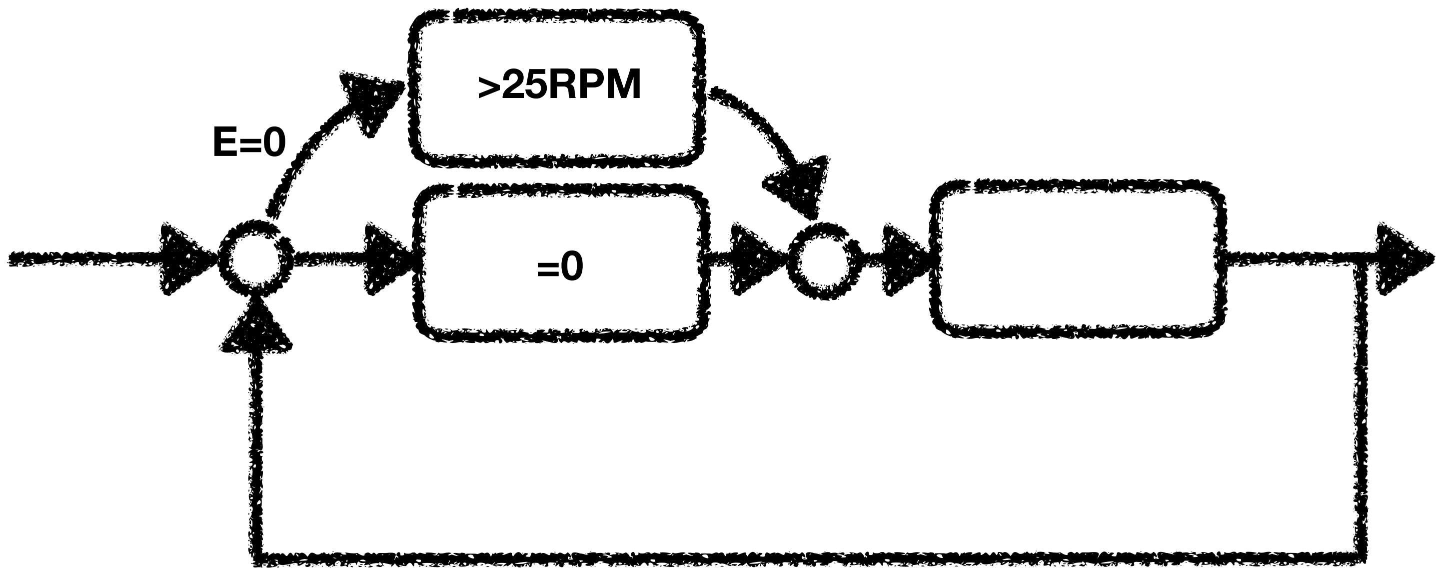
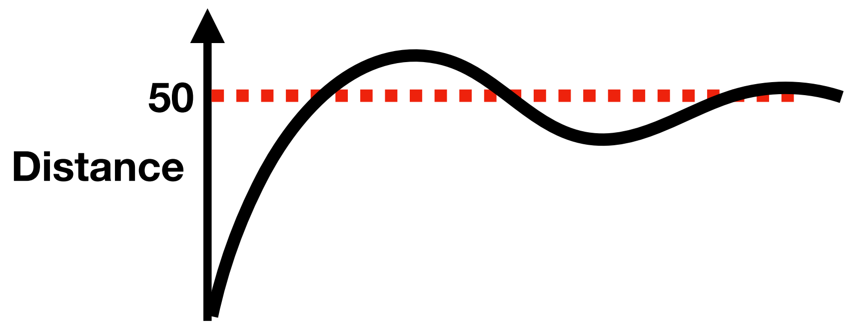
Control System / Feedback Loops

Goal



During target reach the I component might get higher than 25RPM, Inducing an overshoot



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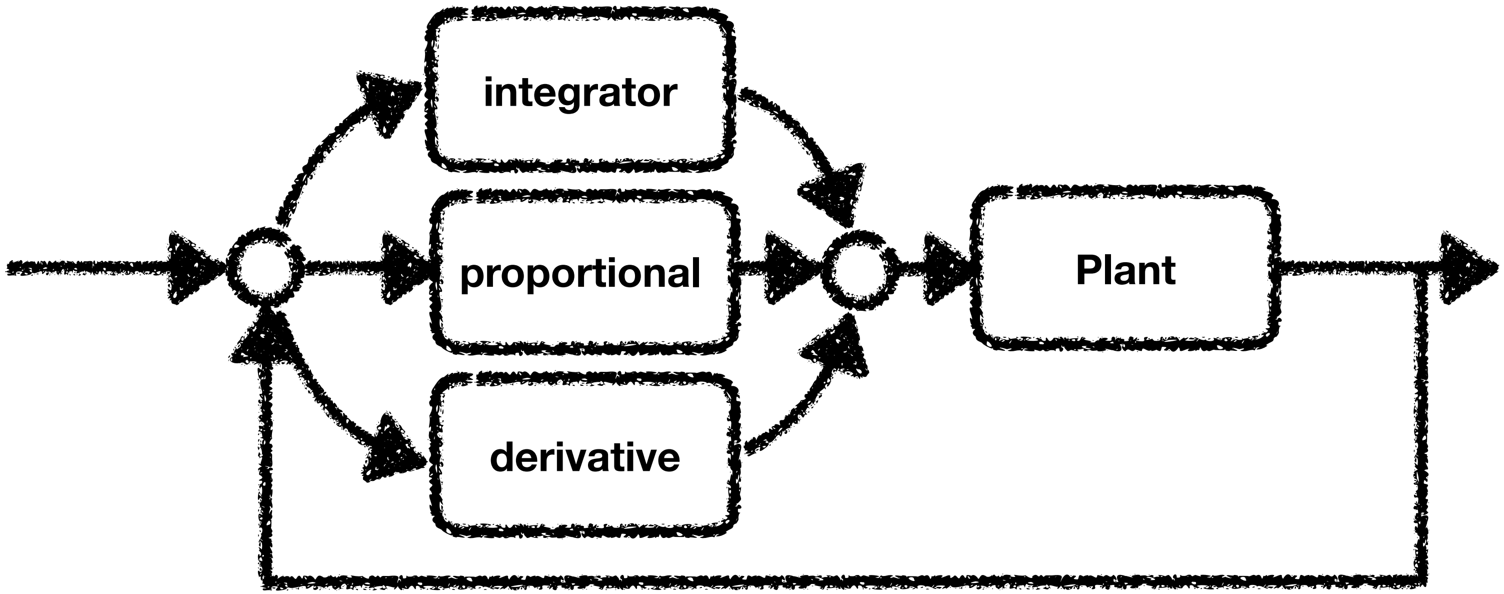

Accounting for the future: how fast the error is growing and shrinking

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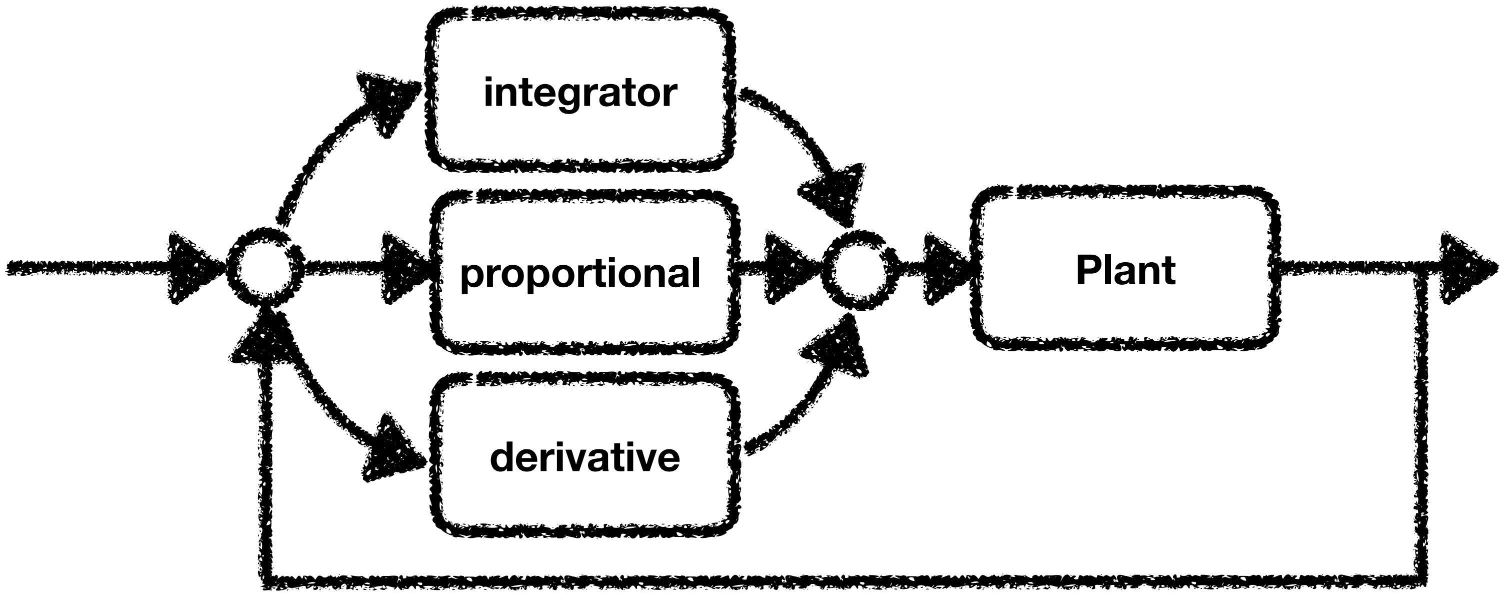
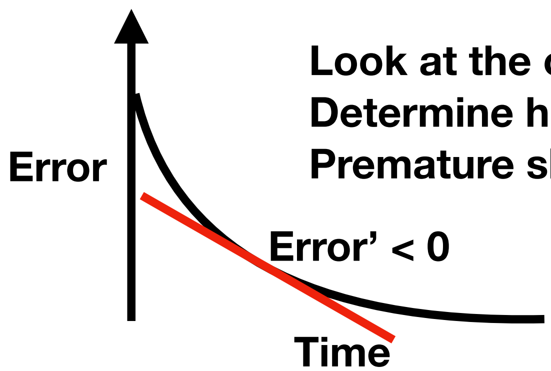
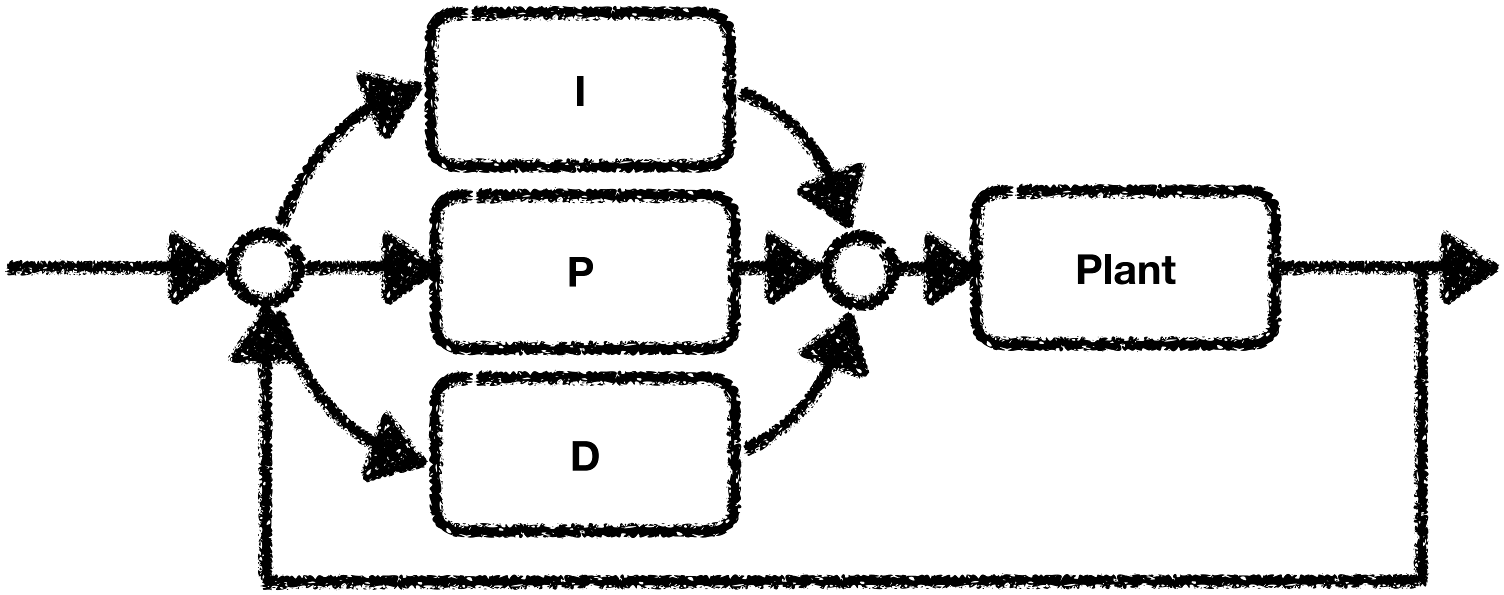




Look at the current rate of change of error
Determine how we are approaching target
Premature slowing down preventing overshooting

Control System / Feedback Loops



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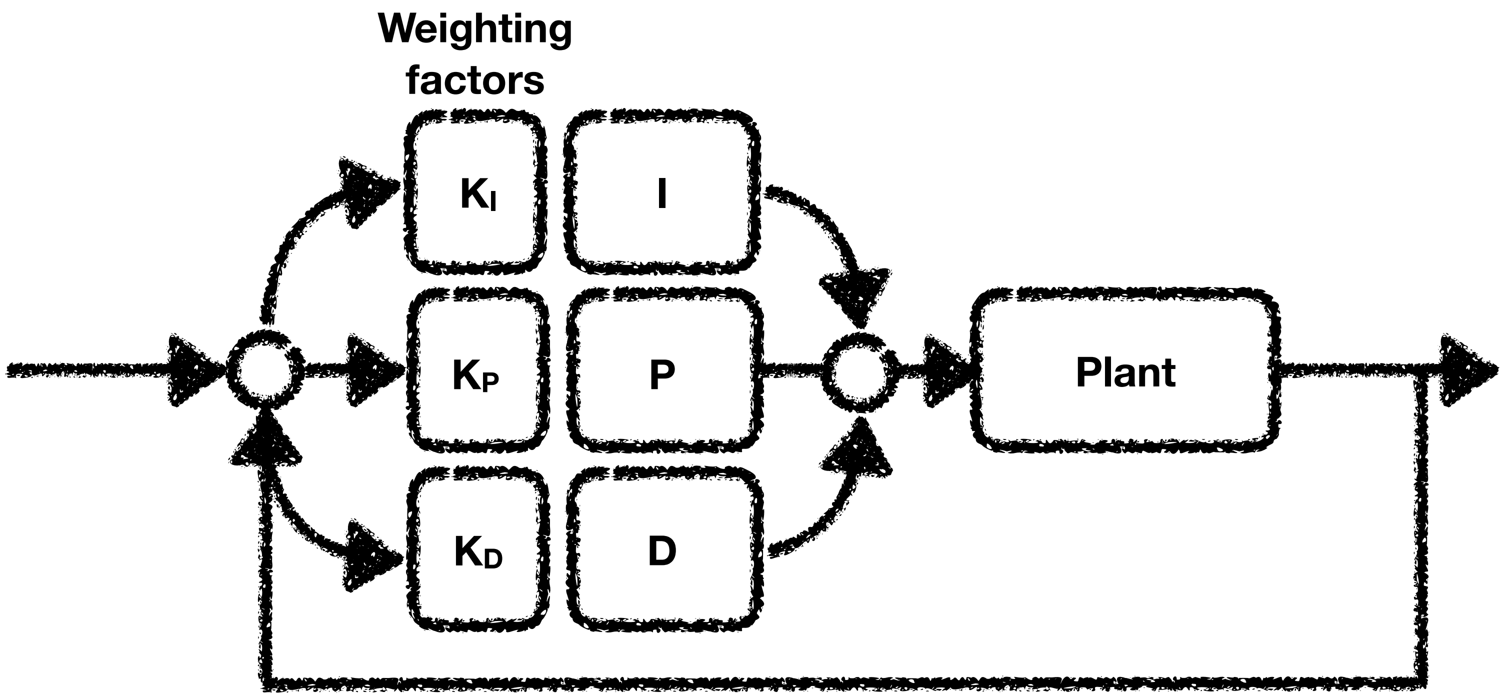

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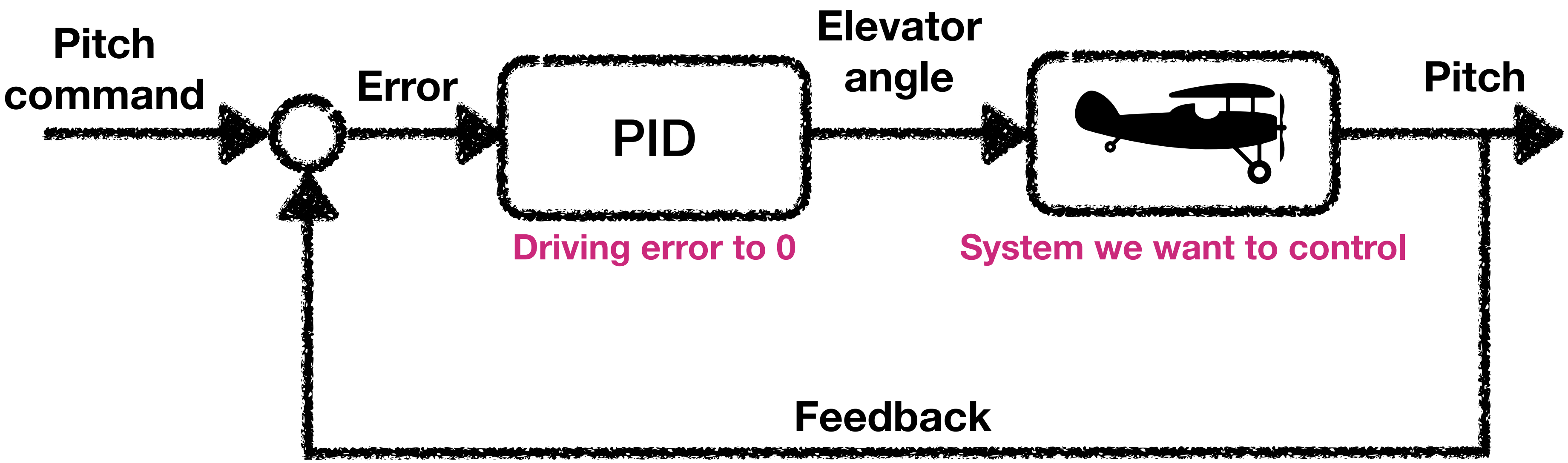
PID Tuning



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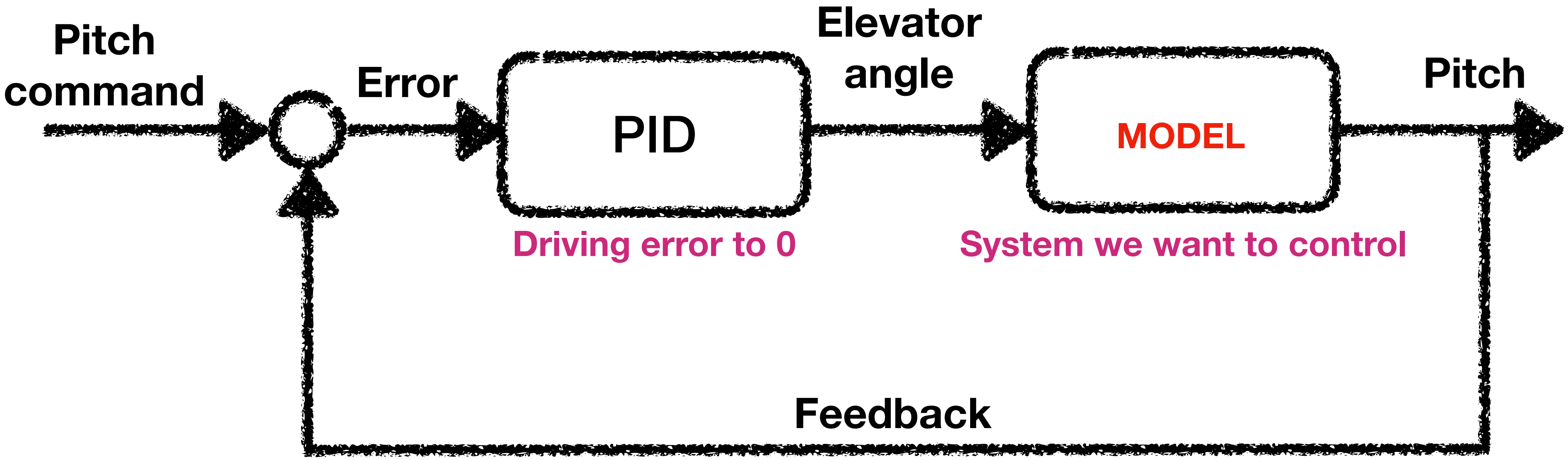

