GECCO

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Enhancing a Model-Free Adaptive Controller through Evolutionary Computation

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Aquatic Robots

Practical uses

- autonomous mobile sensors
- biological studies (elicit natural behaviors)

Research platform

Simple physical design (relatively)

– few actuators

Nonlinear environment

– changing currents

Complex dynamics

– flexible fins

Focus on Control

We'd like controllers to:

1. match oscillating frequency with material properties
2. handle changes in the environment
3. handle changes to the robotic device
4. …unknown conditions?

We do not want to account for these by hand

- Leads us to adaptive control

Adaptive Control

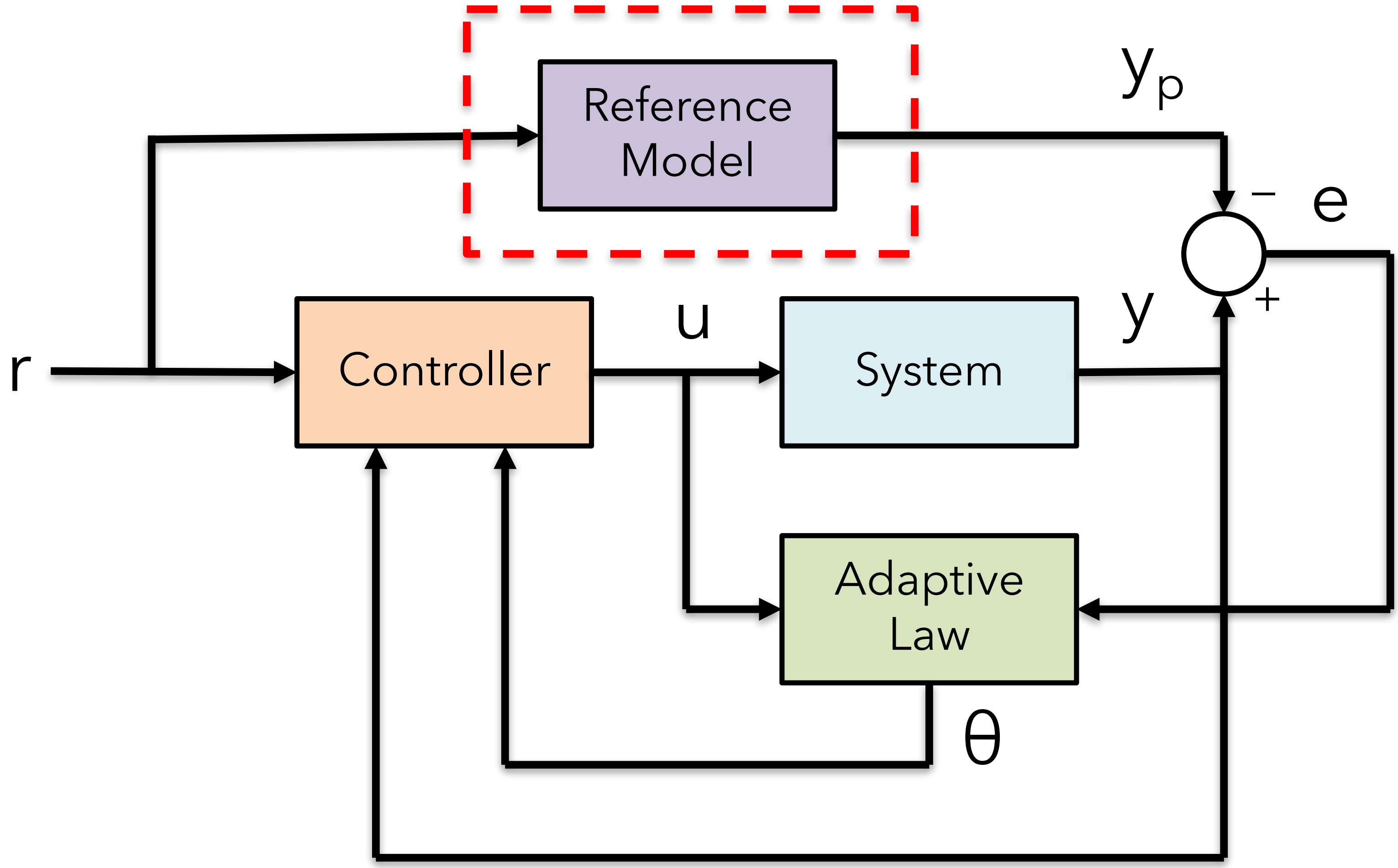
Model-based

- require a <u>precise</u> model
- perform parameter identification

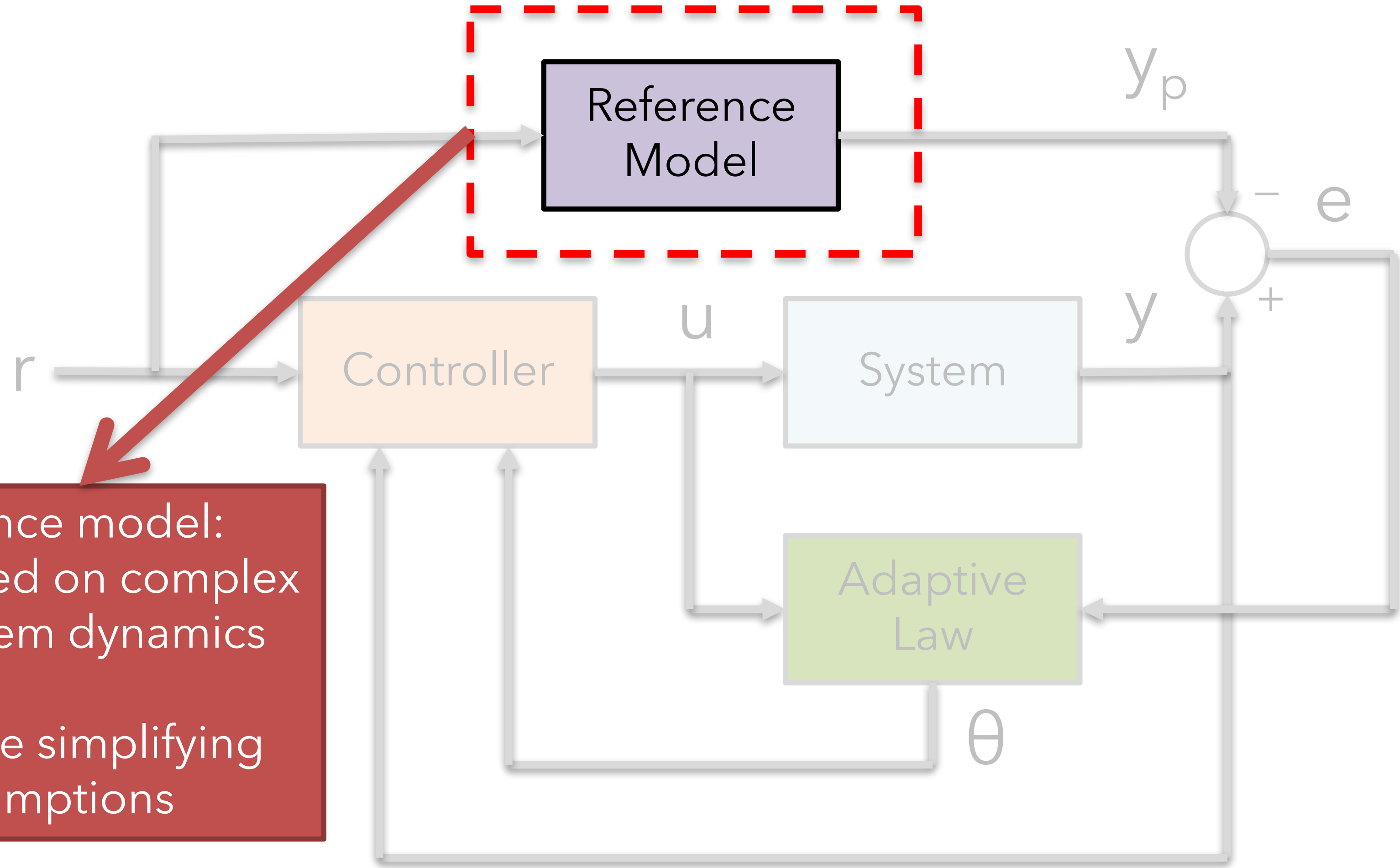
Data-driven

- model-free
- input / output data

Model-based Adaptive Control

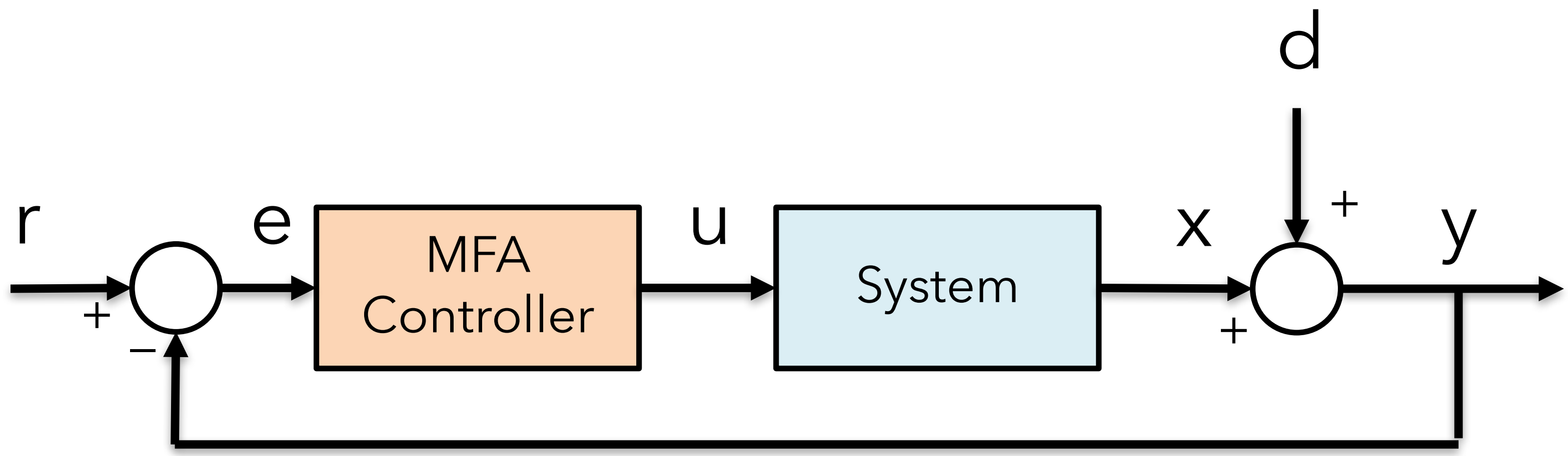


Model-based Adaptive Control



Reference model:
- based on complex system dynamics
- make simplifying assumptions

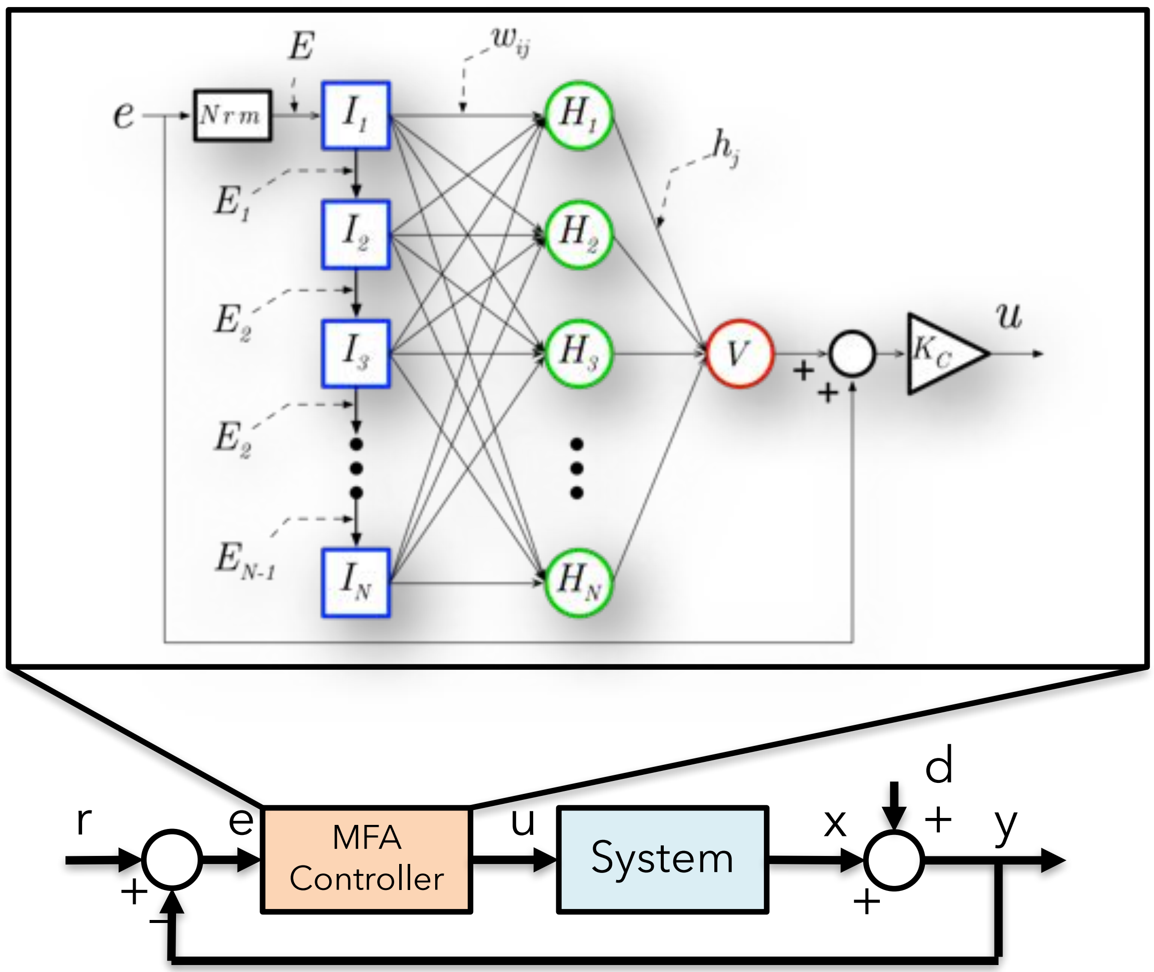
Model-free Adaptive Control



For "gray-box" situations

– partial / incomplete information known about the system

Model-free Adaptive Control



Model-free Adaptive Control

What do we gain?