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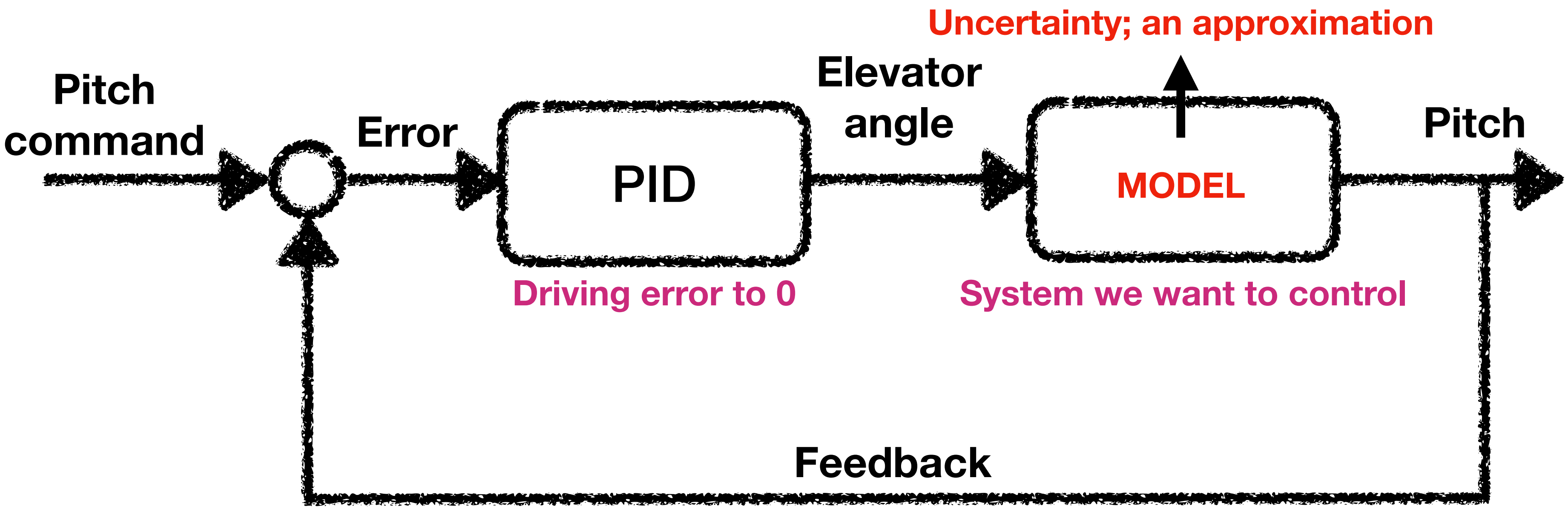

Robust control

Designing a system which can handle uncertainty

Adding margins into the design: how much uncertainty can the system handle?

guarantees that if the changes are within given bounds the control law need not be changed

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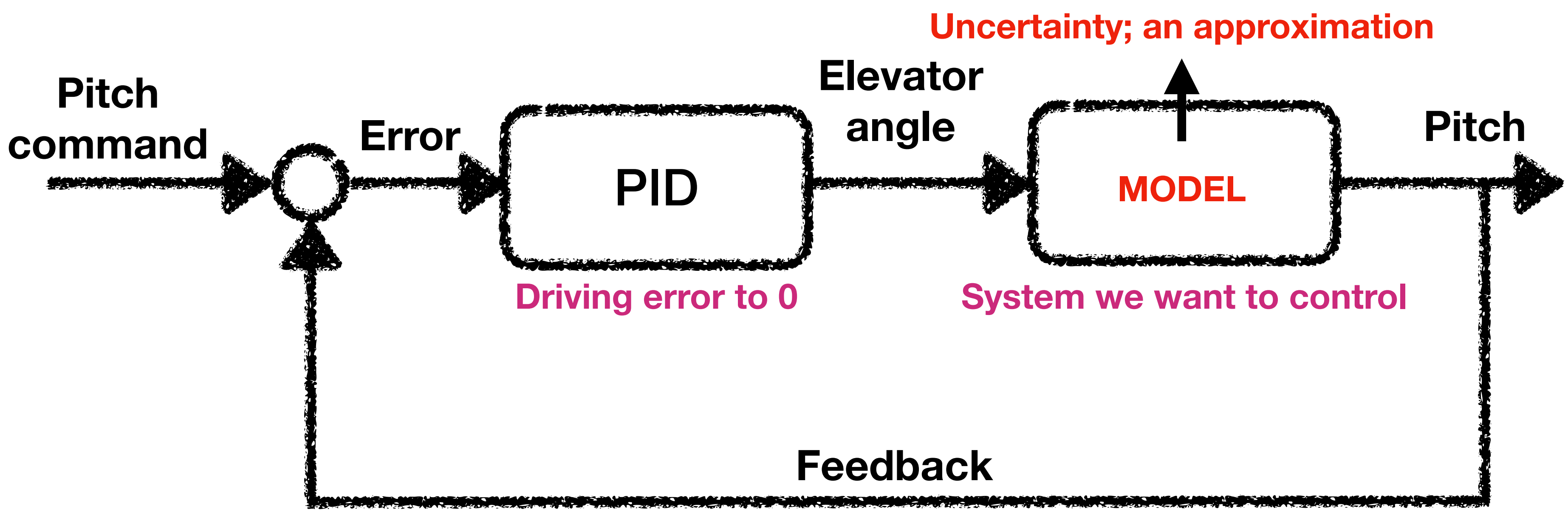
PID Tuning



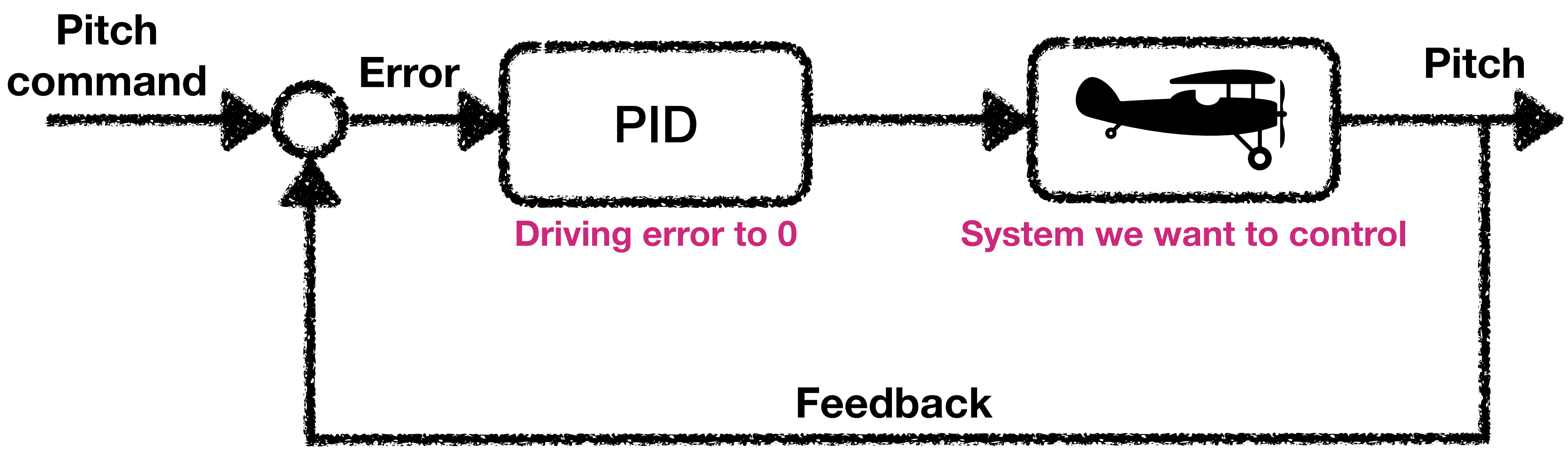
Robust control

Designing a system which can handle uncertainty
Adding merging into the design: how much uncertainty can the system handle?guarantees that if the changes are within given bounds the control law need not be changed

Adaptive control

The capability of the system to modify its own operation to achieve the best possible mode of operation.
Adaptive control is different from robust control in that it does not need *a priori* information about the bounds on these uncertain or time-varying parameters

PID Tuning



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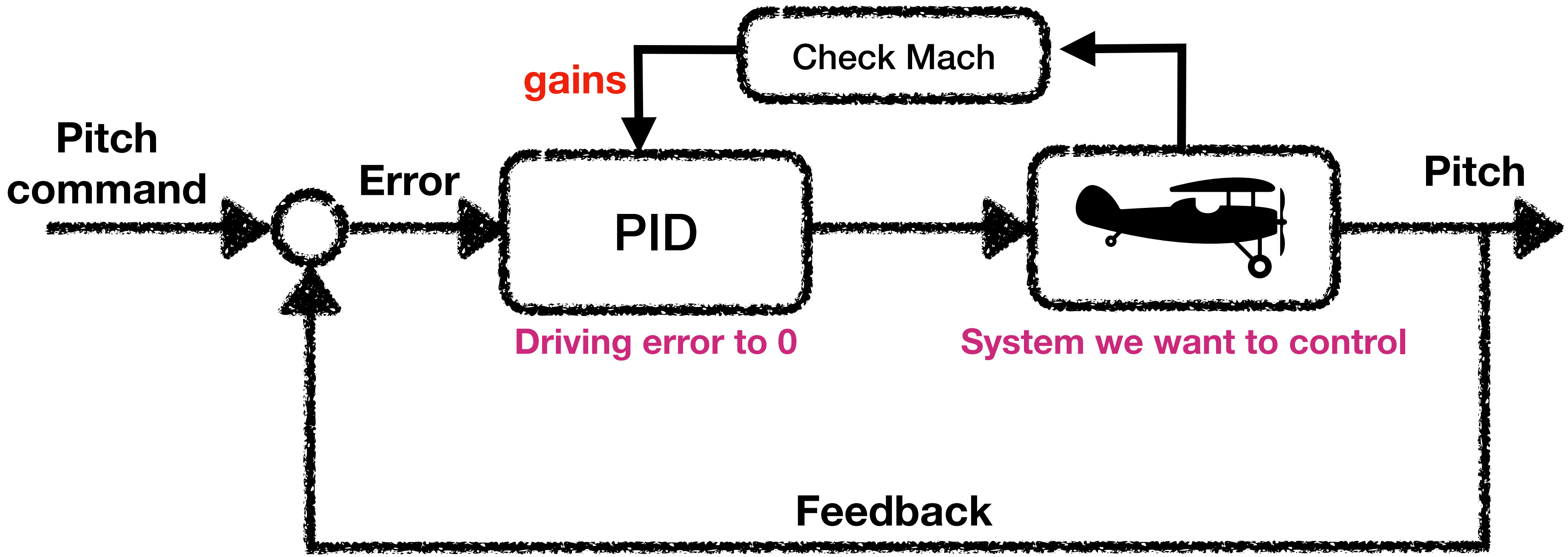
PID Tuning Gain Schedule

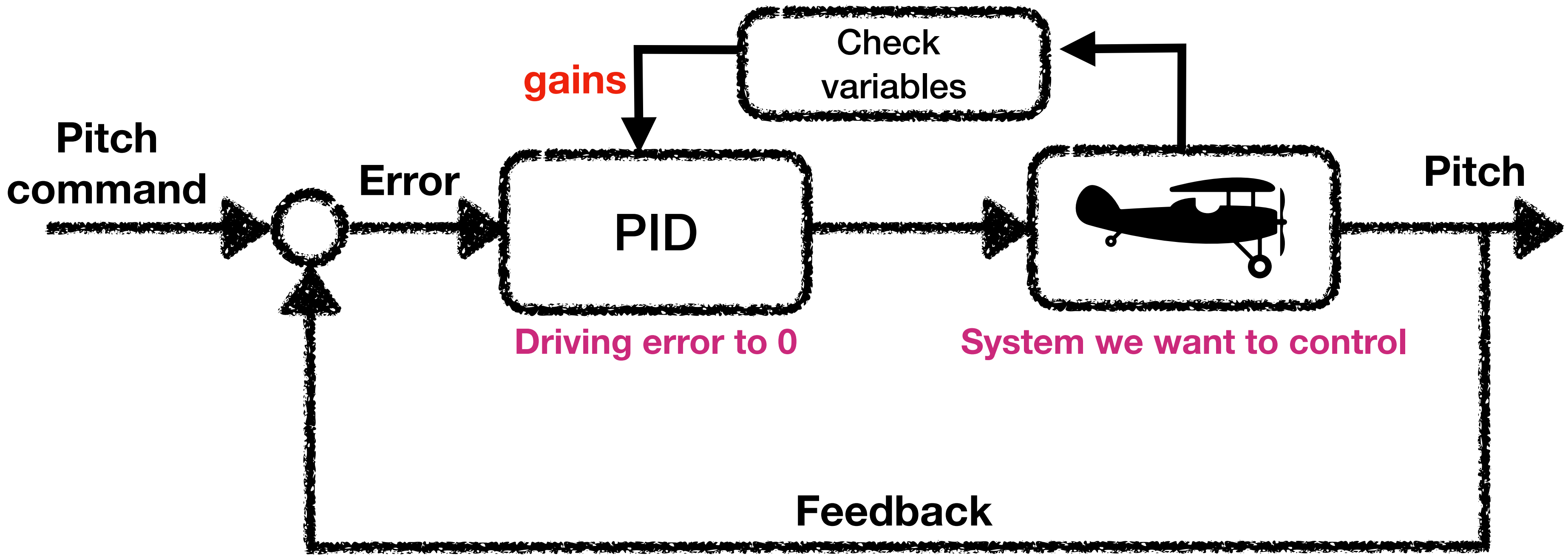


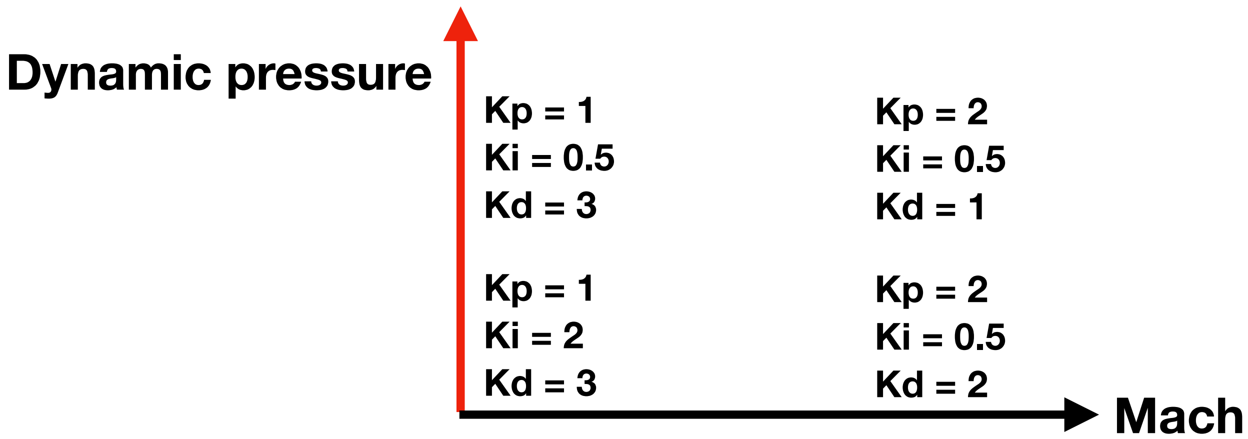
Set of gains

Mach number 0.3: Kp = 1, Ki = 2, Kd = 3

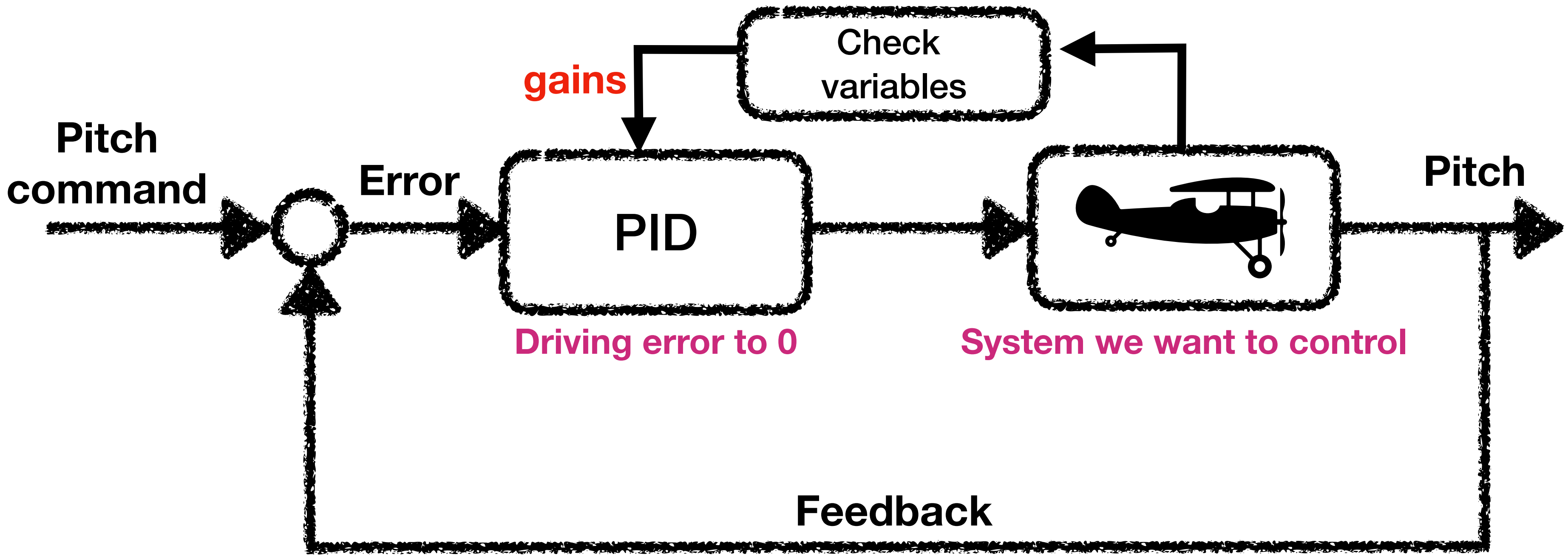
Mach number 0.9: Kp = 2, Ki = 0.5, Kd = 2

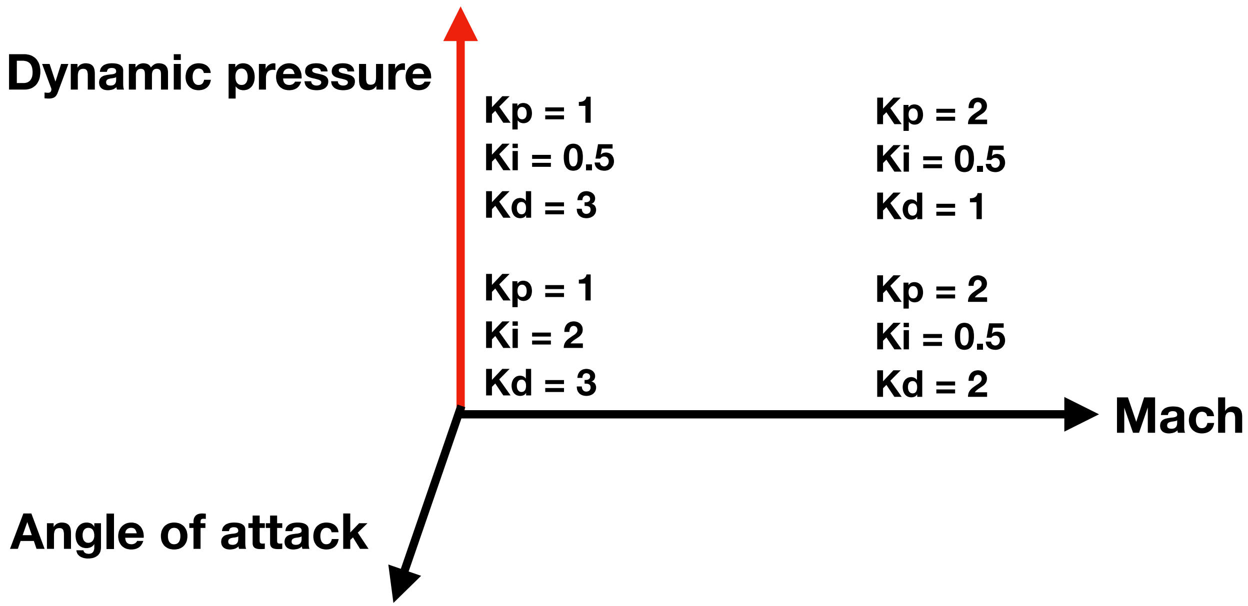
PID Tuning Gain Schedule



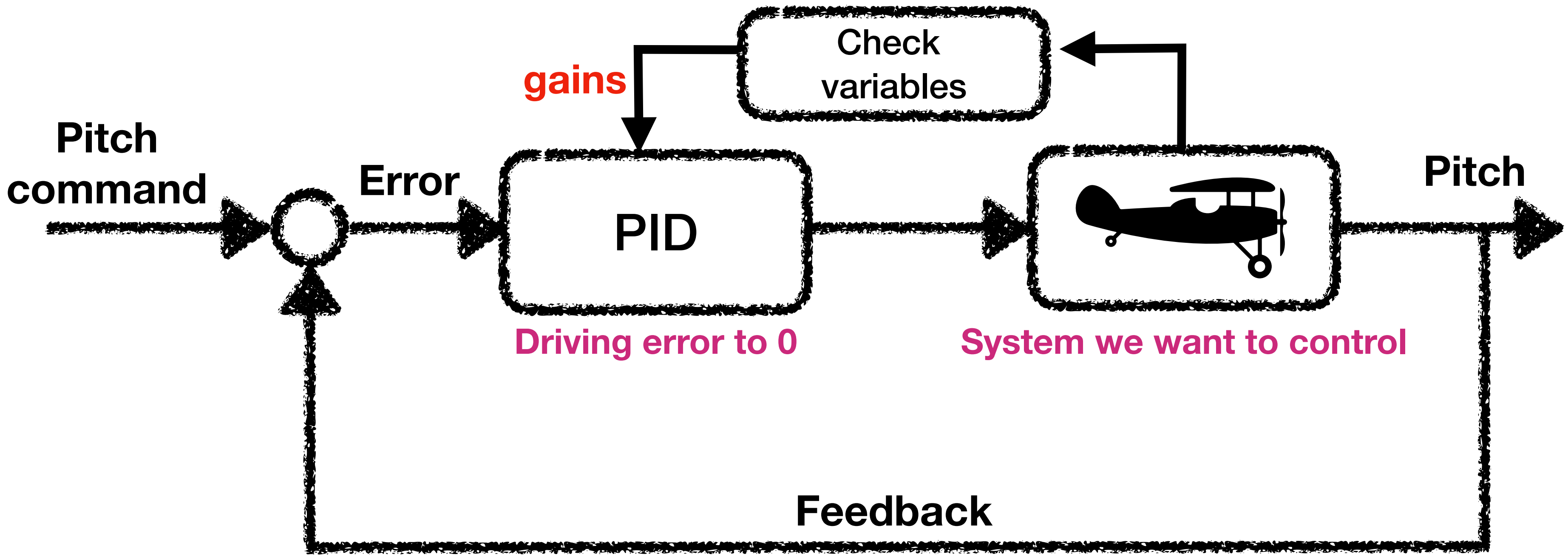


PID Tuning Gain Schedule





PID Tuning Gain Schedule



MANY gain sets
Storage and search
Hard in corner cases

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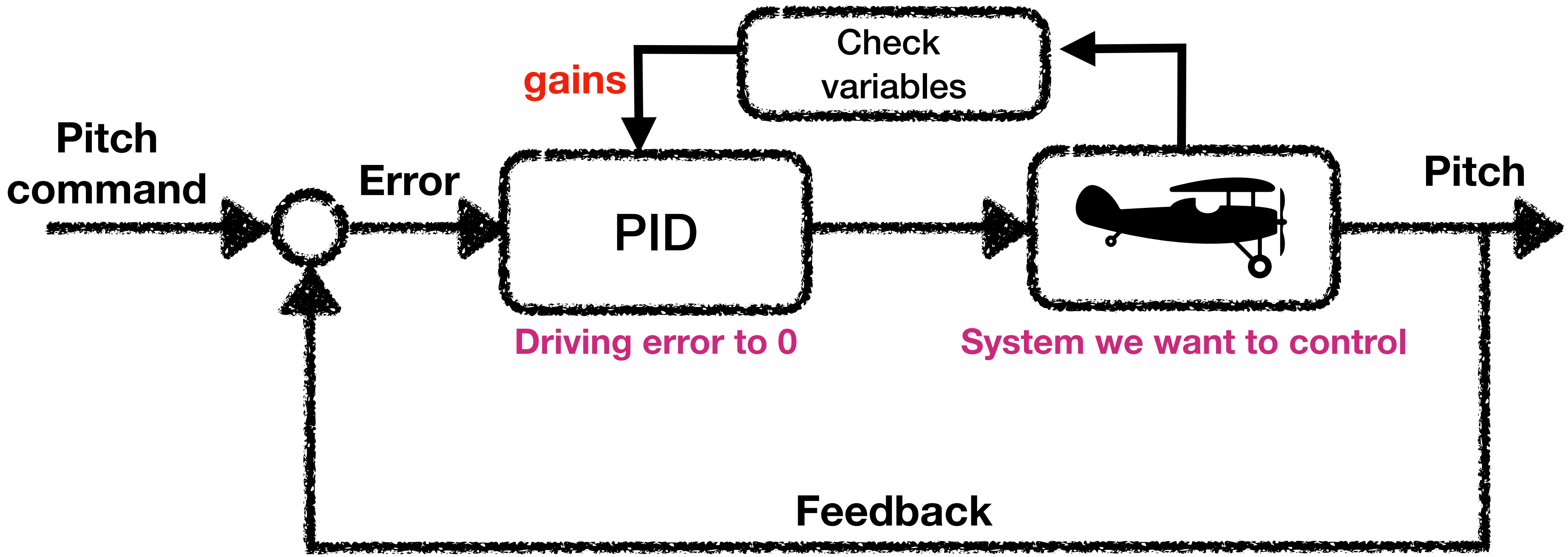
PID Tuning Gain Schedule



MANY gain sets
Storage and search → Many innovations here....
Hard in corner cases

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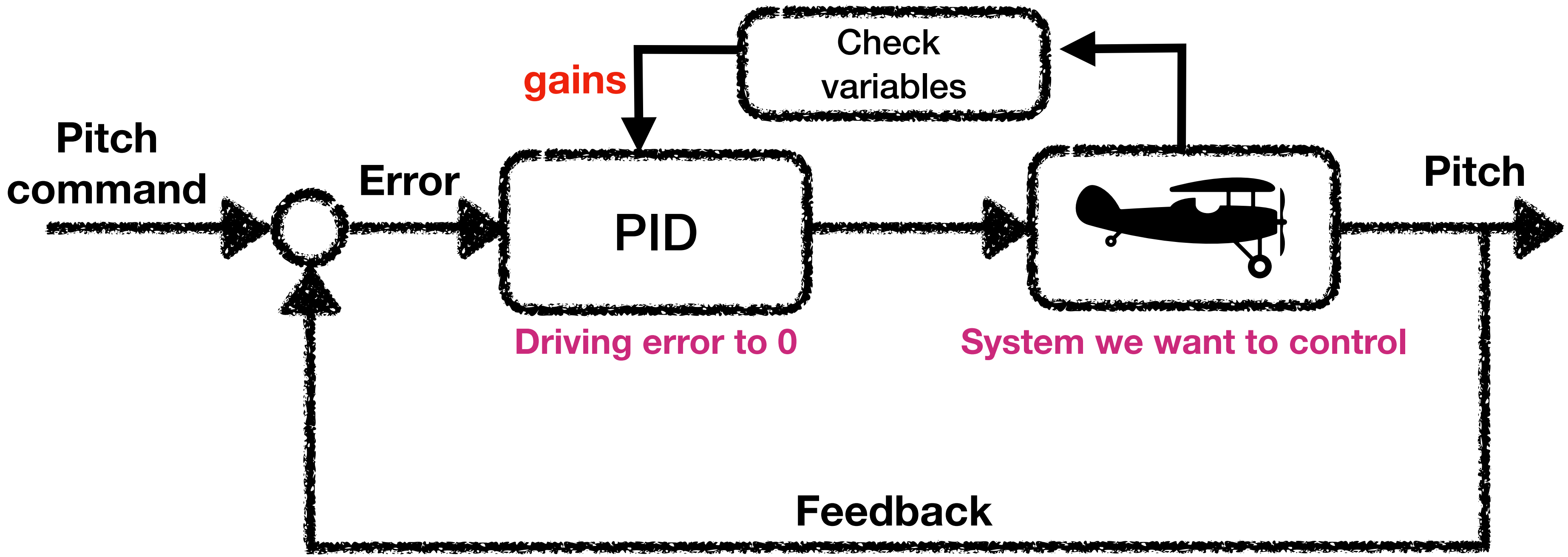
PID Tuning Gain Schedule



Hard switching → **Transient-free switch. Setting transition time**

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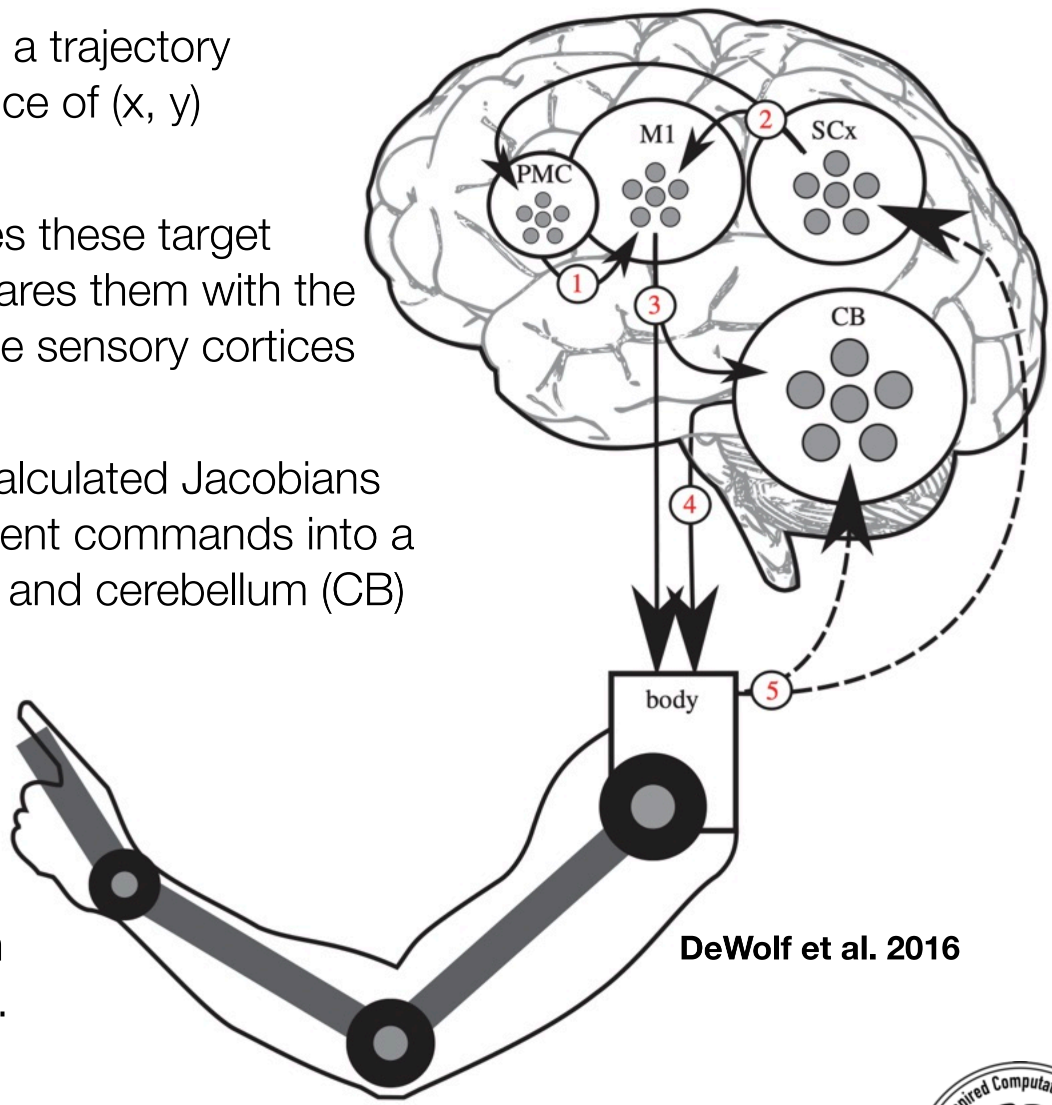
Live Examples

Neuromorphic PID

Adaptive Control

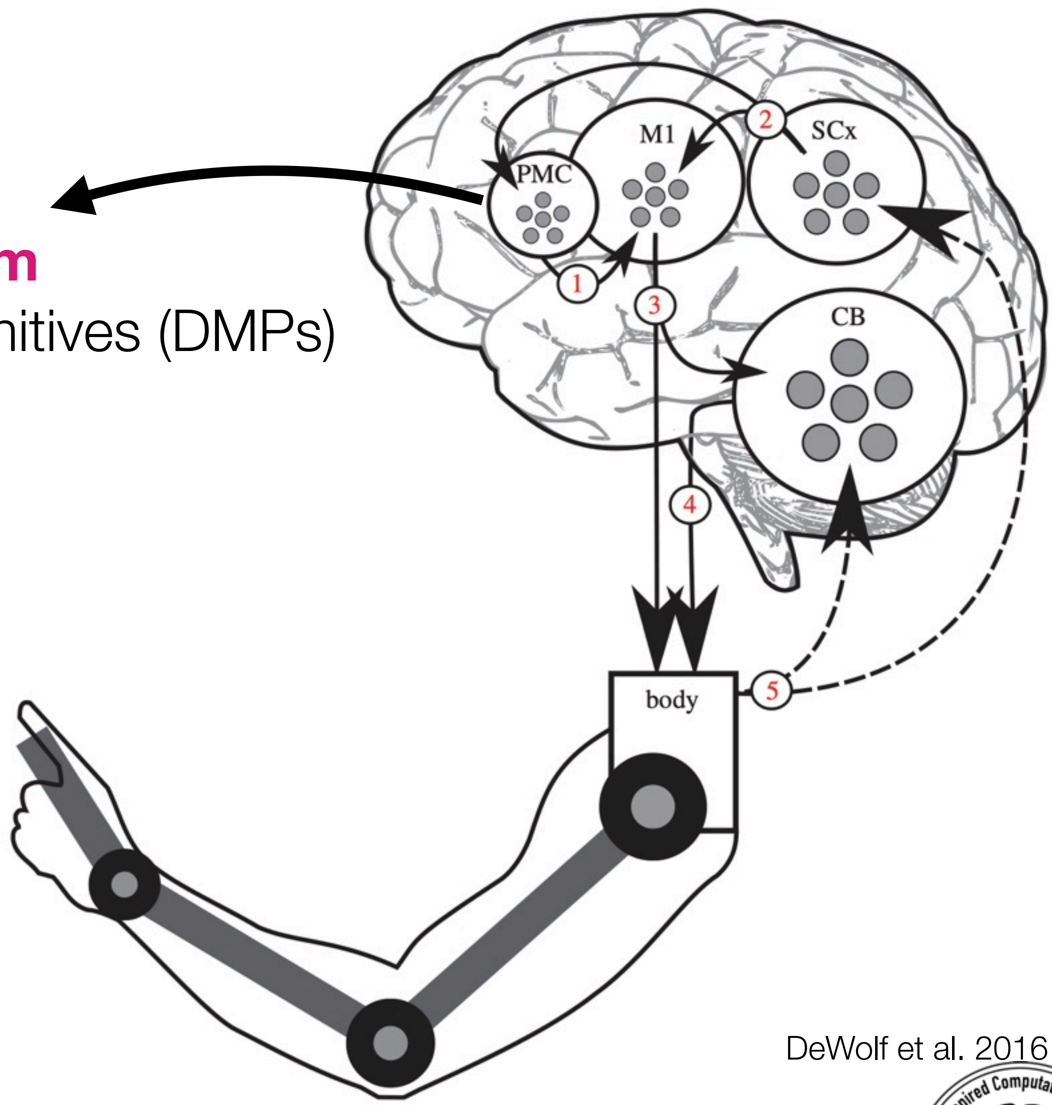
- The premotor cortex (PMC) generates a trajectory for the system to follow with a sequence of (x, y) coordinates.
- The primary motor cortex (M1) receives these target positions (1) from the PMC and compares them with the current system state, received from the sensory cortices (SCx), through (2).
- M1 combines this signal with locally calculated Jacobians to transform the desired hand movement commands into a low-level signal that is sent to the arm and cerebellum (CB) along (3).
- The CB projects an adaptive signal to the body along (4) that compensates for velocity and movement errors. Visual and proprioceptive feedback projects from the body along (5) to the CB and SCx.



DeWolf et al. 2016

Adaptive Control

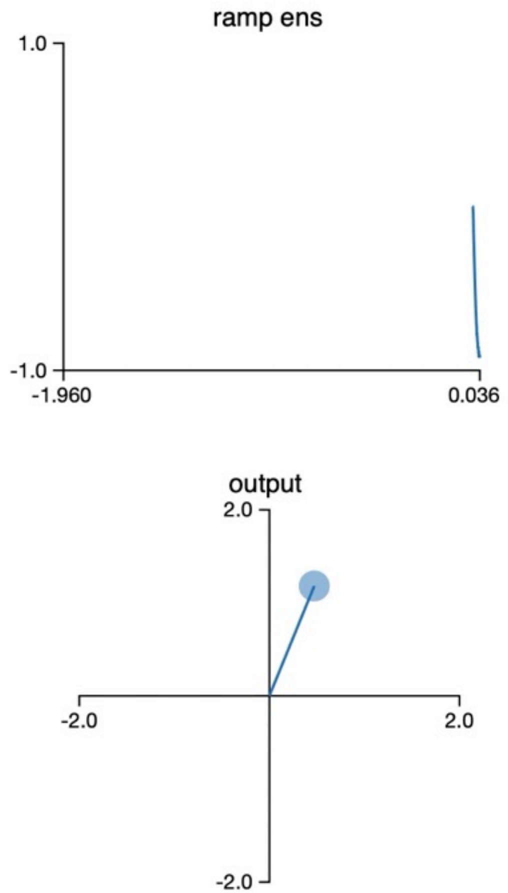
PMC:
Trajectory generation system
Using Dynamic Movement Primitives (DMPs)

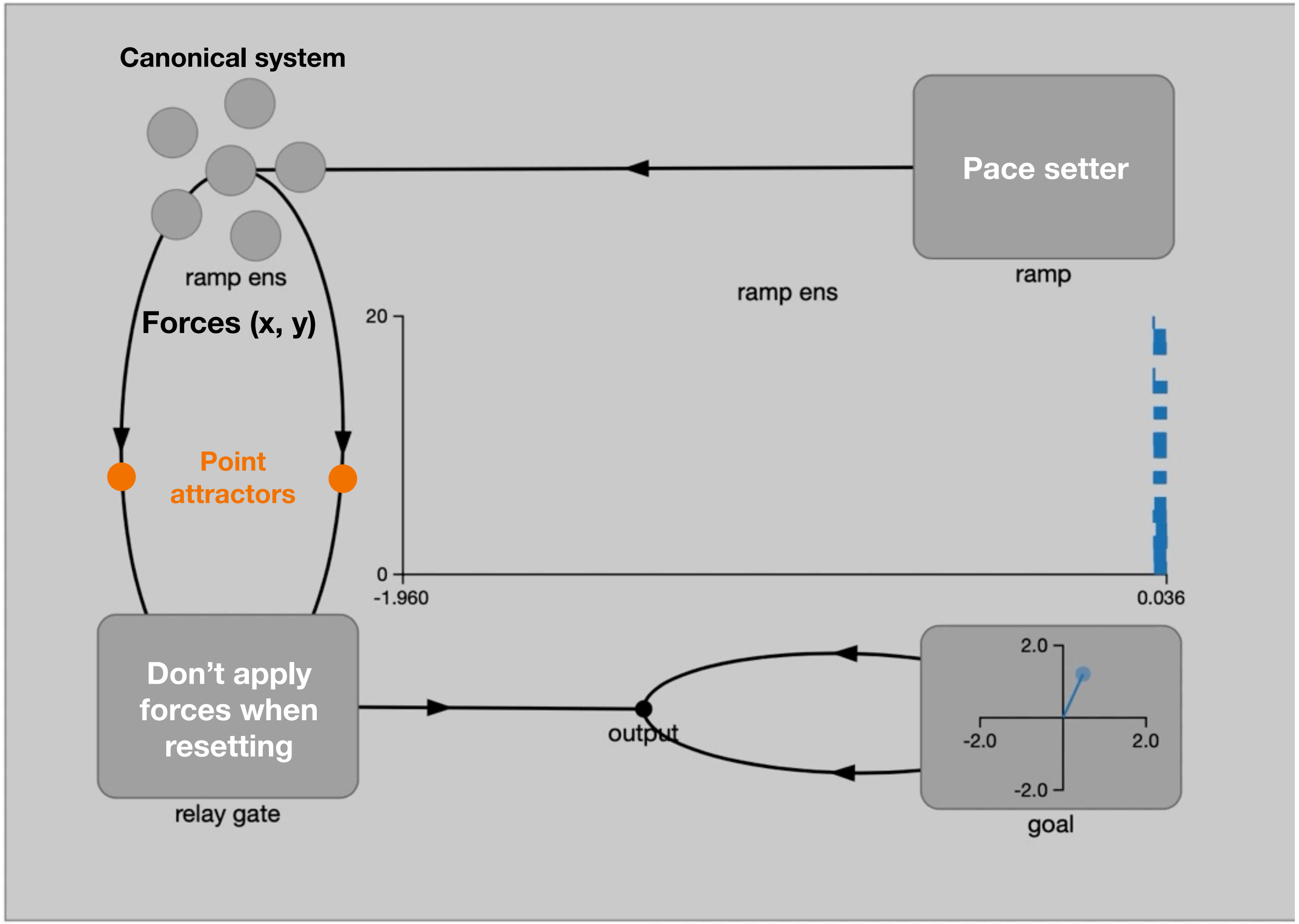


DeWolf et al. 2016

Dynamic movement primitives (DMPs)