1. do <u>not</u> have to create a dynamic model
2. adapts to changing internal dynamics
3. adapts to noisy environment
4. adapts to varying high-level control input

What are the drawbacks?

1. less precise
2. still need to specify a number of parameters
   - ANN topology, learning rate, gain values, error bounds, activation timing, network bias values

This Study

Exploit EC to Enhance

an MFAC

- evolve MFAC parameters
- controlling a robotic fish
- adapt to:
  - changing fin flexibilities
  - changing fin length
  - changing control demands

MFAC vs. Neural Plasticity

Plastic neural networks

- will generally learn (or transition to) a new behavior
- merge high-level logic and low-level control

Adaptive controllers

- regulate a control signal
- behaviors are still determined at a higher level

Adaptive Neural Network

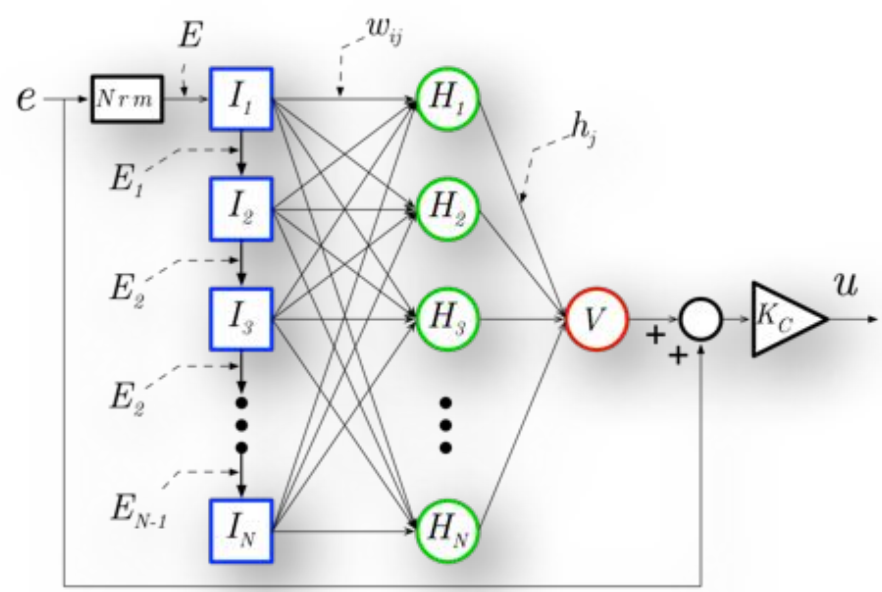
Network Activation

- feed-forward network
- propagated error
- sigmoid activation

Network Update

- minimize error

$$E_s(t) = \frac{1}{2}\, e(t)^2$$



Adaptive Neural Network

$$
\begin{aligned}
\Delta w_{ij}(n) &\propto \frac{\partial E_s}{\partial w_{ij}}, \\
&= \frac{\partial E_s}{\partial y}\frac{\partial y}{\partial w_{ij}}, \\
&= \frac{\partial E_s}{\partial y}\frac{\partial y}{\partial u}\frac{\partial u}{\partial w_{ij}}, \\
&= \frac{\partial E_s}{\partial y}\frac{\partial y}{\partial u}\frac{\partial u}{\partial o}\frac{\partial o}{\partial w_{ij}}, \\
&= \frac{\partial E_s}{\partial y}\frac{\partial y}{\partial u}\frac{\partial u}{\partial o}\frac{\partial o}{\partial q}\frac{\partial q}{\partial w_{ij}}, \\
&= \frac{\partial E_s}{\partial y}\frac{\partial y}{\partial u}\frac{\partial u}{\partial o}\frac{\partial o}{\partial q}\frac{\partial q}{\partial p}\frac{\partial p}{\partial w_{ij}}. \\
&= -\eta\, K_c\, S_f(n)\, e(n)\, q_j(n)\,(1 - q_j(n))\, E_i(n) \sum_{k=1}^{N} h_k(n),
\end{aligned}
$$

$$
\begin{aligned}
\Delta h_j(n) &\propto \frac{\partial E_s}{\partial h_j}, \\
&= \frac{\partial E_s}{\partial y}\frac{\partial y}{\partial h_j}, \\
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&= -\eta\, K_c\, S_f(n)\, e(n)\, q_j.
\end{aligned}
$$

Simulation

Task

- Swim at a given speeds

Optimize

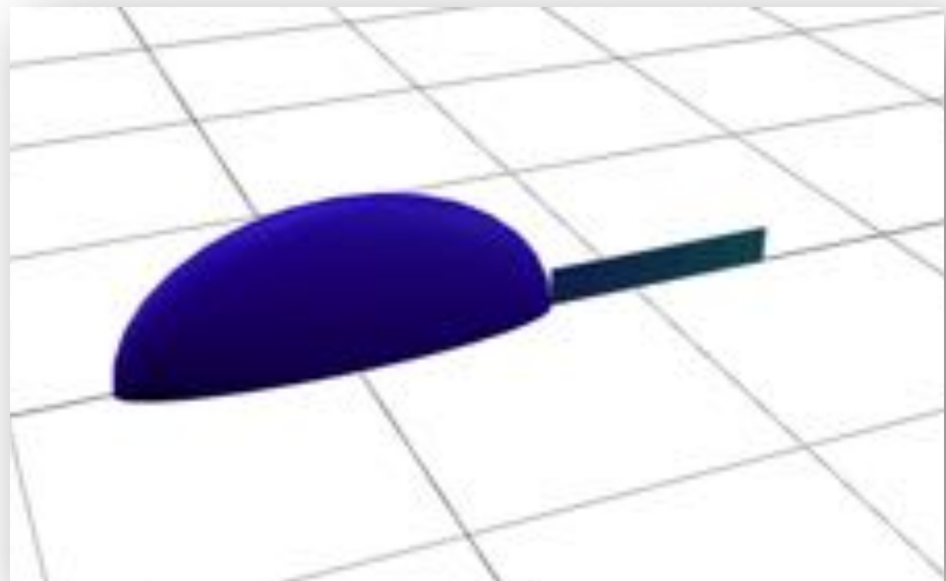
- MFAC parameters

Adapt to:

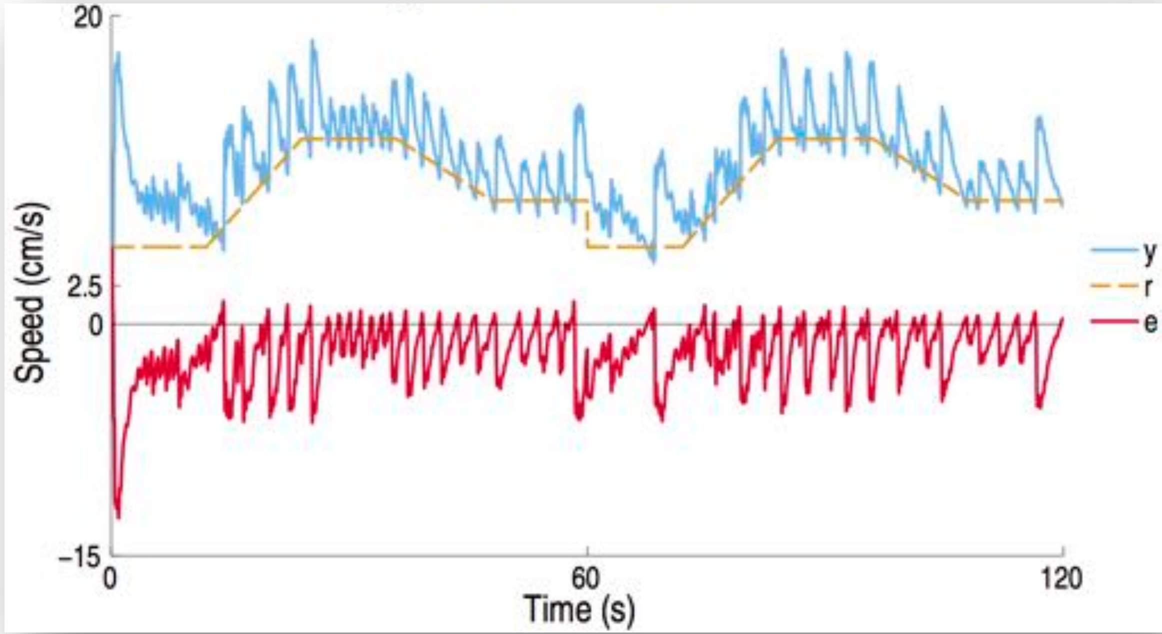
- different control signals
- changing fin flexibilities
- changing fin lengths