In Spiking Neurons





PMC

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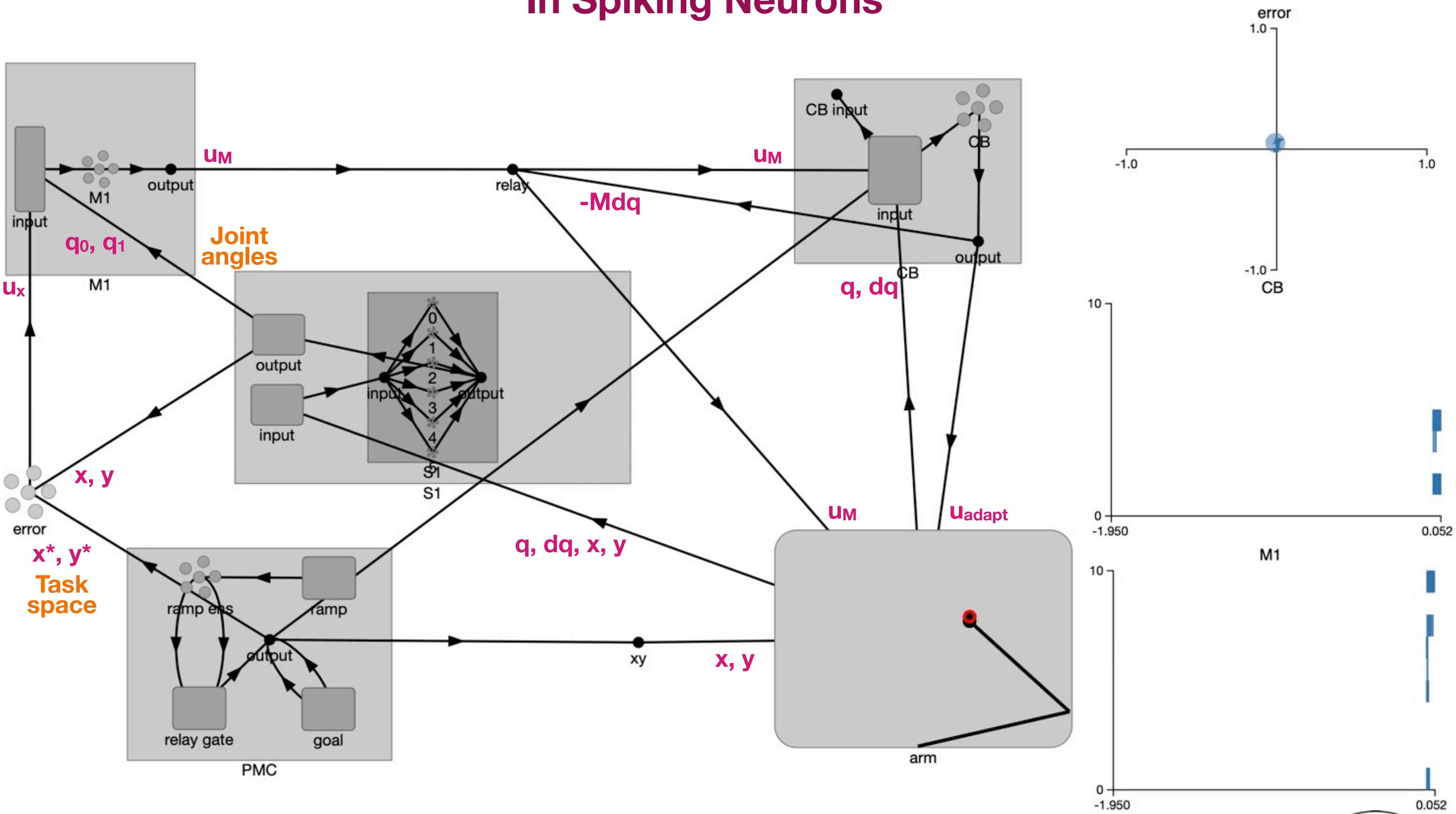
Dynamic movement primitives (DMPs)

In Spiking Neurons



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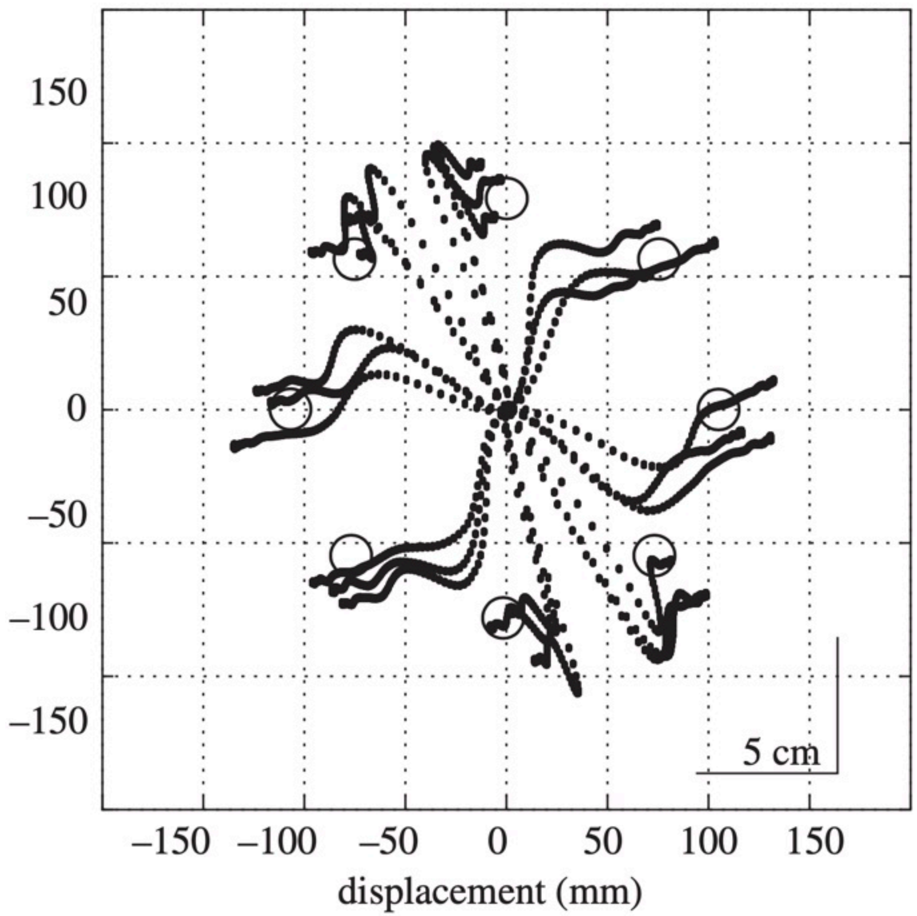
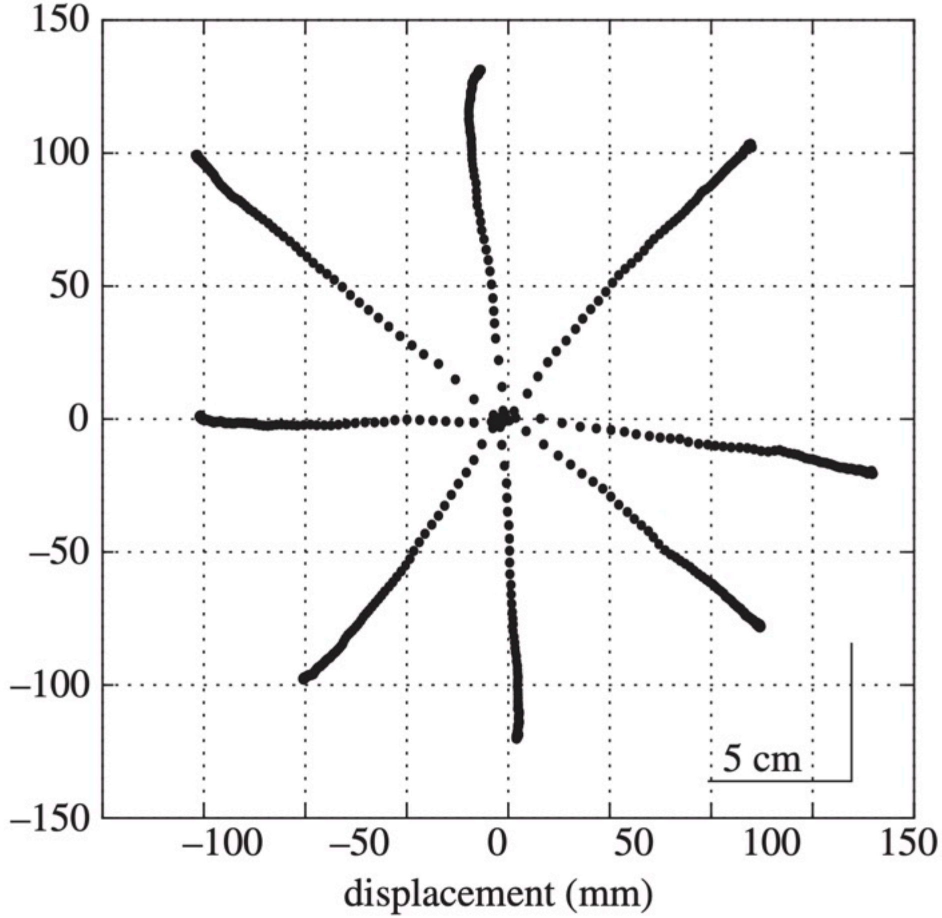
No adaptation



with adaptation



DeWolf et al. 2016

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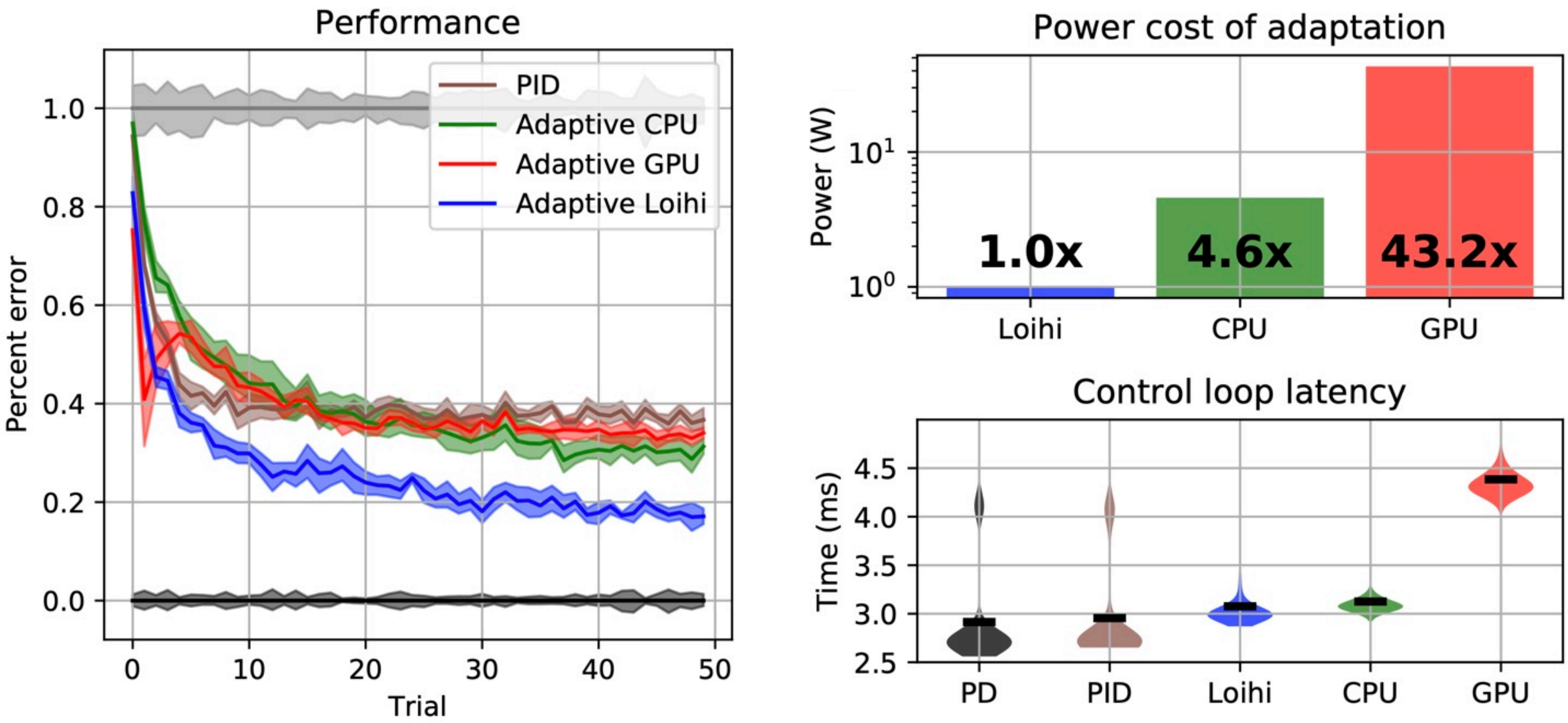
Adaptive Control



DeWolf et al. 2020

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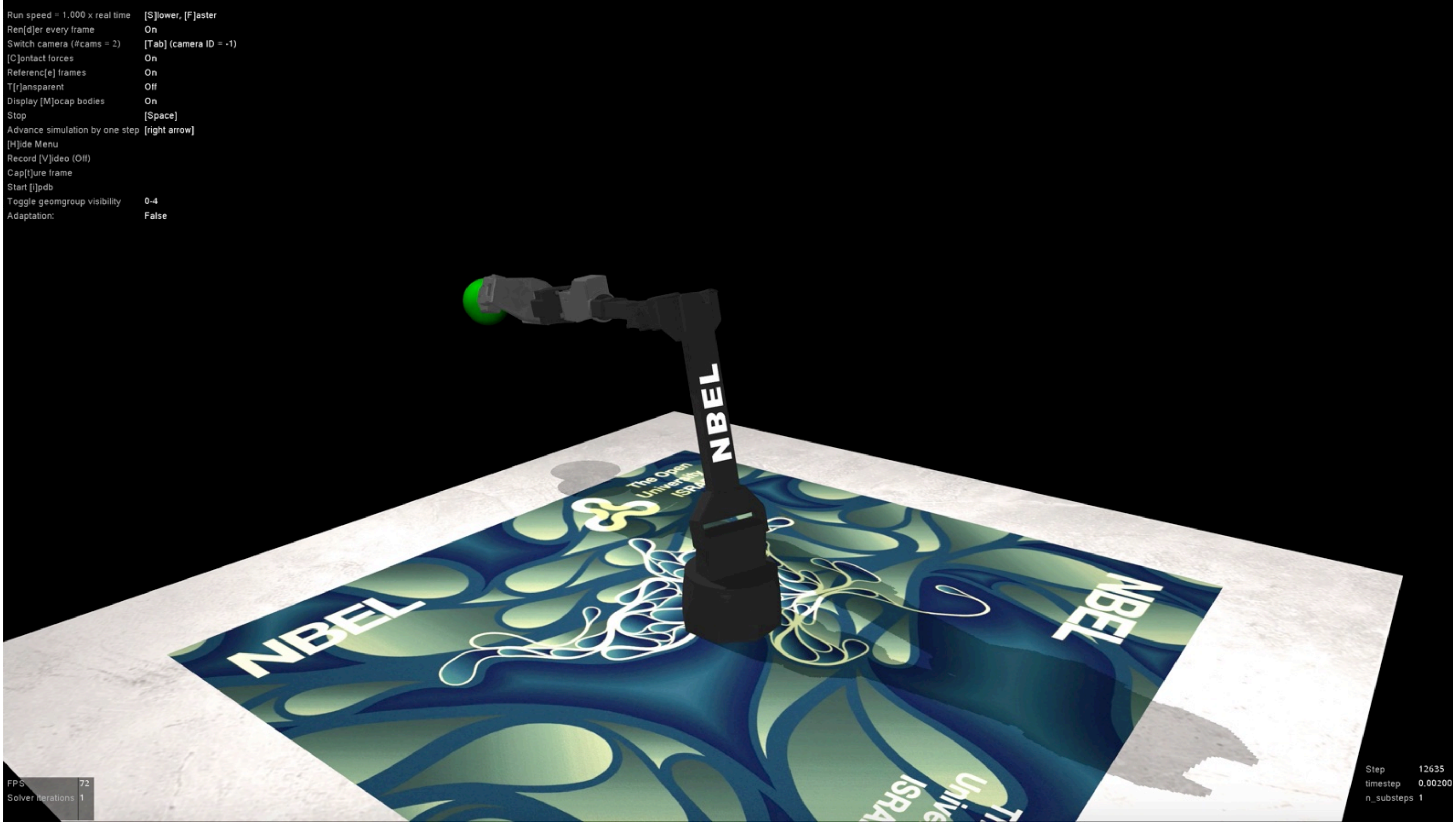
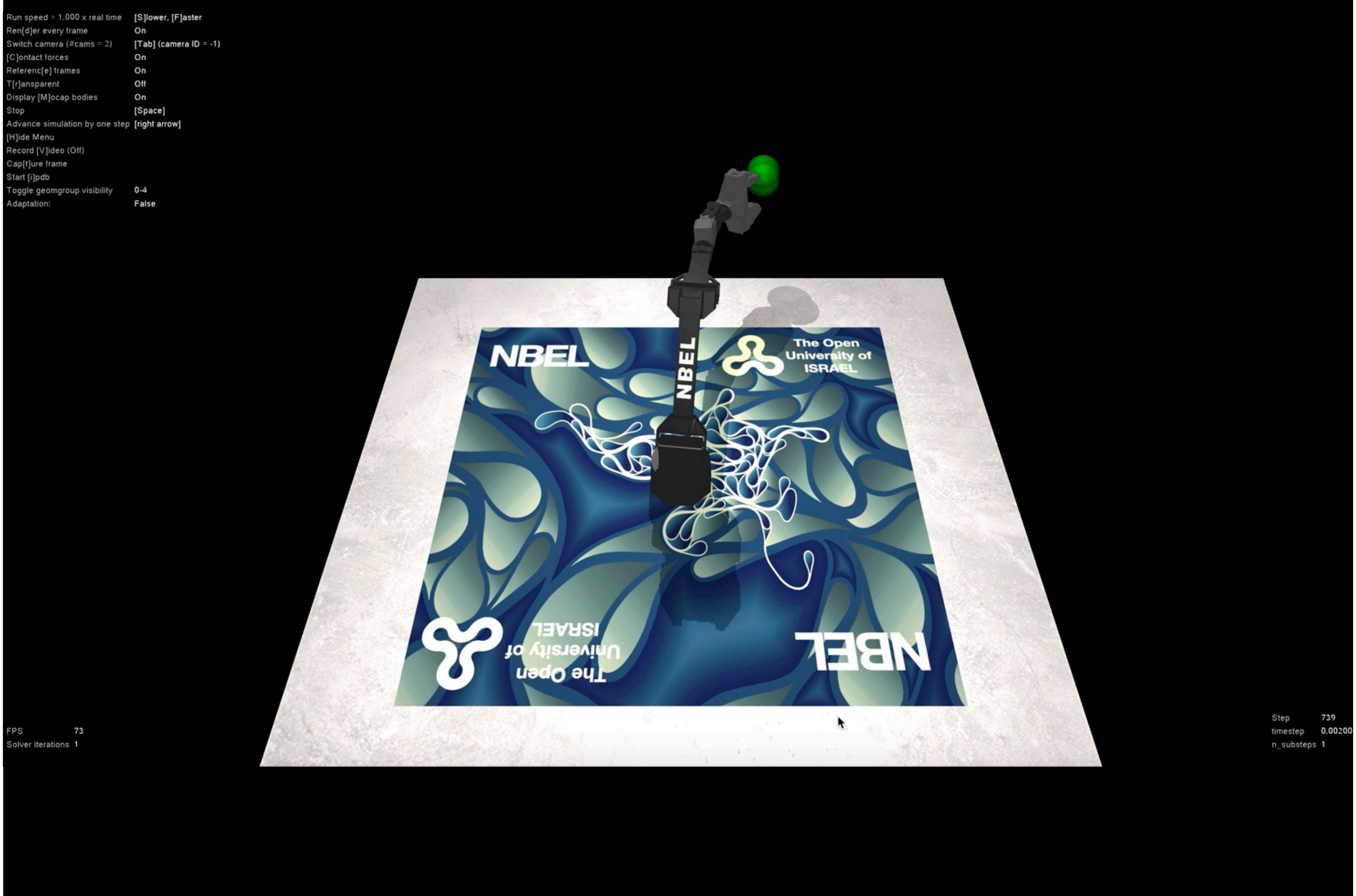
In Simulation
No External Force

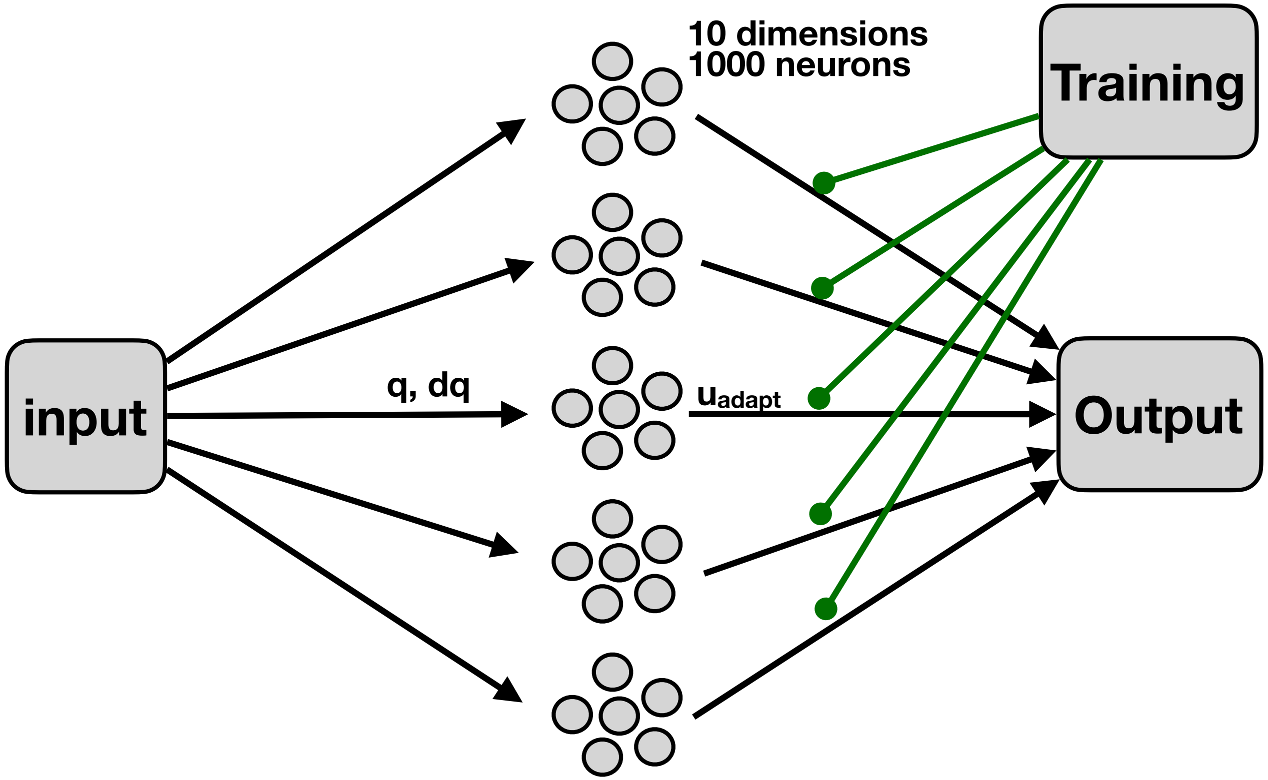


In Simulation
With External Force



On-line Learning

Adaptive control is held neuromorphically



Representing values in 10 dimensions is not trivial. Tuning curves has to be (very) carefully defined. Values should be scaled experimentally.

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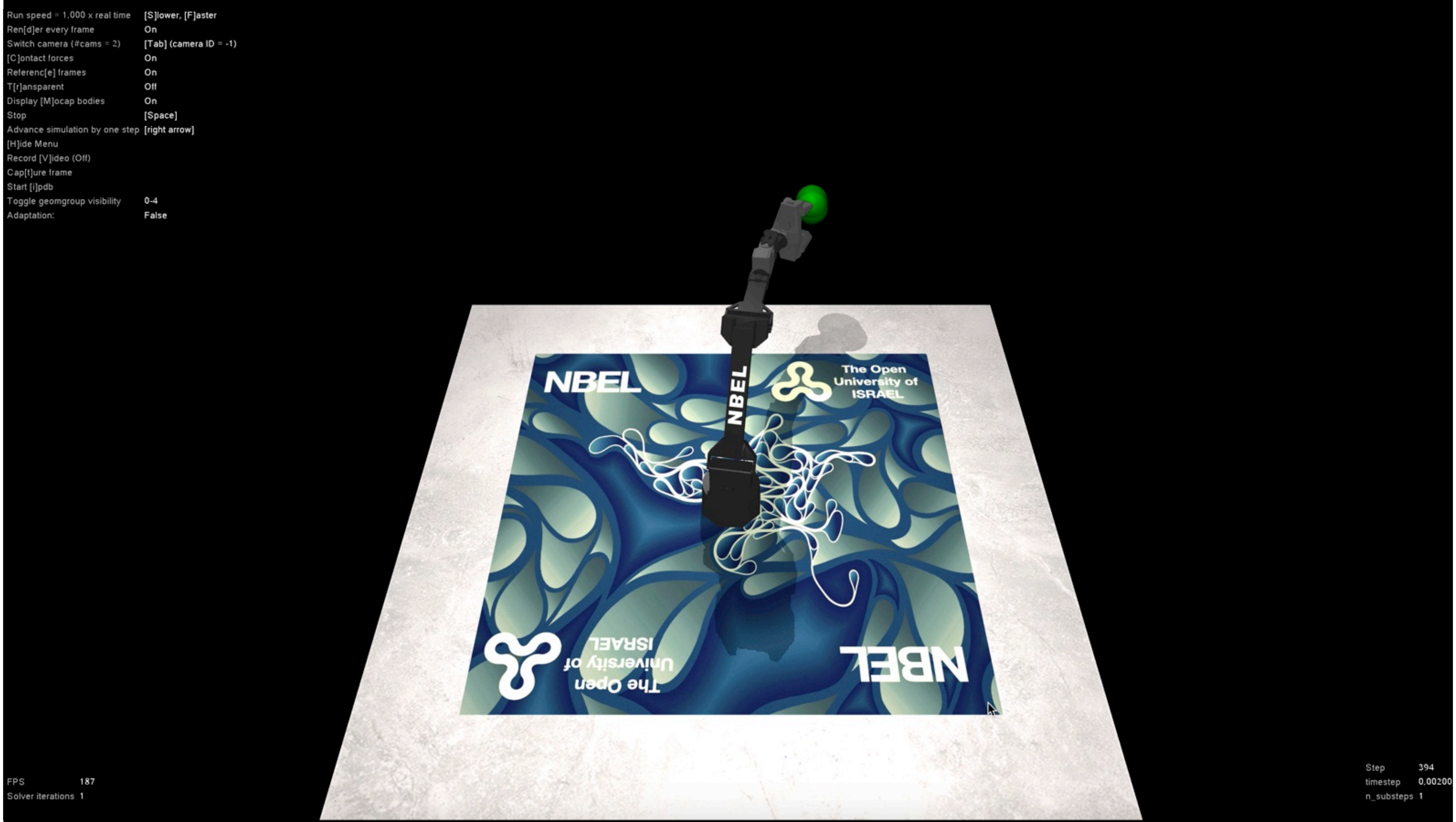
In Simulation
With External Force and Adaptation



frontiers | Frontiers in Neuroscience

TYPE Original Research
PUBLISHED 29 September 2022
DOI 10.3389/fnins.2022.1007736

Adaptive control of a wheelchair mounted robotic arm with neuromorphically integrated velocity readings and online-learning

Michael Ehrlich[1†], Yuval Zaidel[1†], Patrice L. Weiss[2,3], Arie Melamed Yekel[3], Naomi Gefen[3], Lazar Supic[4] and Elishai Ezra Tsur[1*]

[1]Neuro-Biomorphic Engineering Lab, Open University of Israel, Ra'anana, Israel, [2]Department of Occupational Therapy, University of Haifa, Haifa, Israel, [3]The Helmsley Pediatric & Adolescent Rehabilitation Research Center, ALYN Hospital, Jerusalem, Israel, [4]Accenture Labs, San Francisco, CA, United States

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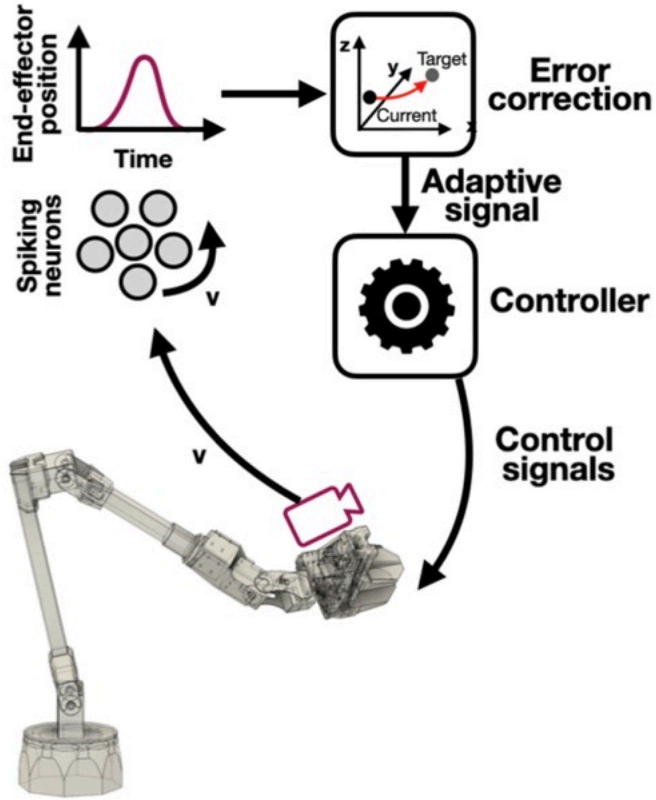
Clinical Usability Study



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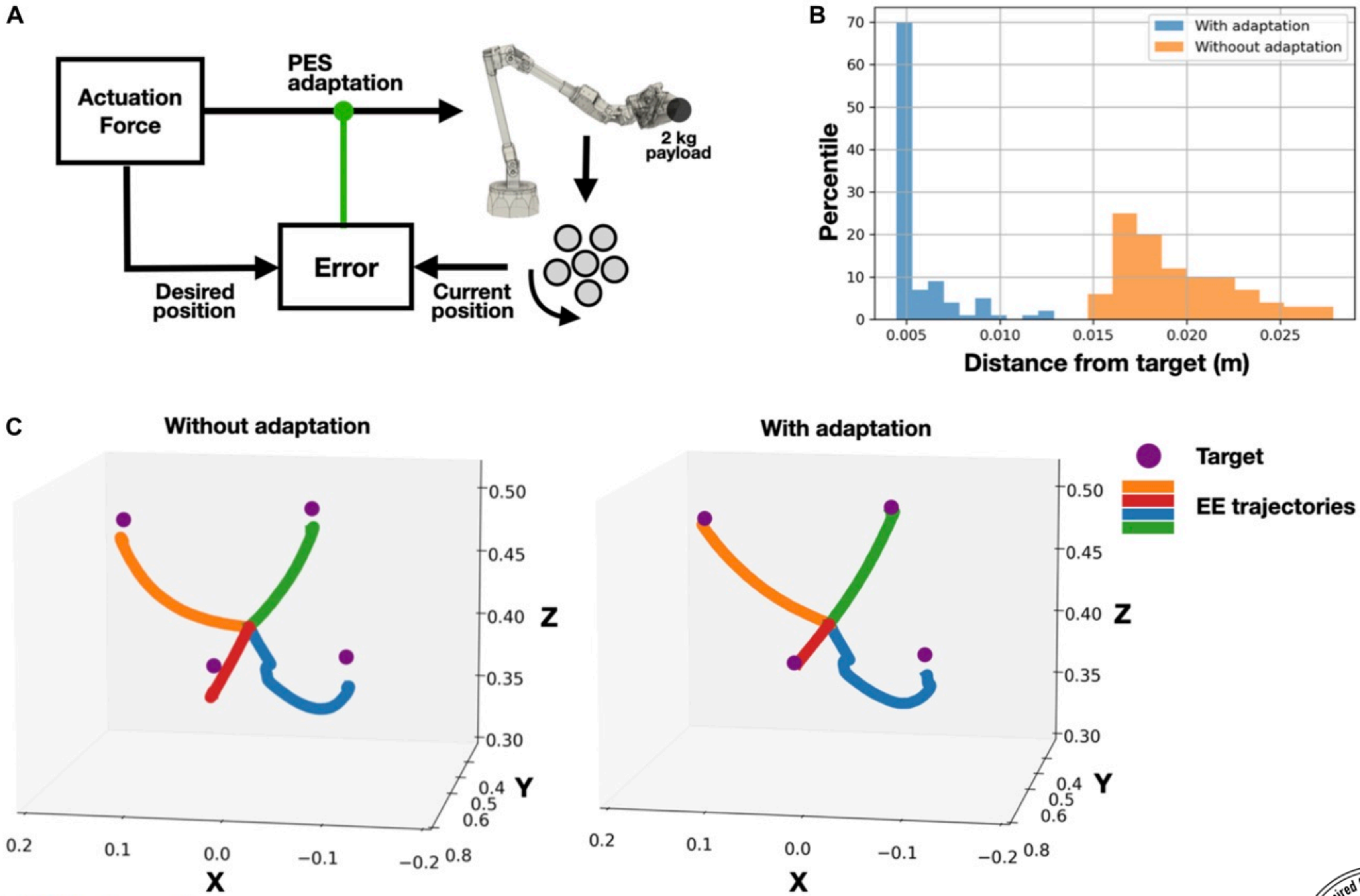
Adaptive Control



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Neuro-Inspired Computational Elements
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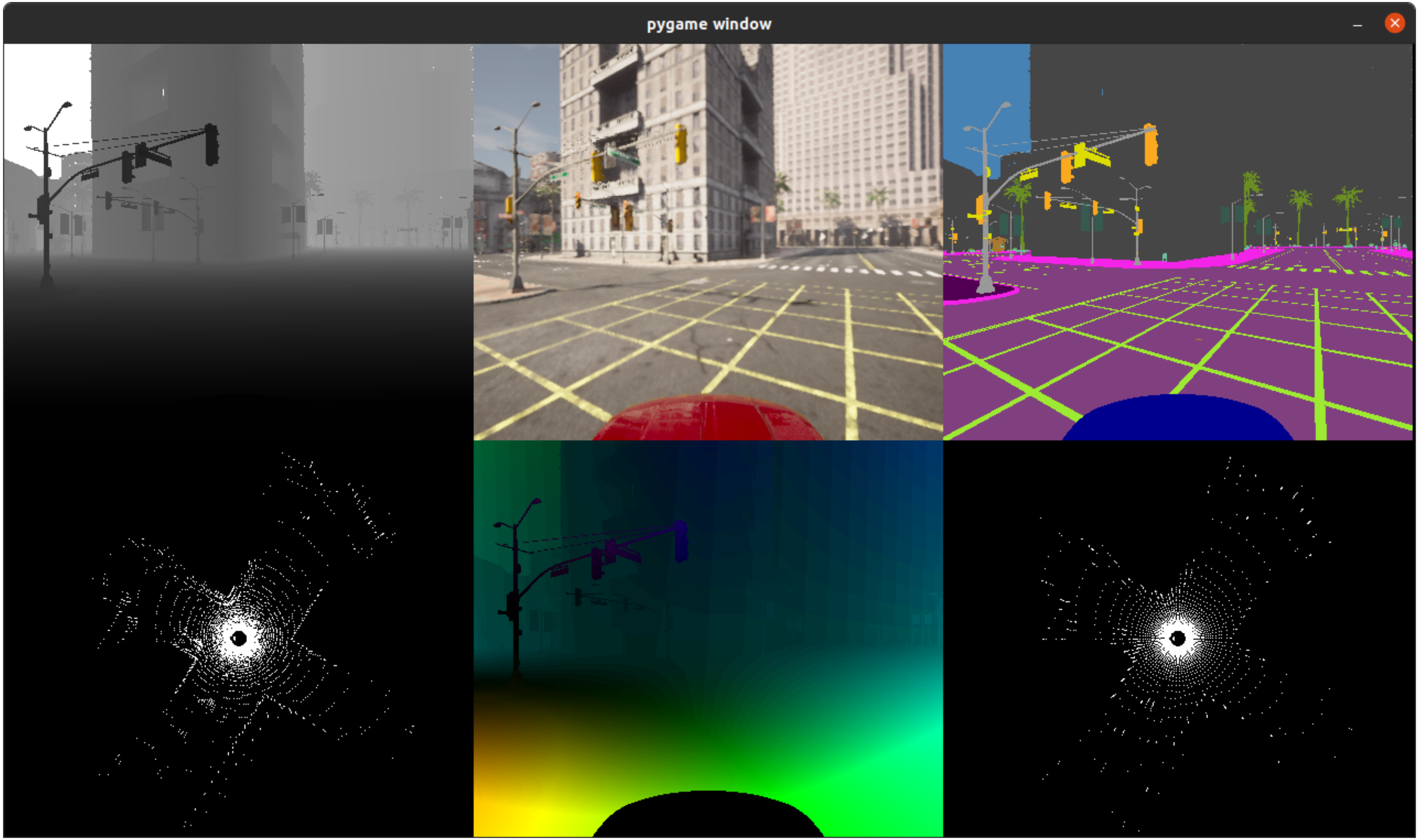
Objective: Zero-Shot Trajectory Optimization

Simulation Frameworks

AirSim (microsoft)

Simulation Frameworks

CARLA



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Bioinspiration & Biomimetics

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PAPER

LiDAR-driven spiking neural network for collision avoidance in autonomous driving

Albert Shalumov, Raz Halaly and Elishai Ezra Tsur*

Neuro-Biomorphic Engineering Lab at the Open University of Israel, Ra'anana, Israel

* Author to whom any correspondence should be addressed.