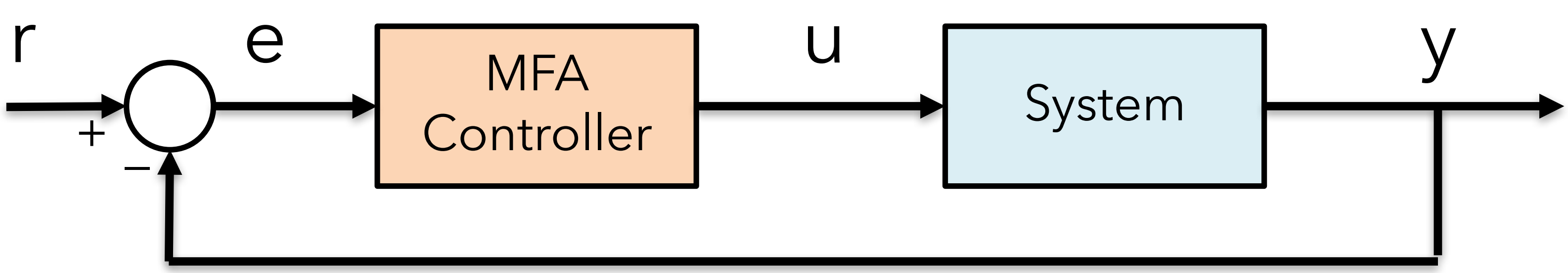
Evaluation

- simulate for **60 seconds**
- mean absolute error

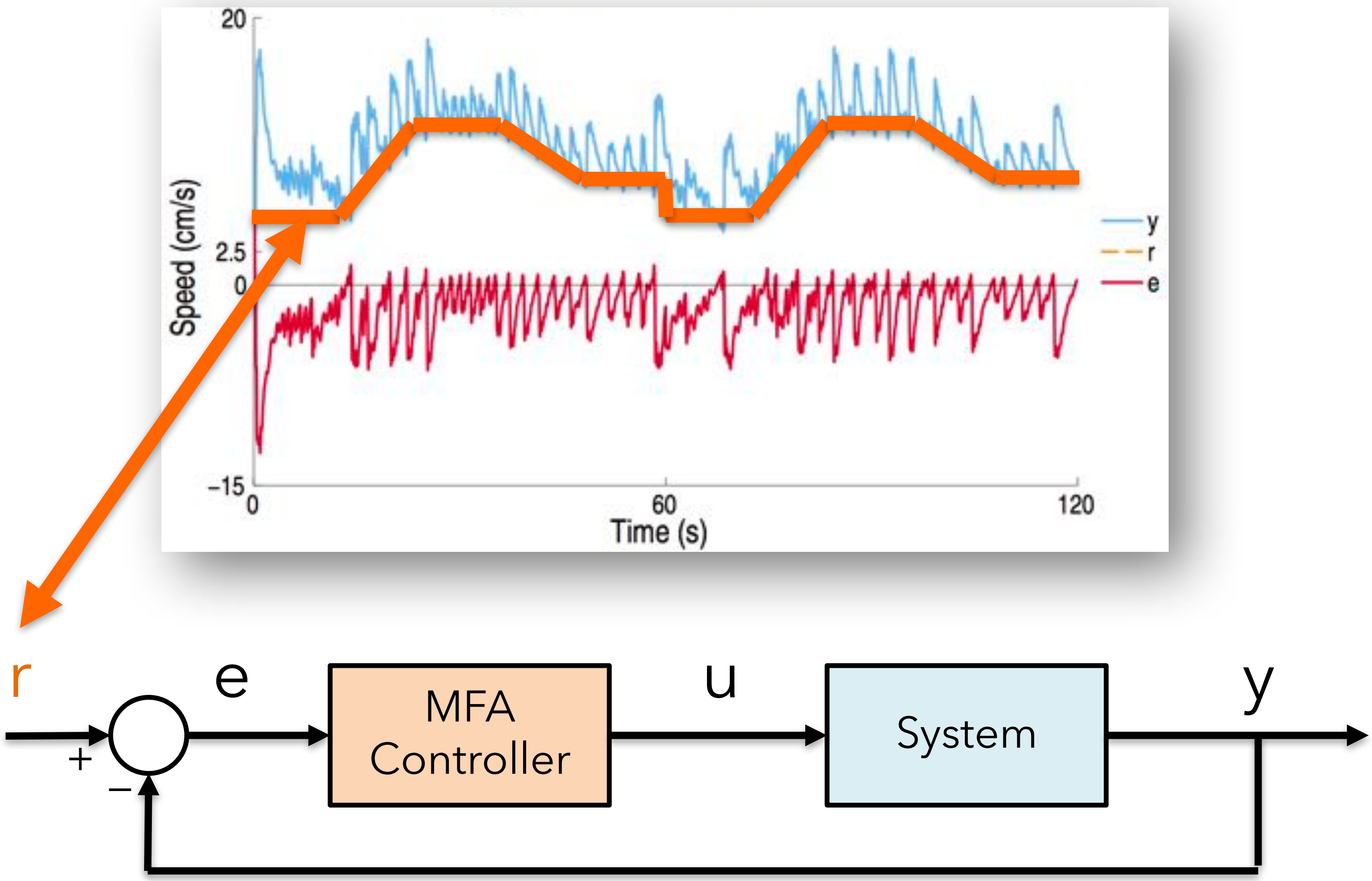


Baseline Experiment





Baseline Experiment