E-mail: elishai@nbel-lab.com

Keywords: neuromorphic control, neuromorphic engineering, neural engineering framework, autonomous driving, PID control, online learning

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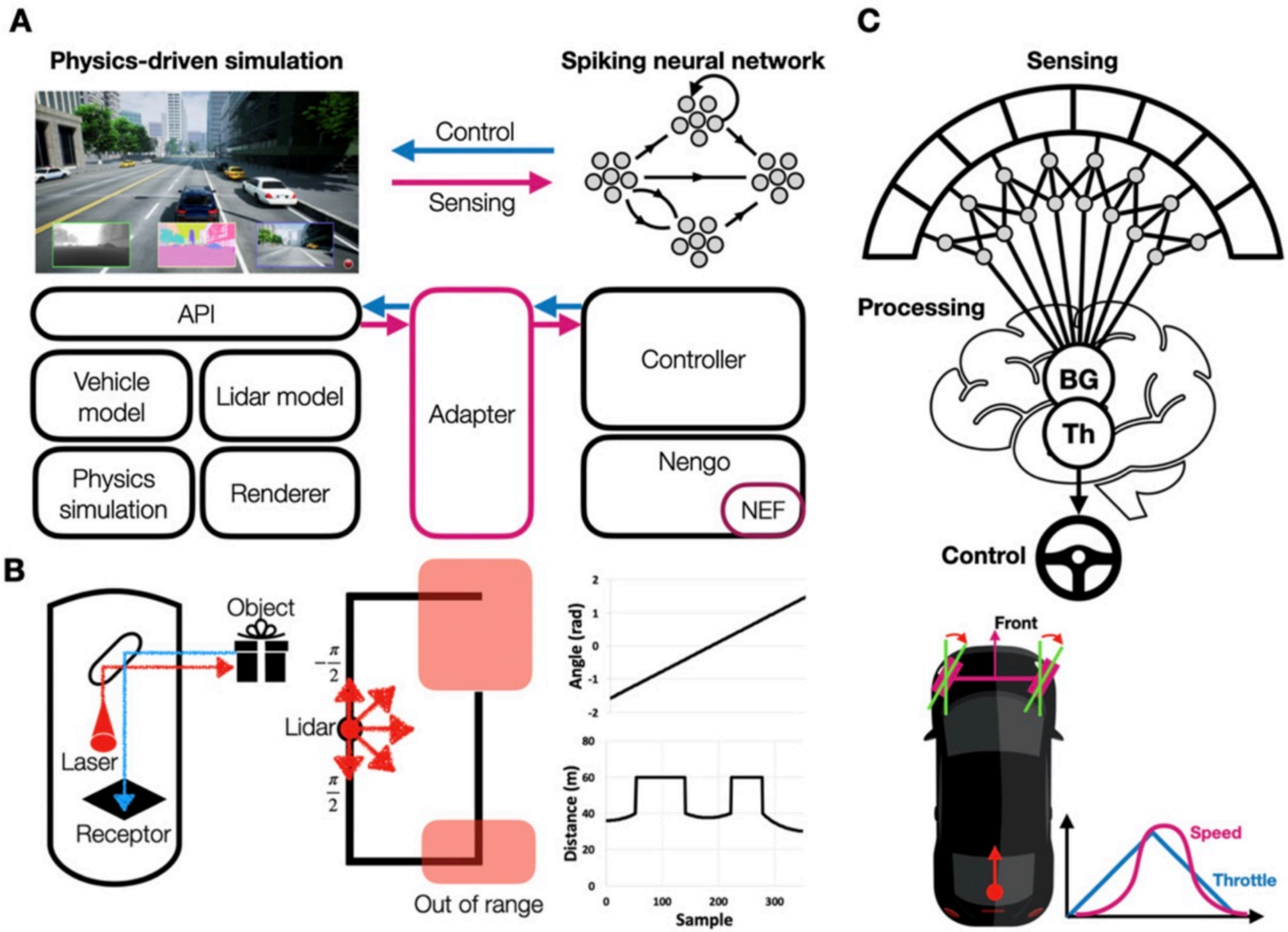

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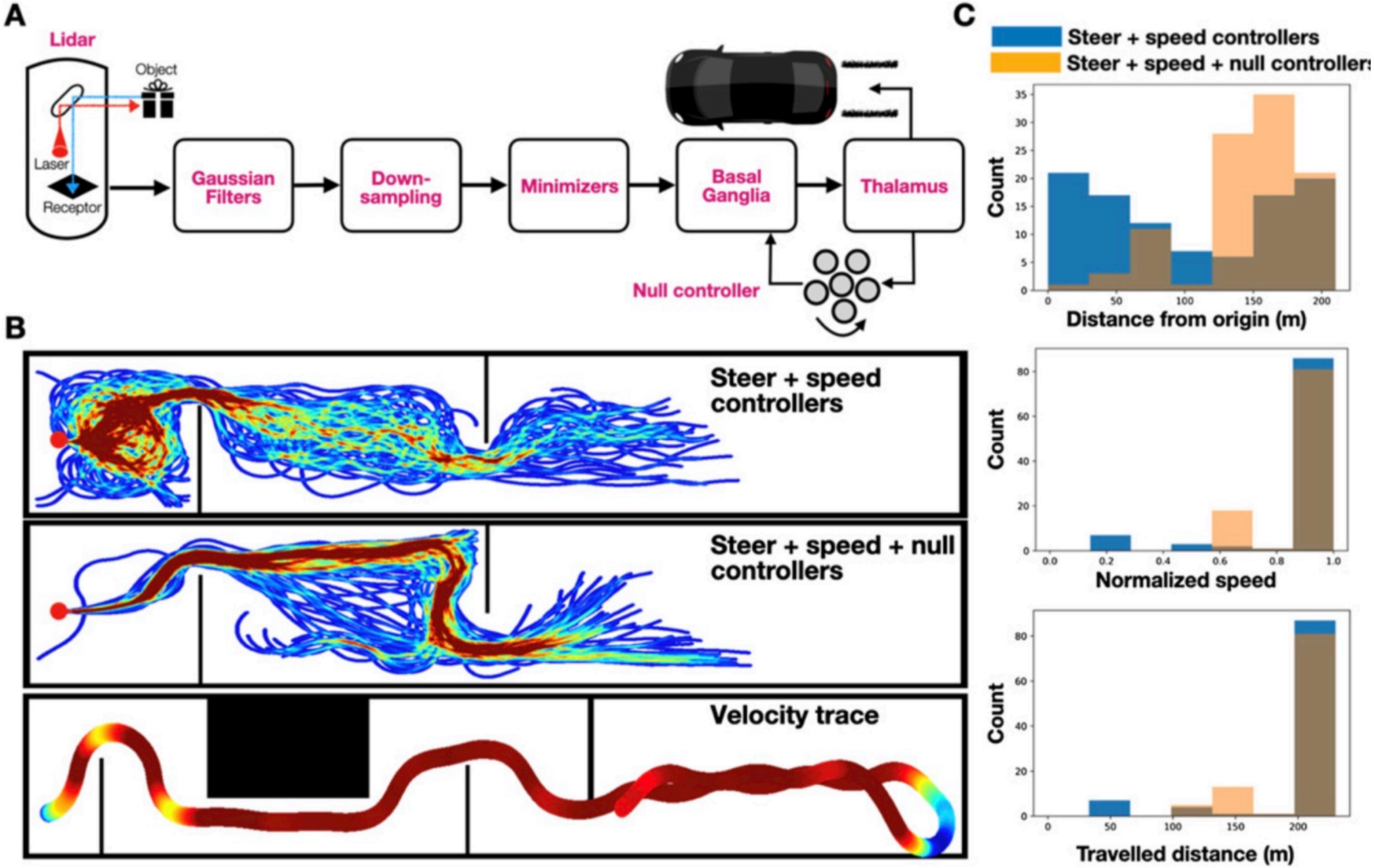

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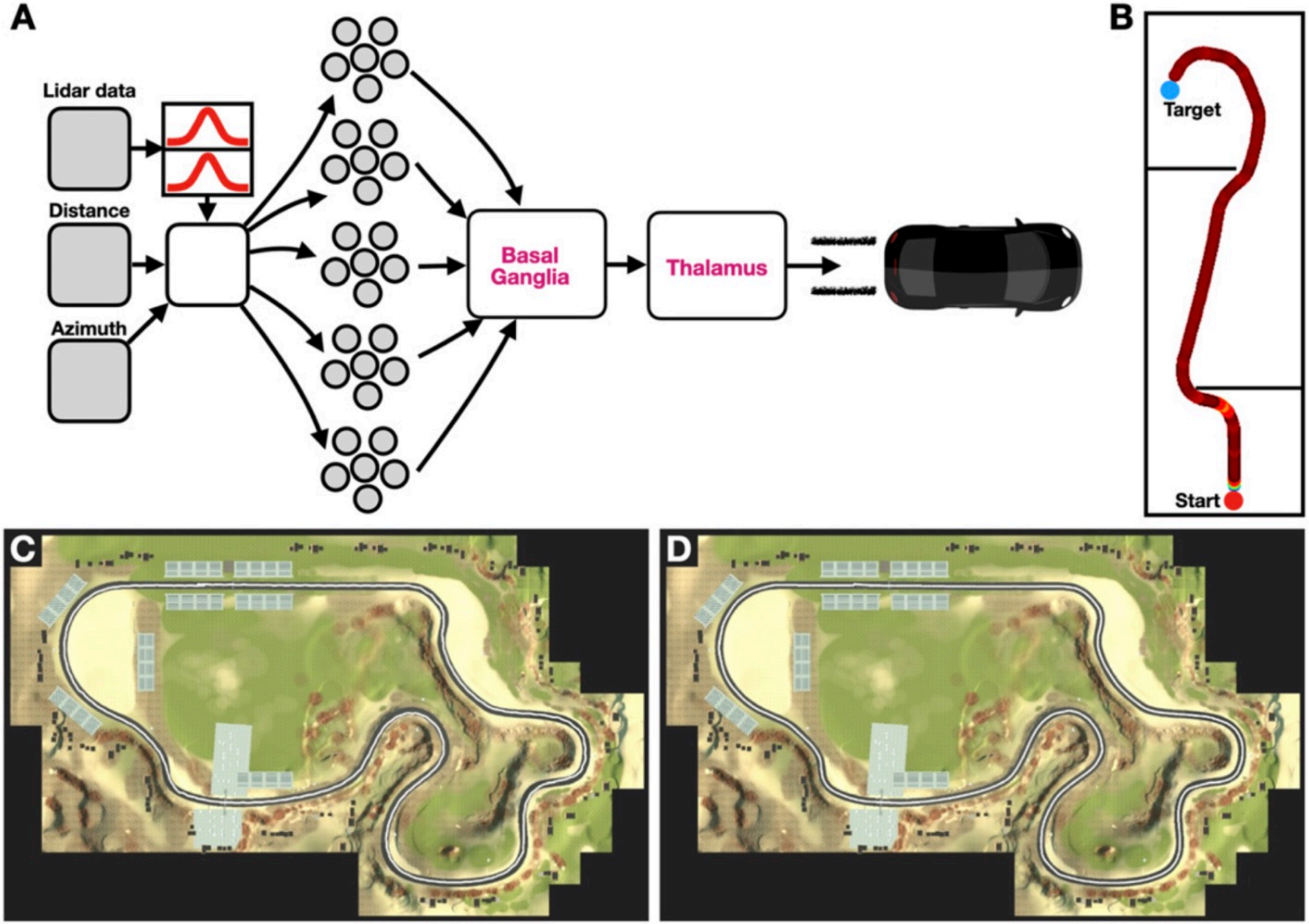
A
Lidar data
Distance
Azimuth
Basal Ganglia
Thalamus
B
Target
Start
C
D

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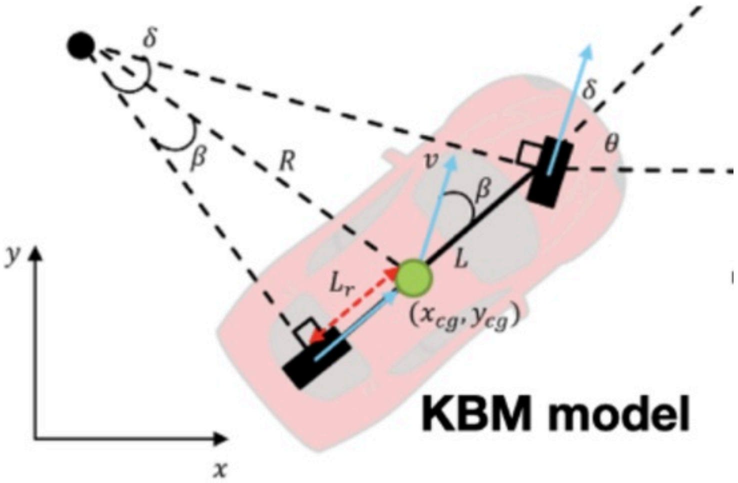
Kinematic Bicycle Model



$$\theta_t = \tan\left(\theta_{\cos_t}/\theta_{\sin_t}\right)$$
$$\dot{x} = v_t \cos\left(\theta_t + \beta\right)$$
$$\dot{y} = v_t \sin\left(\theta_t + \beta\right)$$
$$\dot{\theta} = v_t \tan\left(\delta_t\right)\cos\left(\beta\right)/L$$
$$\dot{v}_x = \phi_t \theta_{\cos_t}$$
$$\dot{v}_y = \phi_t \theta_{\sin_t}$$
$$\dot{a}_x = 0$$
$$\dot{a}_y = 0$$
$$\dot{v}_r = 0$$

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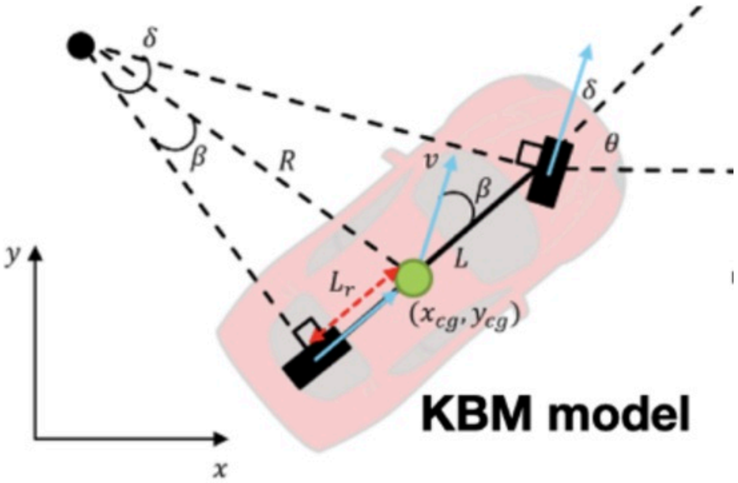
Kinematic Bicycle Model



$$\theta_t = \tan\left(\theta_{\cos_t}/\theta_{\sin_t}\right)$$
$$\dot{x} = v_t \cos\left(\theta_t + \beta\right)$$
$$\dot{y} = v_t \sin\left(\theta_t + \beta\right)$$
$$\dot{\theta} = v_t \tan\left(\delta_t\right) \cos\left(\beta\right)/L$$
$$\dot{v}_x = \phi_t \theta_{\cos_t}$$
$$\dot{v}_y = \phi_t \theta_{\sin_t}$$
$$\dot{a}_x = 0$$
$$\dot{a}_y = 0$$
$$\dot{v}_r = 0$$

$$x_{t+1} = x_t + \dot{x}\Delta t$$
$$y_{t+1} = y_t + \dot{y}\Delta t$$
$$\theta_{\cos_{t+1}} = \cos\left(\theta_t + \dot{\theta}\Delta t\right)$$
$$\theta_{\sin_{t+1}} = \sin\left(\theta_t + \dot{\theta}\Delta t\right)$$
$$v_{x_{t+1}} = v_{x_t} + \dot{v}_x \Delta t$$
$$v_{y_{t+1}} = v_{y_t} + \dot{v}_y \Delta t$$
$$a_{x_{t+1}} = a_{x_t} + \dot{a}_x \Delta t$$
$$a_{y_{t+1}} = a_{y_t} + \dot{a}_y \Delta t$$
$$v_{r_{t+1}} = v_{r_t} + \dot{v}_r \Delta t.$$

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Neuro-Inspired Computational Elements NICE 2025

Live Examples

Neuromorphic PID with KBM

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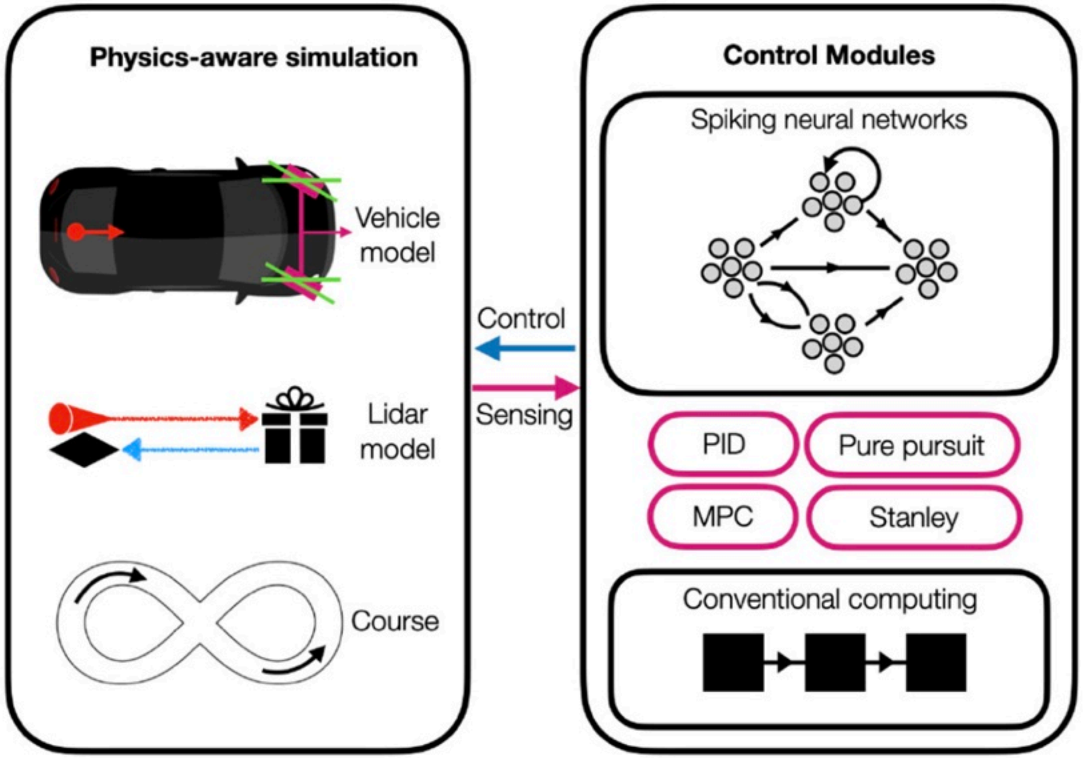
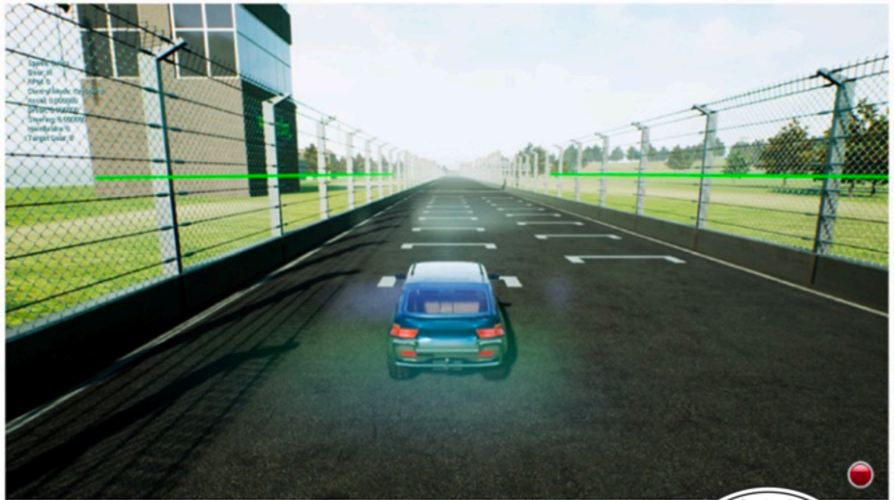
Autonomous driving controllers with neuromorphic spiking neural networks

frontiers in Neurorobotics

Raz Halaly and Elishai Ezra Tsur*





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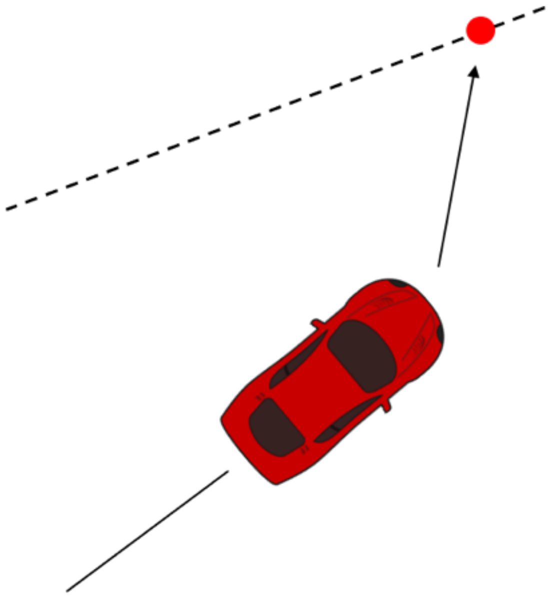
Pure Pursuit

- Geometric path tracking controller
- Uses a look-ahead point
- Fixed distance on the reference path
- Computes the steering angle based on the point
- Does not control the velocity of the vehicle