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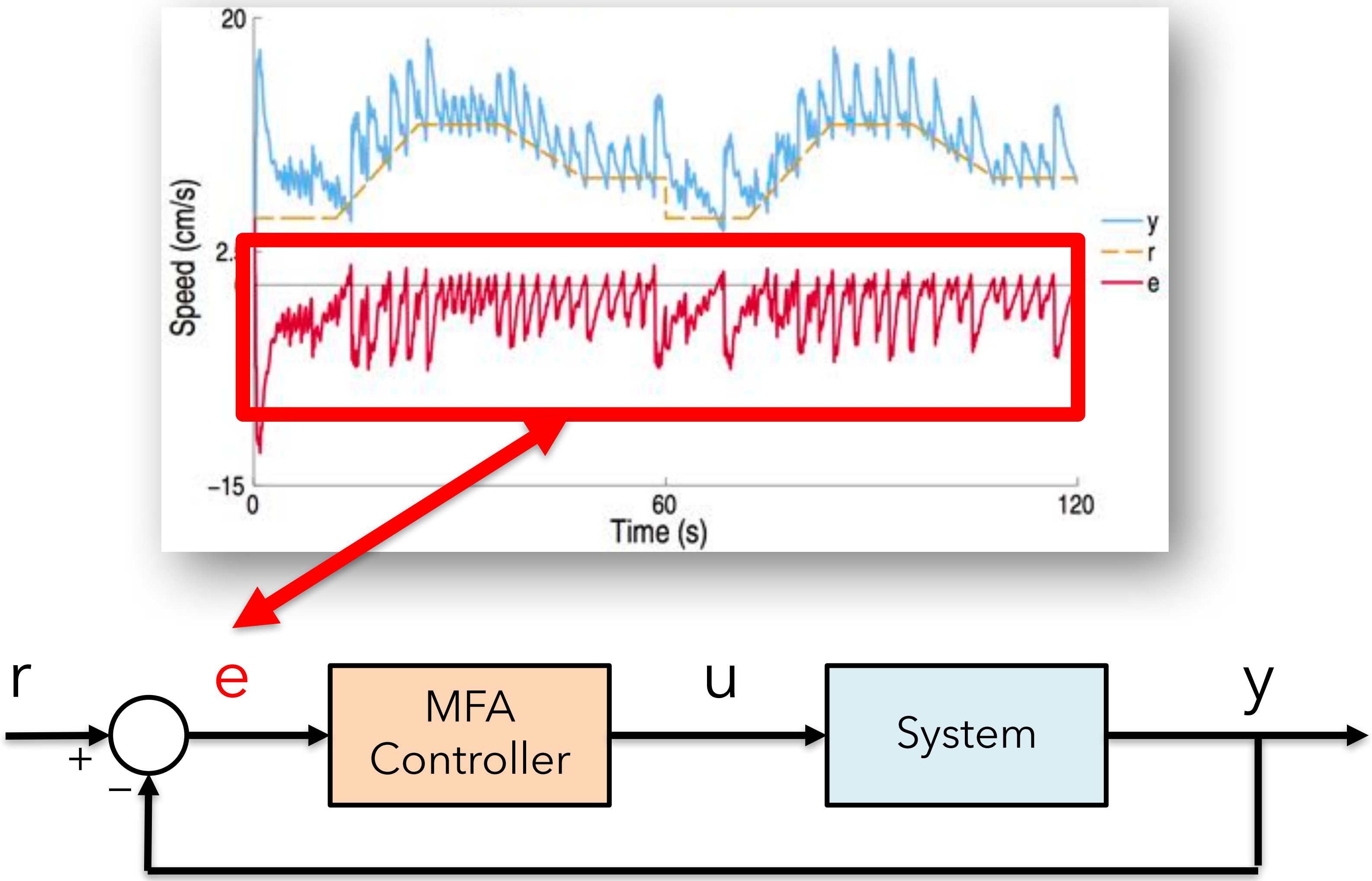
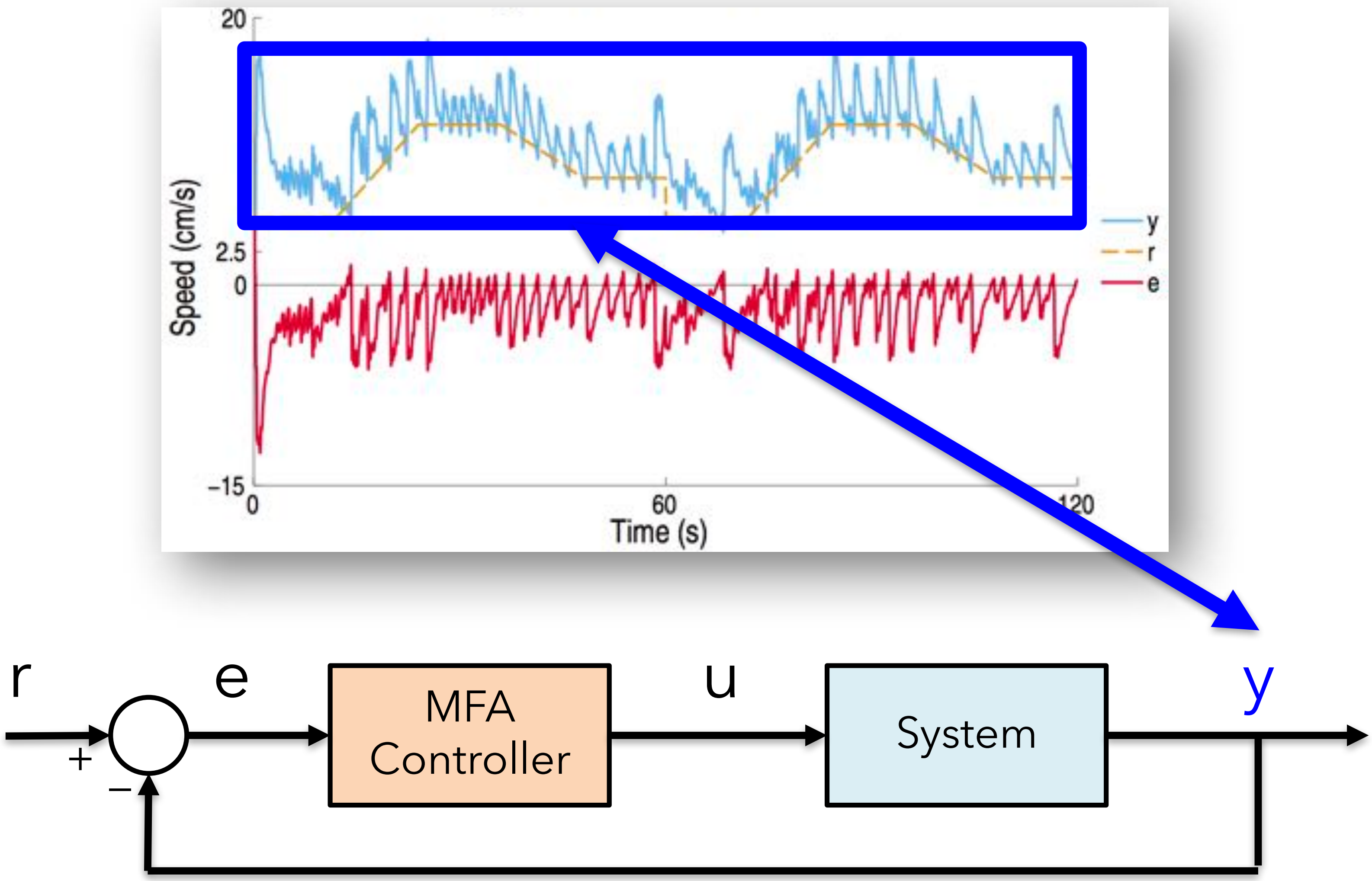
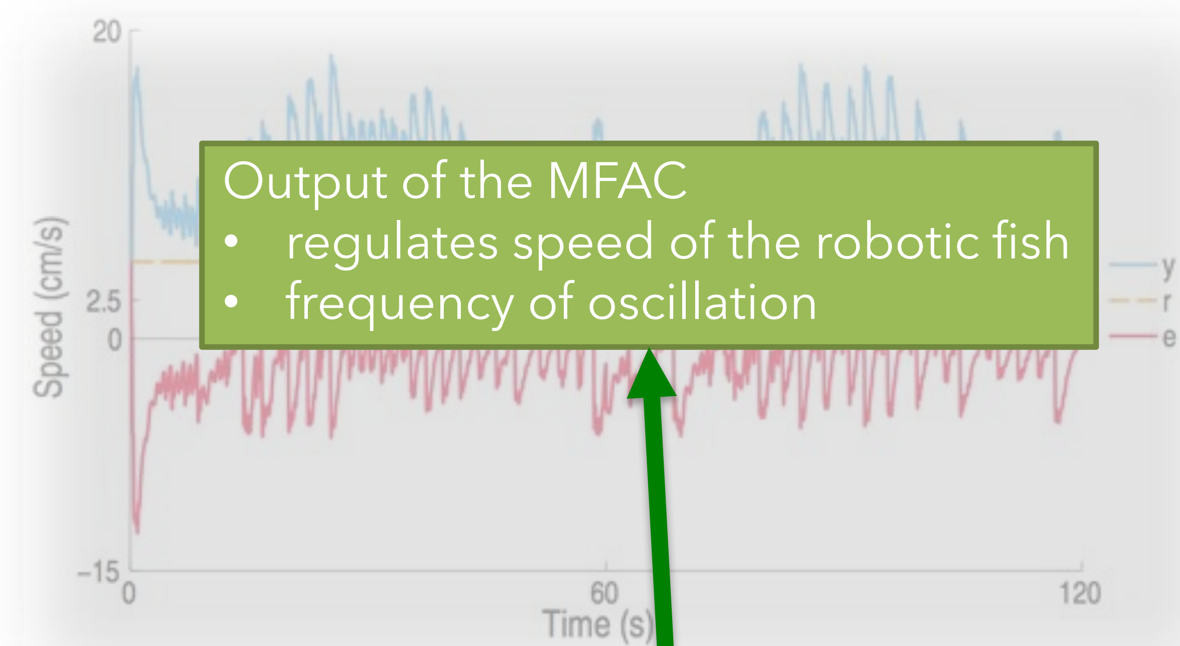


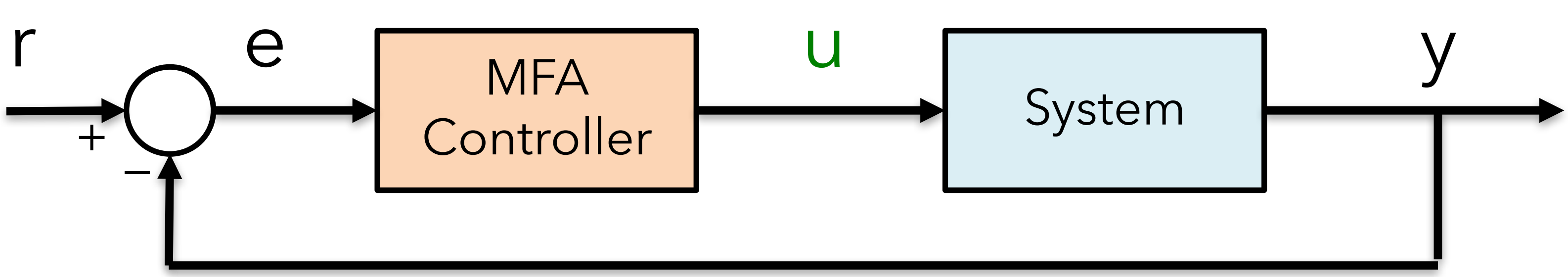
Baseline Experiment



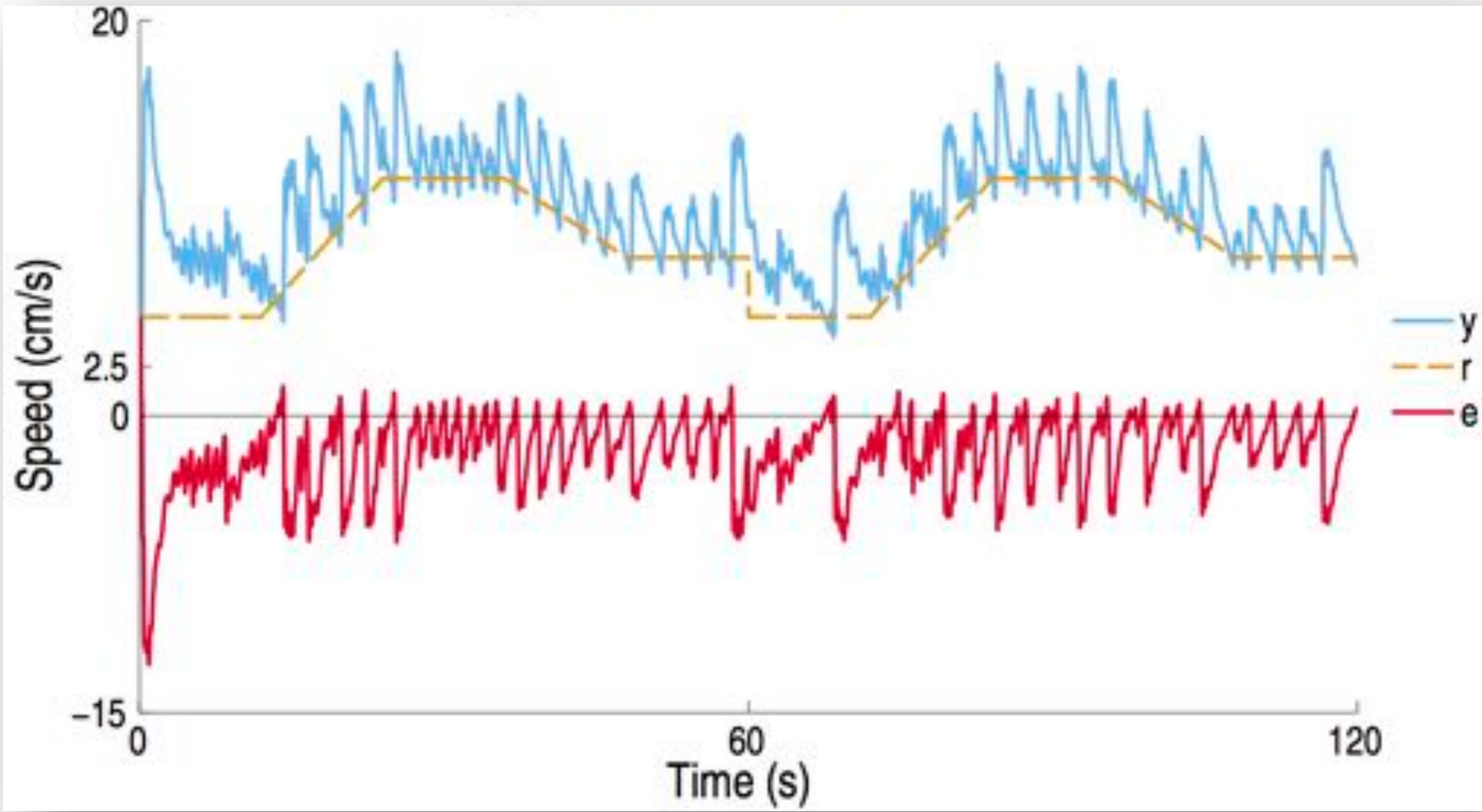
Baseline Experiment



Output of the MFAC
- regulates speed of the robotic fish
- frequency of oscillation