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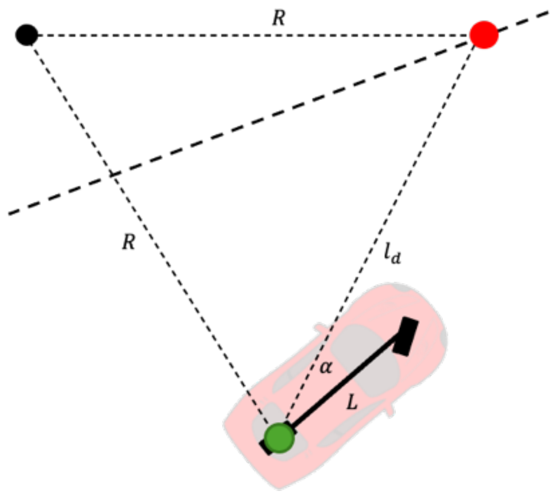
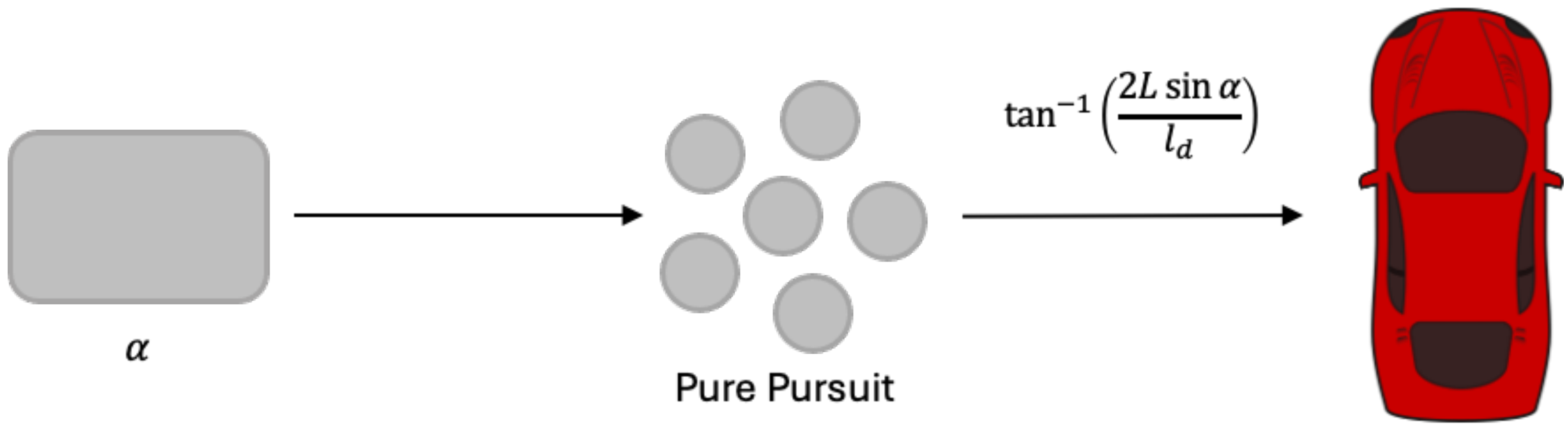
Pure Pursuit

$$\delta(t) = \arctan\left(\frac{2L\sin\alpha}{l_d}\right)$$

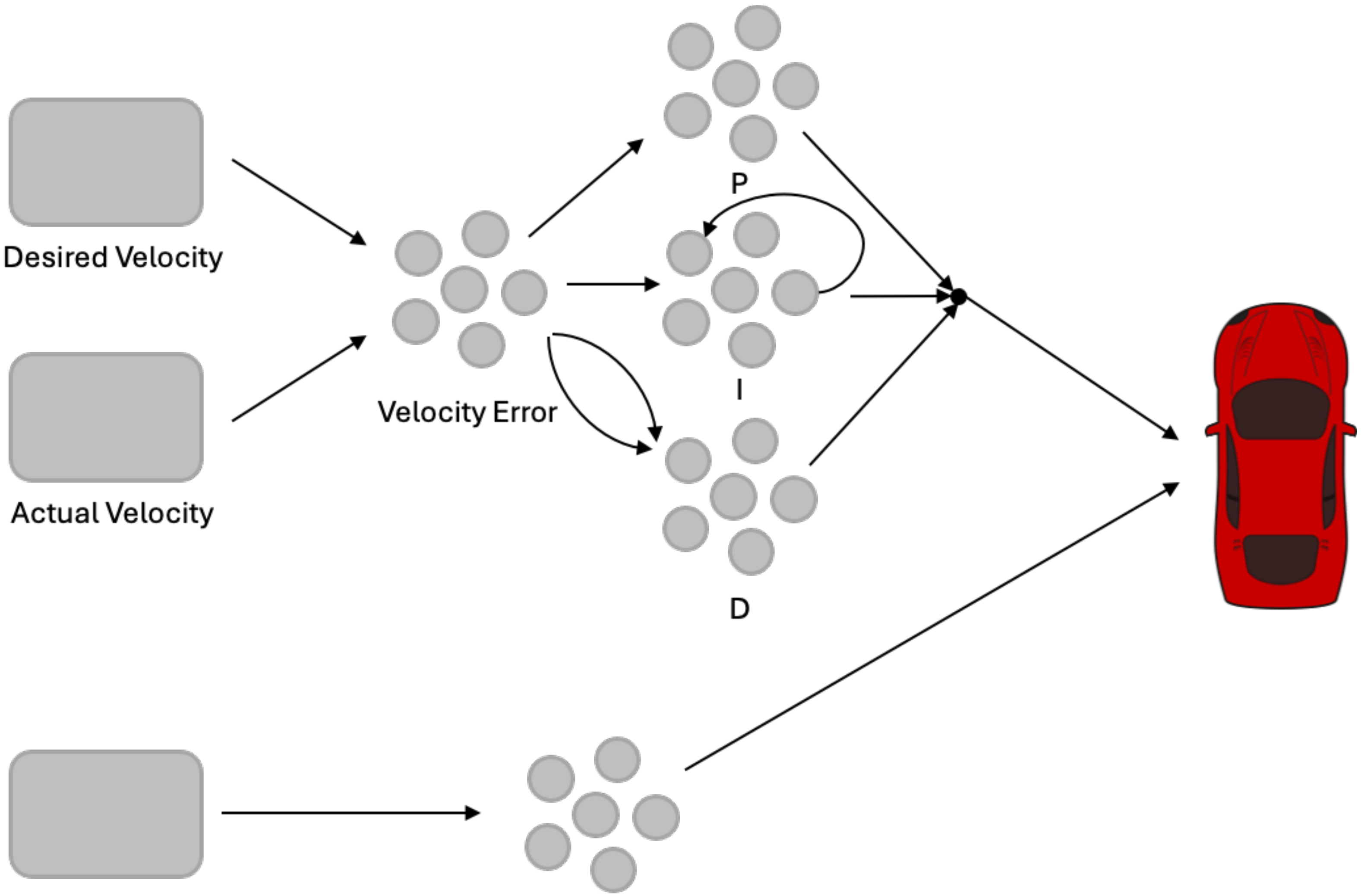


Pure Pursuit



And using PID to control velocity…

Pure Pursuit



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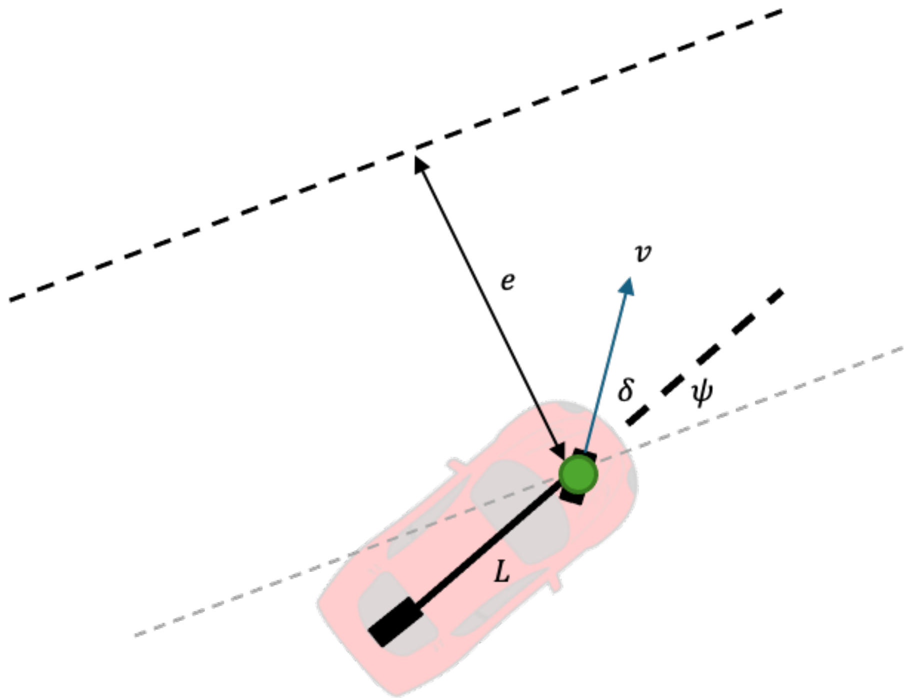
Live Examples

Pure pursuit with KBM

Stanley Controller

- Geometric path tracking controller
- Looks for reducing the heading and cross-track errors
- Computes the steering angle

$$\delta = \underbrace{\psi}_{\text{Heading error}} + \tan^{-1} \underbrace{\frac{e}{v}}_{\text{CTE}}$$



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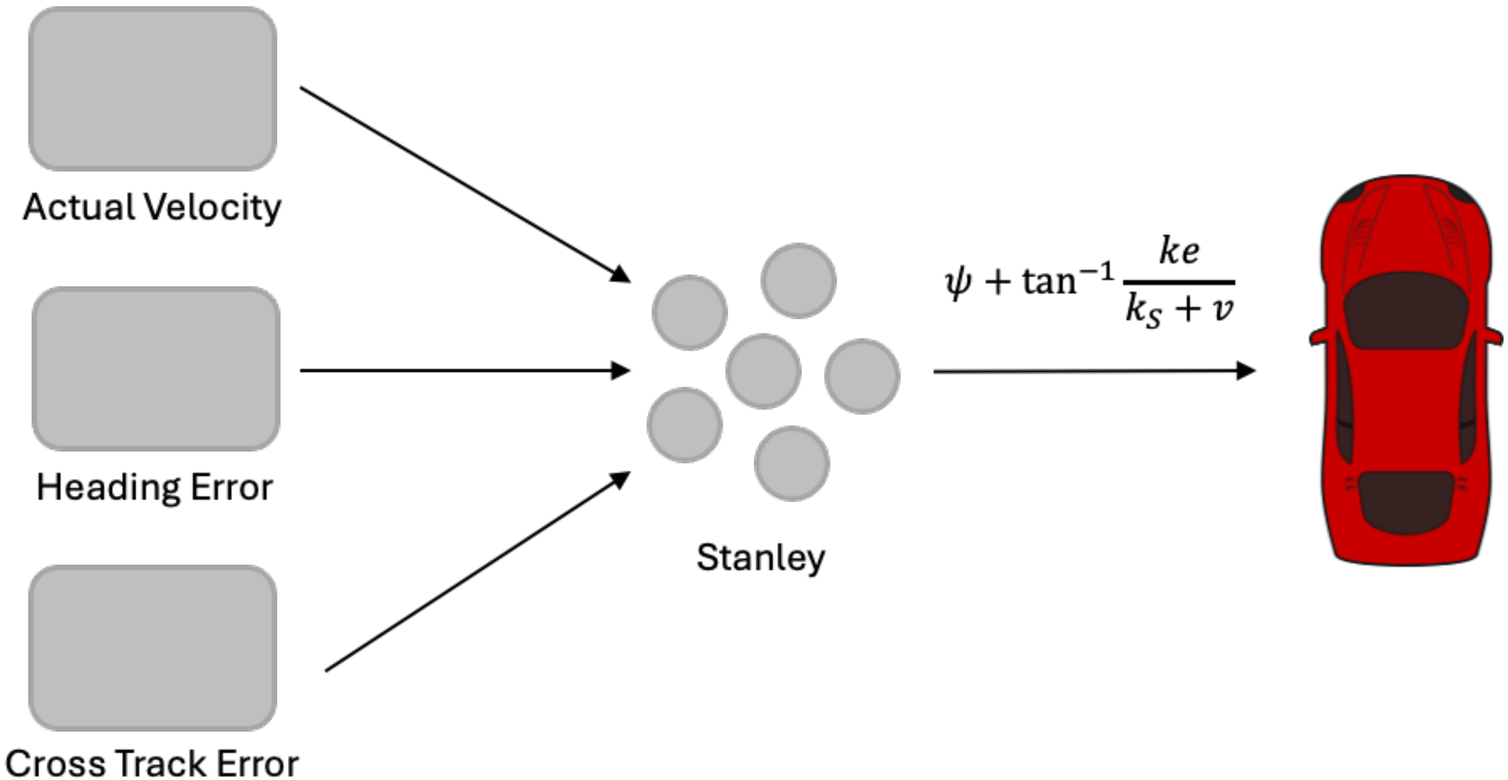
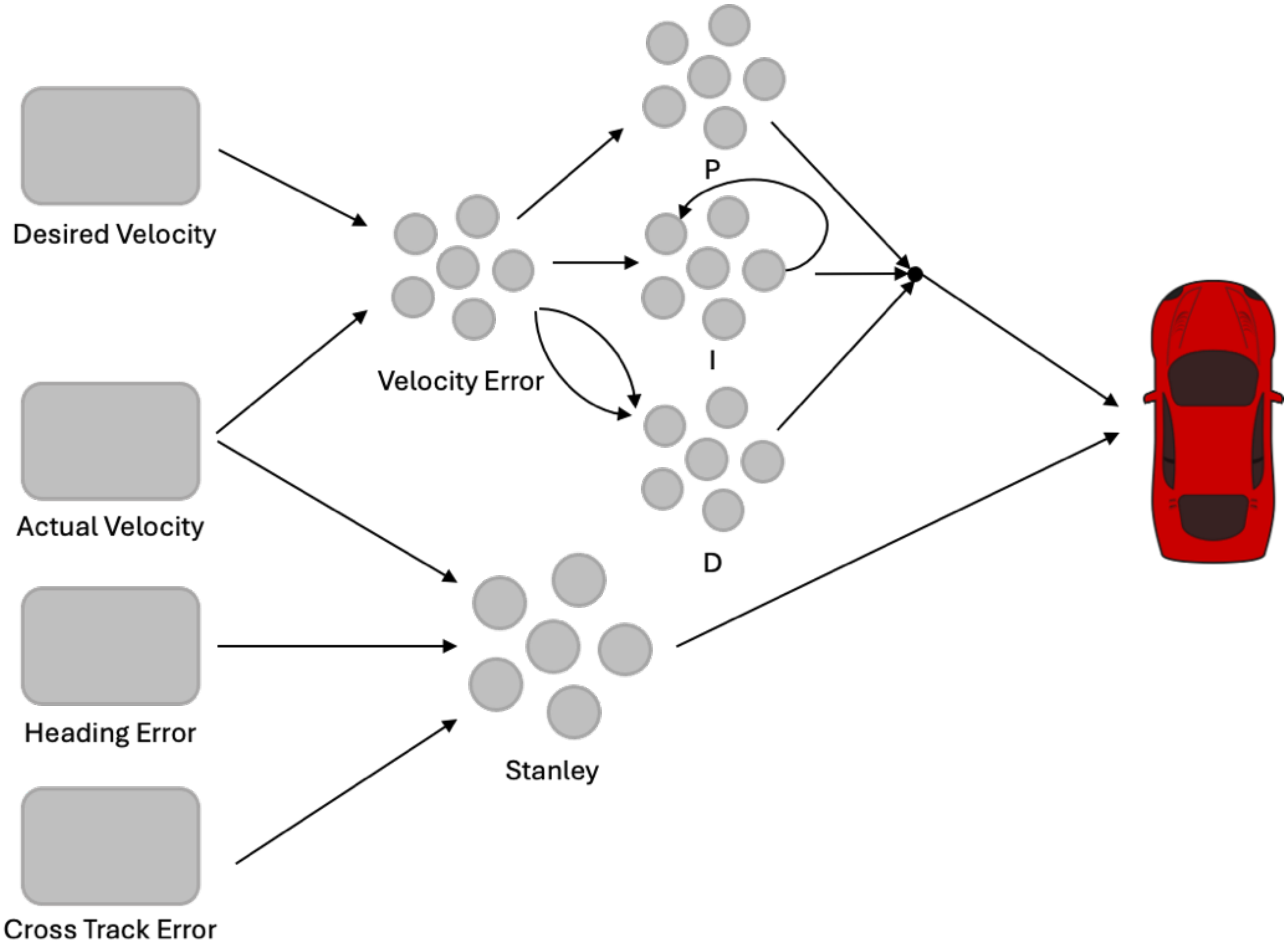
Stanley Controller



Stanley Controller

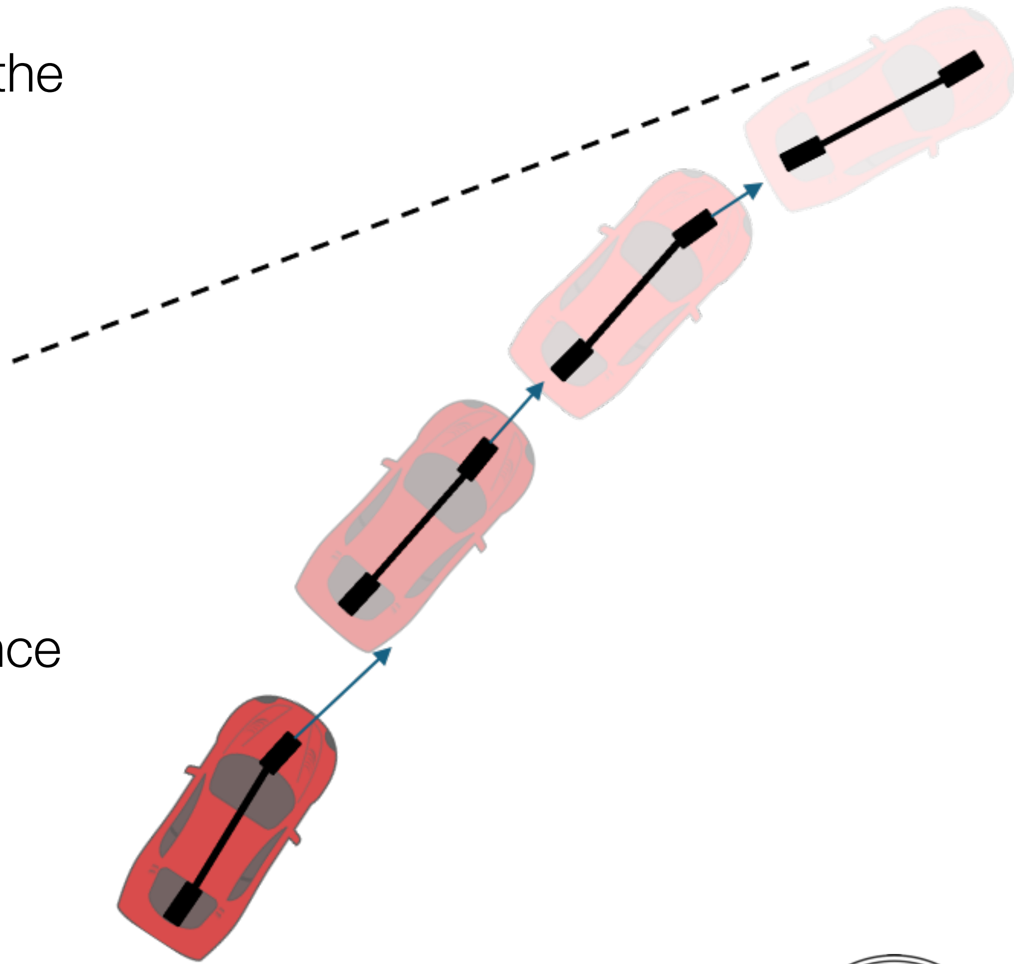


Live Examples

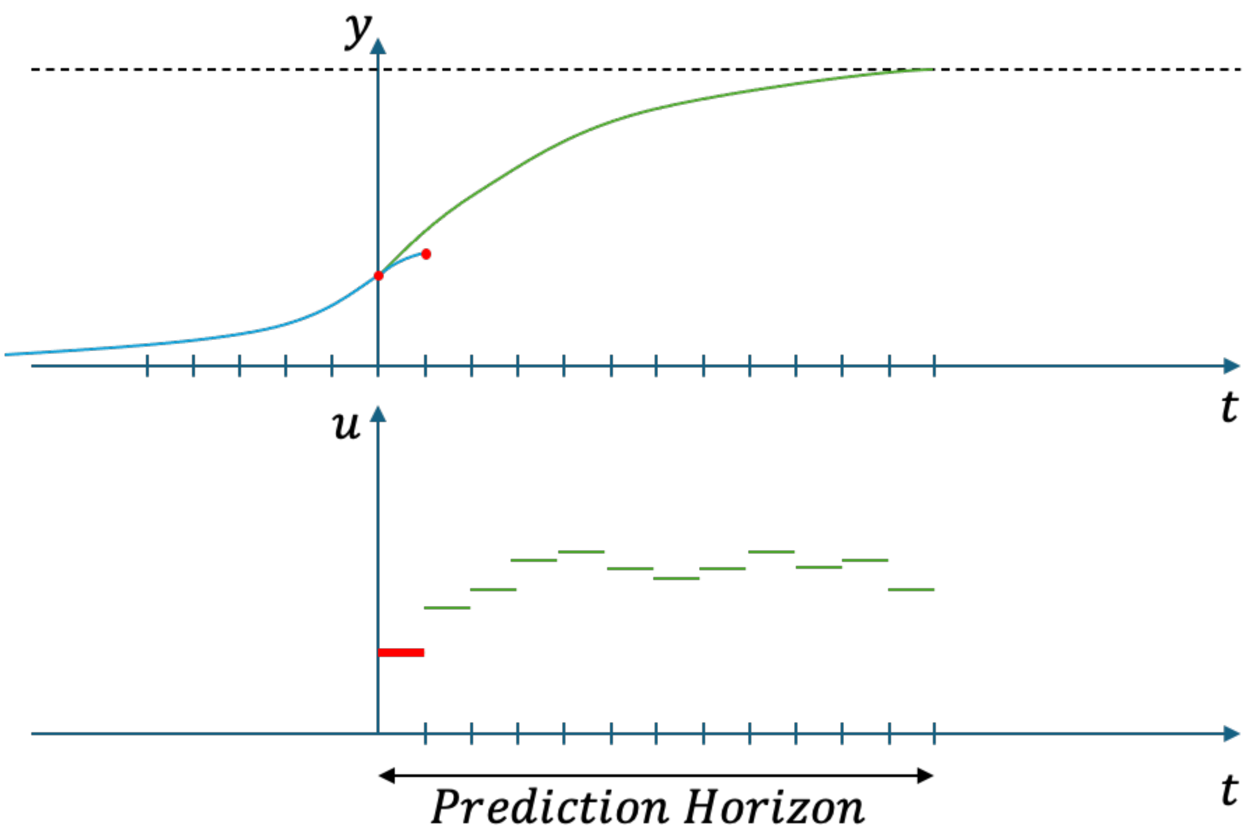
Stanley with KBM

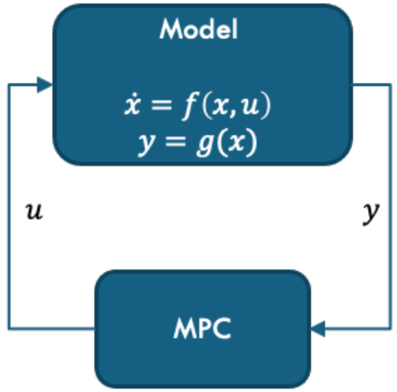
MPC

- Optimization based controller
- Predicts where the vehicle will be in the future
- Looks for minimizing a cost function
  - Can compute complex function
  - Can satisfy constrains
- Computational heavy
- Computes multiple parameters at once