Baseline Experiment



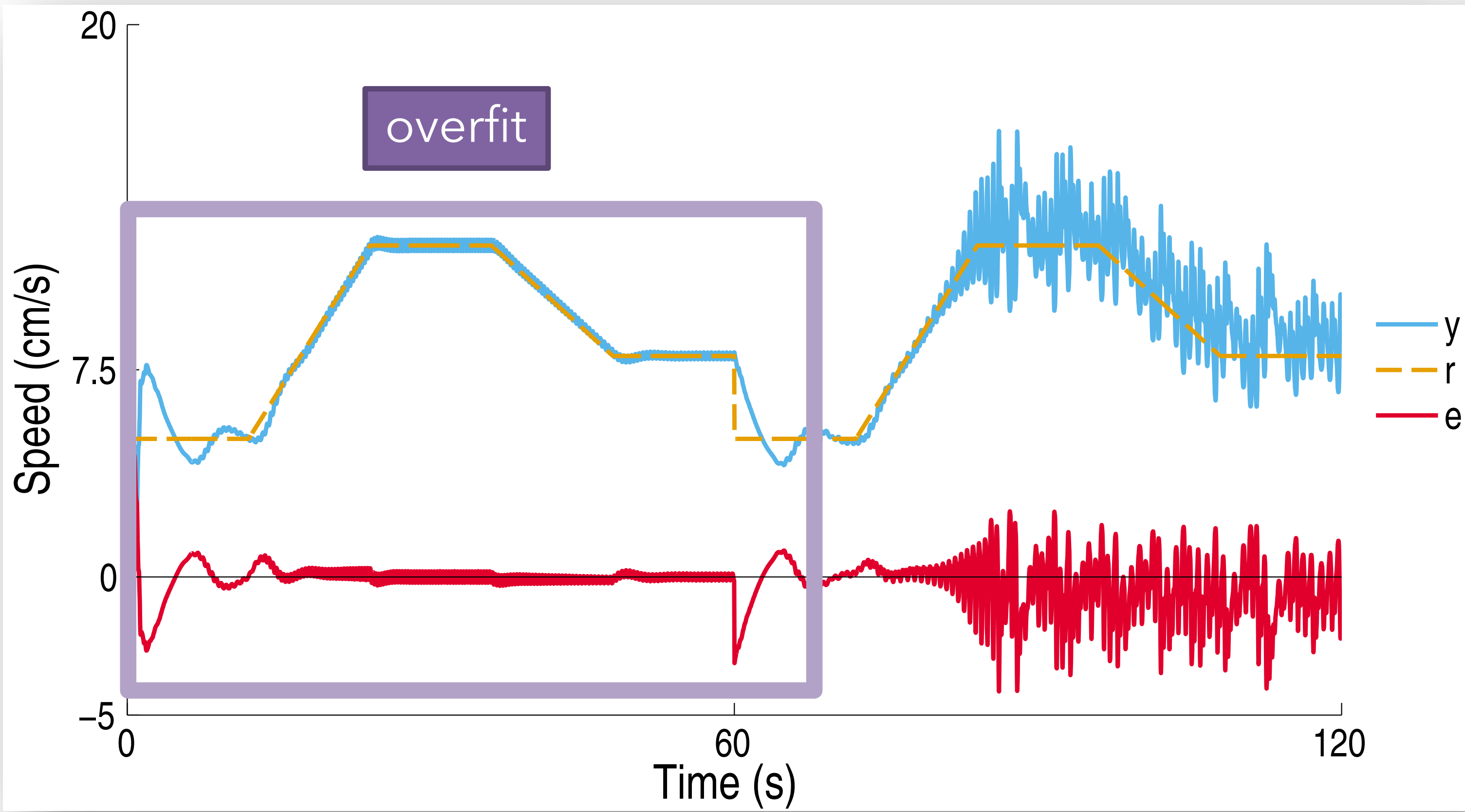
Differential Evolution

Evolutionary algorithm for real-valued problems

Evolved parameters

- neural network size
- learning rate
- upper and lower error bounds
- controller gain
- controller update timing

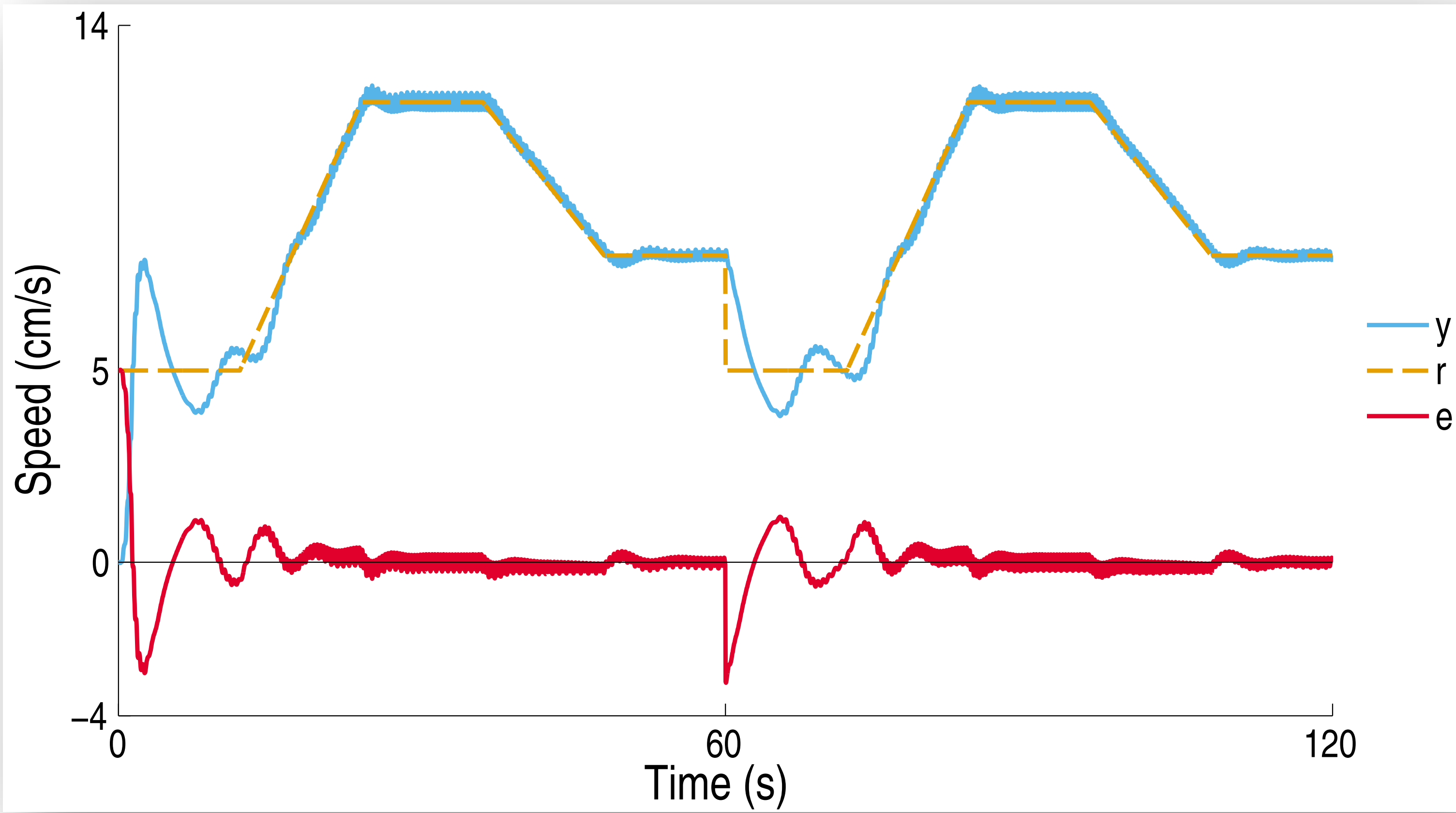
Single Evaluation Experiment



Multiple Evaluations

Trial	Flexibility	Length
sim1	100 %	100 %
sim2	200 %	100 %
sim3	50 %	100 %
sim4	100 %	110 %
sim5	200 %	110 %
sim6	50 %	110 %
sim7	100 %	90 %
sim8	200 %	90 %
sim9	50 %	90 %