MPC





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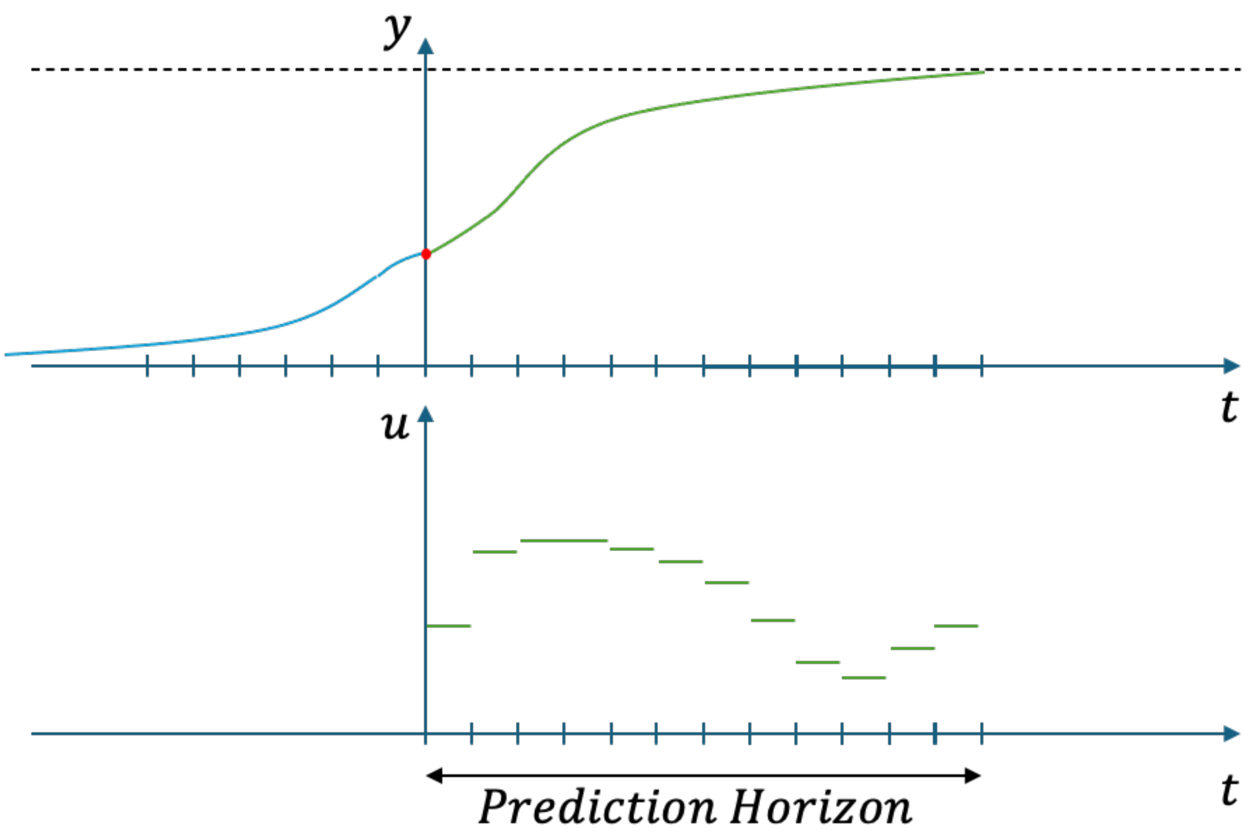
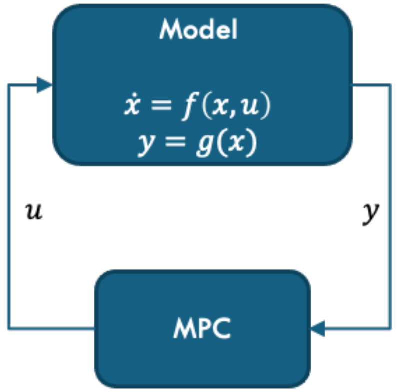
MPC





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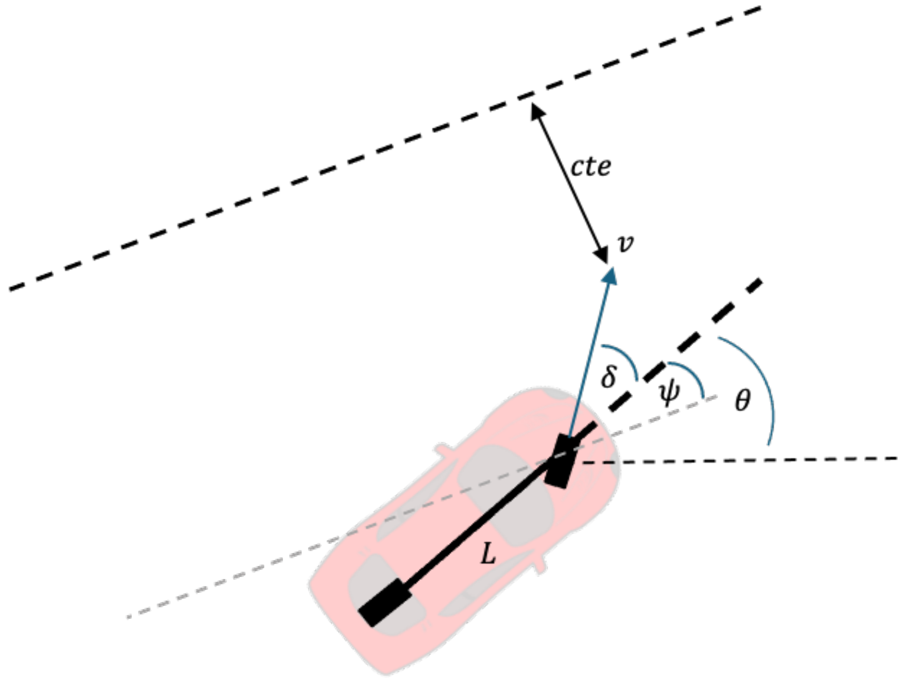
MPC

What we optimize?

$$
\begin{aligned}
Cost = & 50\Sigma_{k\in N} e_k^2 + 100\Sigma_{k\in N}\psi_k^2 + \\
& 100\Sigma_{k\in N}(v_{ref} - v_k)^2 + 100\Sigma_{k\in N}\delta_k^2 + \\
& 1\Sigma_{k\in N} a_k^2 + 200\Sigma_{k\in N}(\delta_k - \delta_{k-1})^2 + \\
& 10\Sigma_{k\in N}(a_k - a_{k-1})^2,
\end{aligned}
$$



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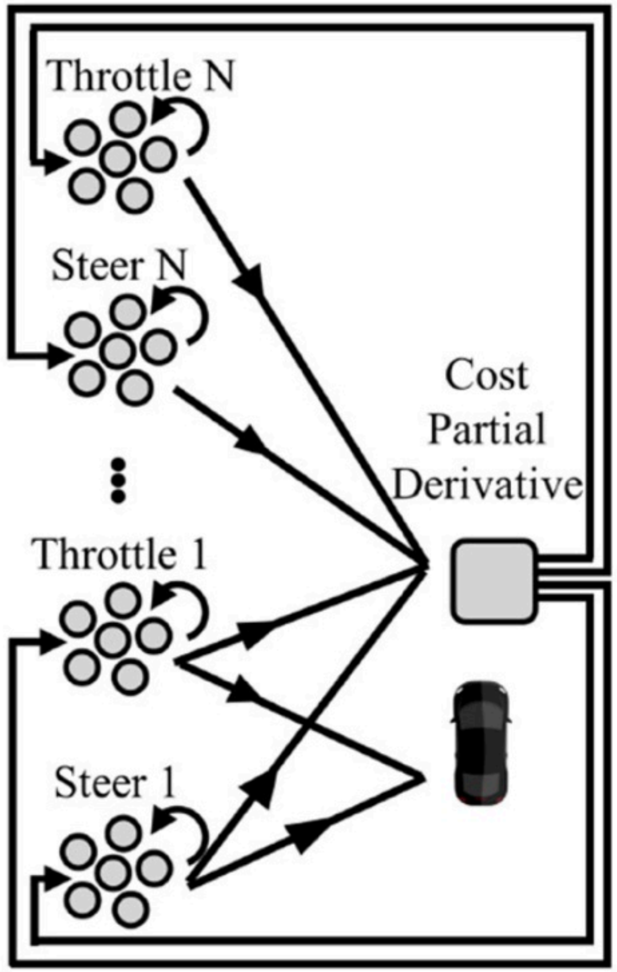
MPC

How we optimize?

$$\frac{\partial f}{\partial x_k} = \frac{f(x_1, ..., x_k - \varepsilon, ..., x_n) - f(x_1, ..., x_k, ..., x_n)}{\varepsilon}$$

- 2N (throttle and steering) ensembles for n predictions
- Each ensemble was defined as an integrator with a recurrent synapse, which acts as a memory.
- All ensembles were connected through synapses to a CPU block that calculates the cost function.
- A CPU node applied root mean squared propagation (RMSprop) on the estimated partial derivative of the cost function.



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RESULTS (manuscript)

Live Examples

MPC with KBM

Neuromorph. Comput. Eng. **4** (2024) 024006 https://doi.org/10.1088/2634-4386/ad4209

NEUROMORPHIC
Computing and Engineering

Continuous adaptive nonlinear model predictive control using spiking neural networks and real-time learning

Raz Halaly and Elishai Ezra Tsur*

Neuro-Biomorphic Engineering Lab, Open University of Israel, Ra'anana, Israel
* Author to whom any correspondence should be addressed.

We tested our design with various vehicles (from a Tesla Model 3 to an Ambulance) experiencing malfunctioning and swift steering scenarios.

We demonstrate significant improvements in dynamic error rate compared with traditional MPC implementation with up to 89.15% median prediction error reduction with 5 spiking neurons and up to 96.08% with 5,000 neurons.

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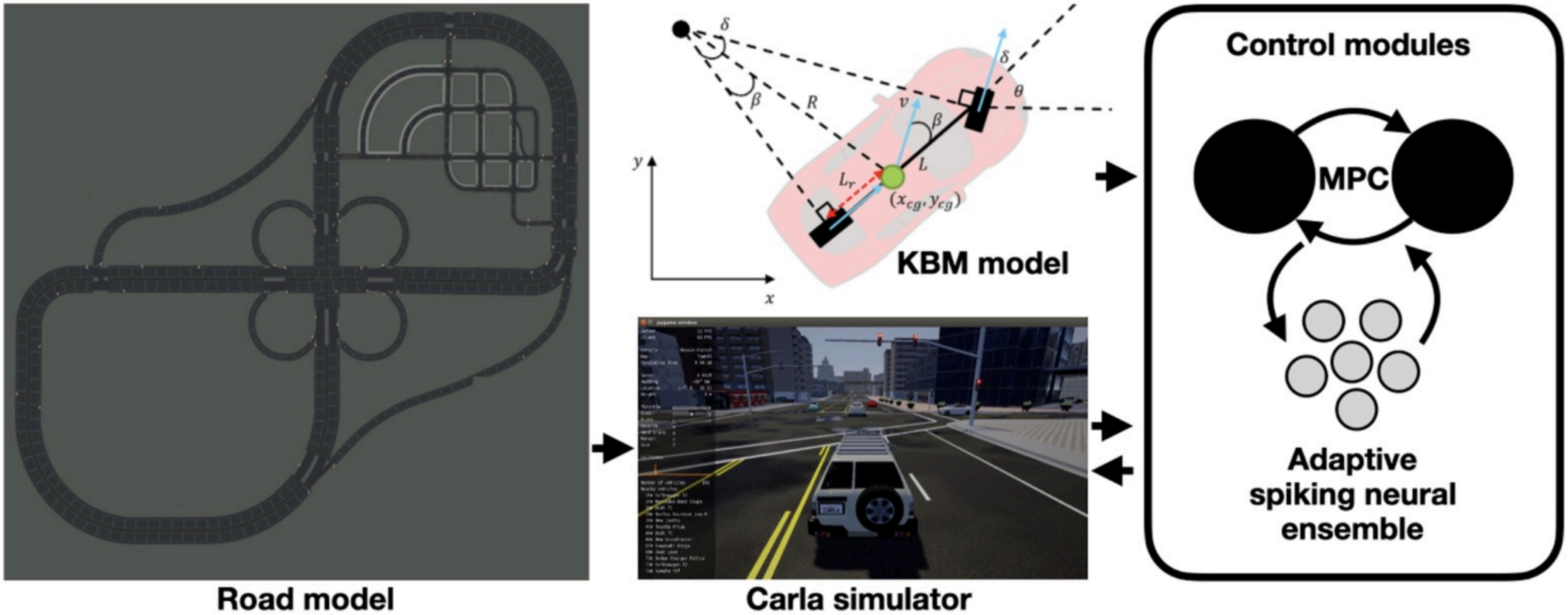
Continuous adaptive nonlinear model predictive control using spiking neural networks and real-time learning



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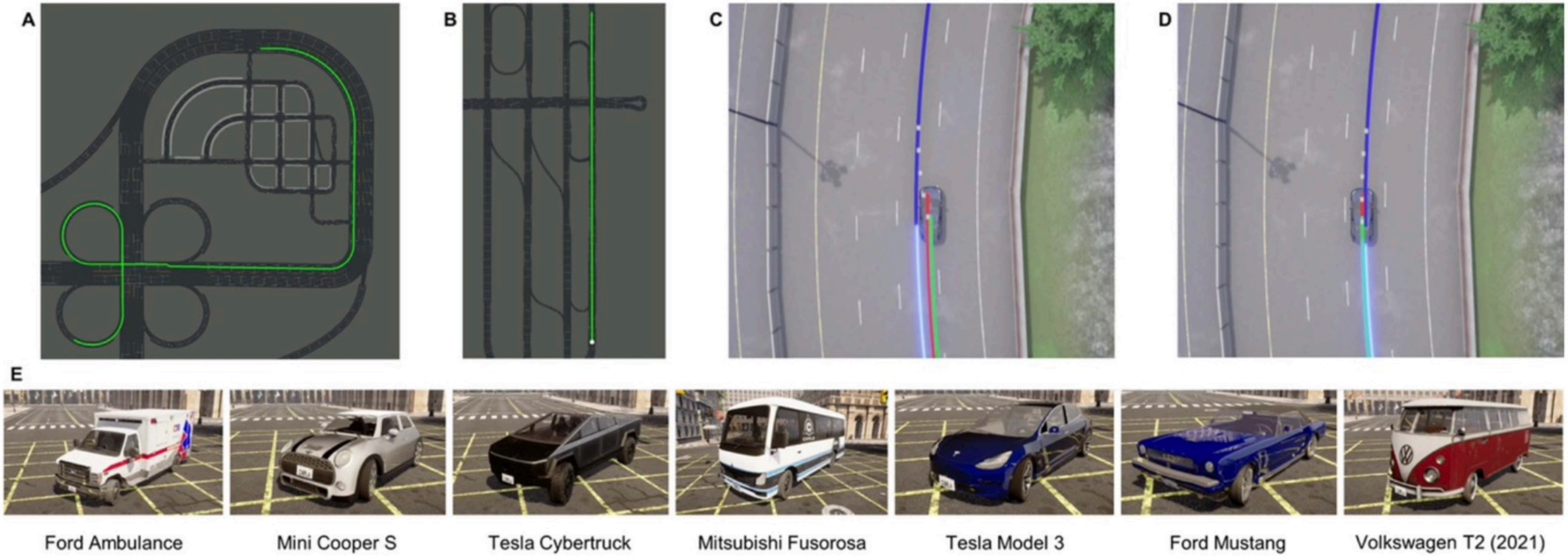
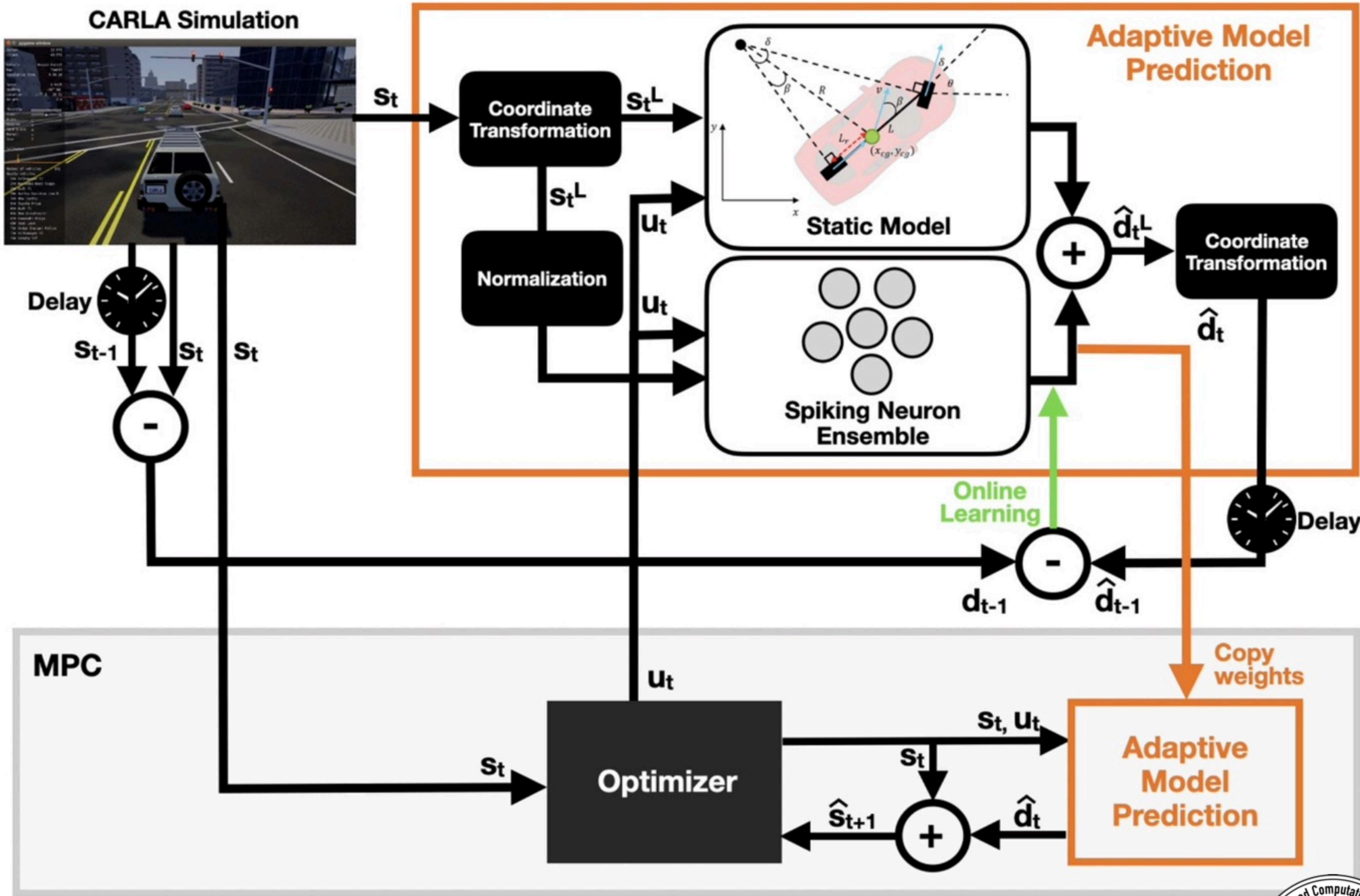
Continuous adaptive nonlinear model predictive control using spiking neural networks and real-time learning



NEURO-BIOMORPHIC ENGINEERING LAB

Neuro-Inspired Computational Elements
NICE 2025



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Scenarios

Normal Driving | Malfunctional Steering | Swift Changes

Metrics

Dynamics Error | CTE | Driving Smoothness

RESULTS (manuscript)