Multiple Evaluations Experiment



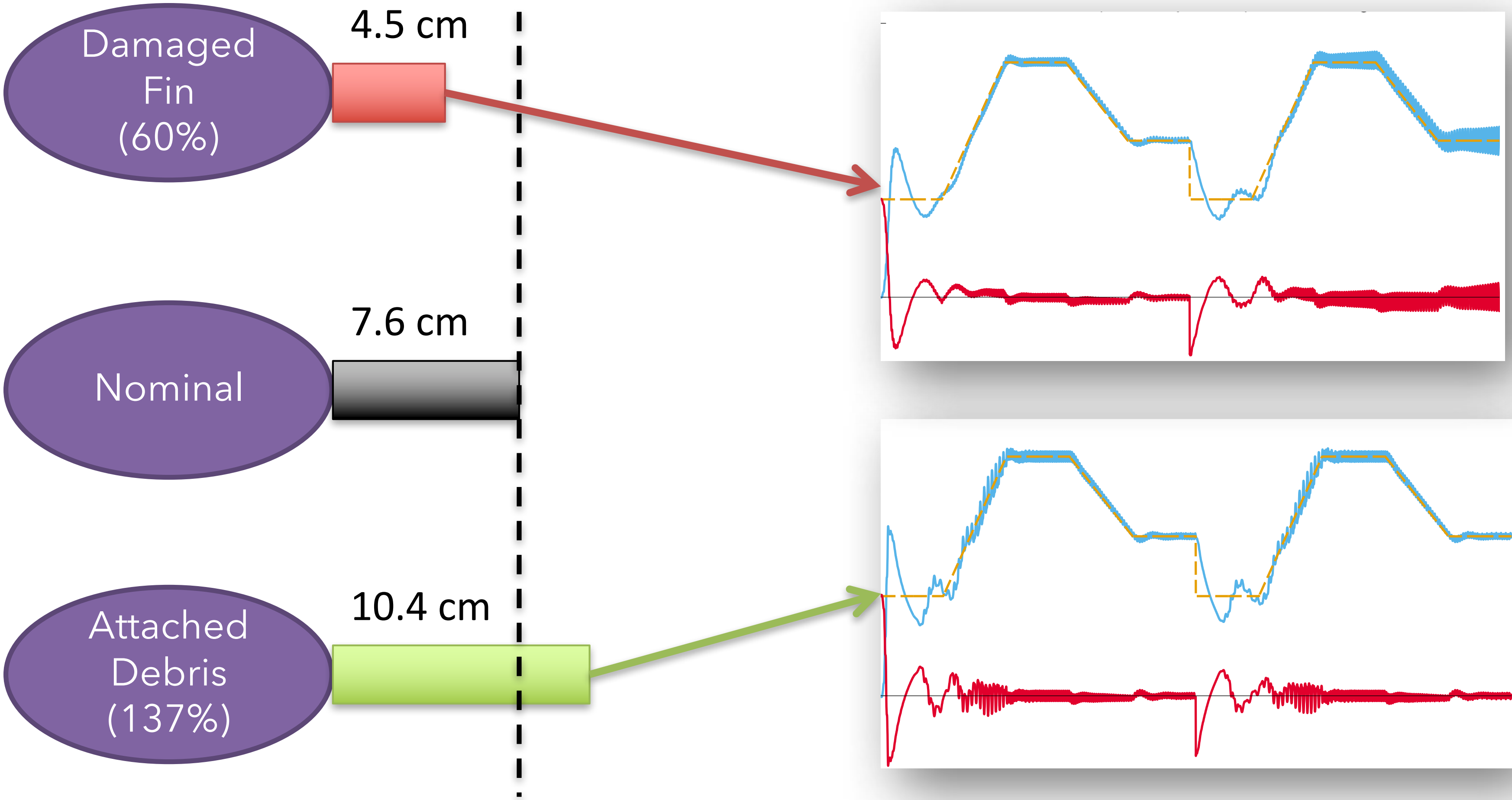
Goals of the Study

We want to adapt to:

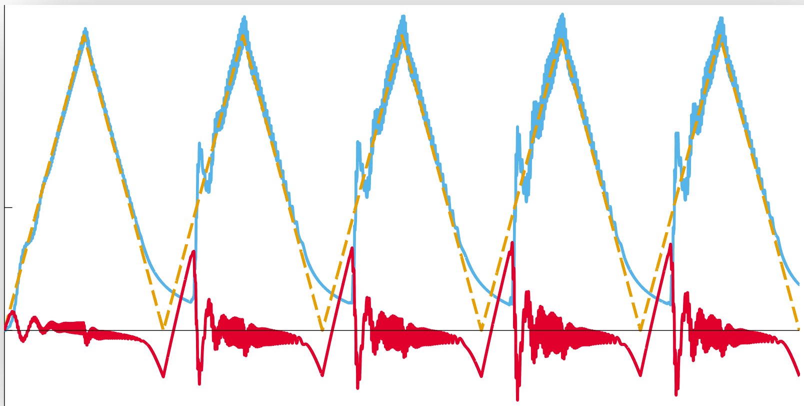
- changing fin flexibilities
- changing fin length
- changing control signal dynamics

- any <u>combination</u> of the above changes

Fin Length



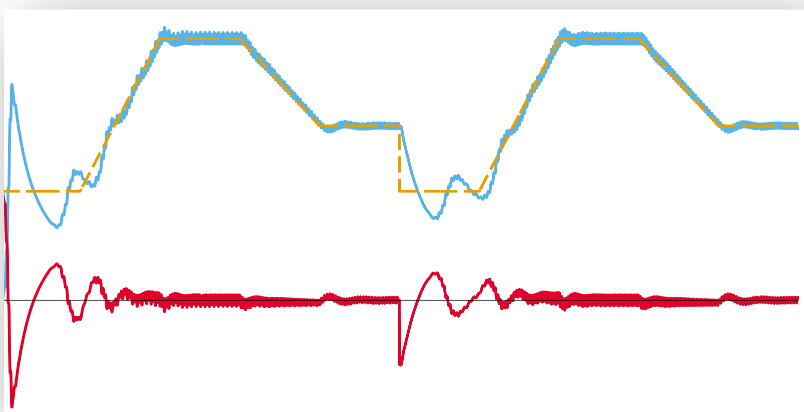
Control and Flexibility



Different speeds

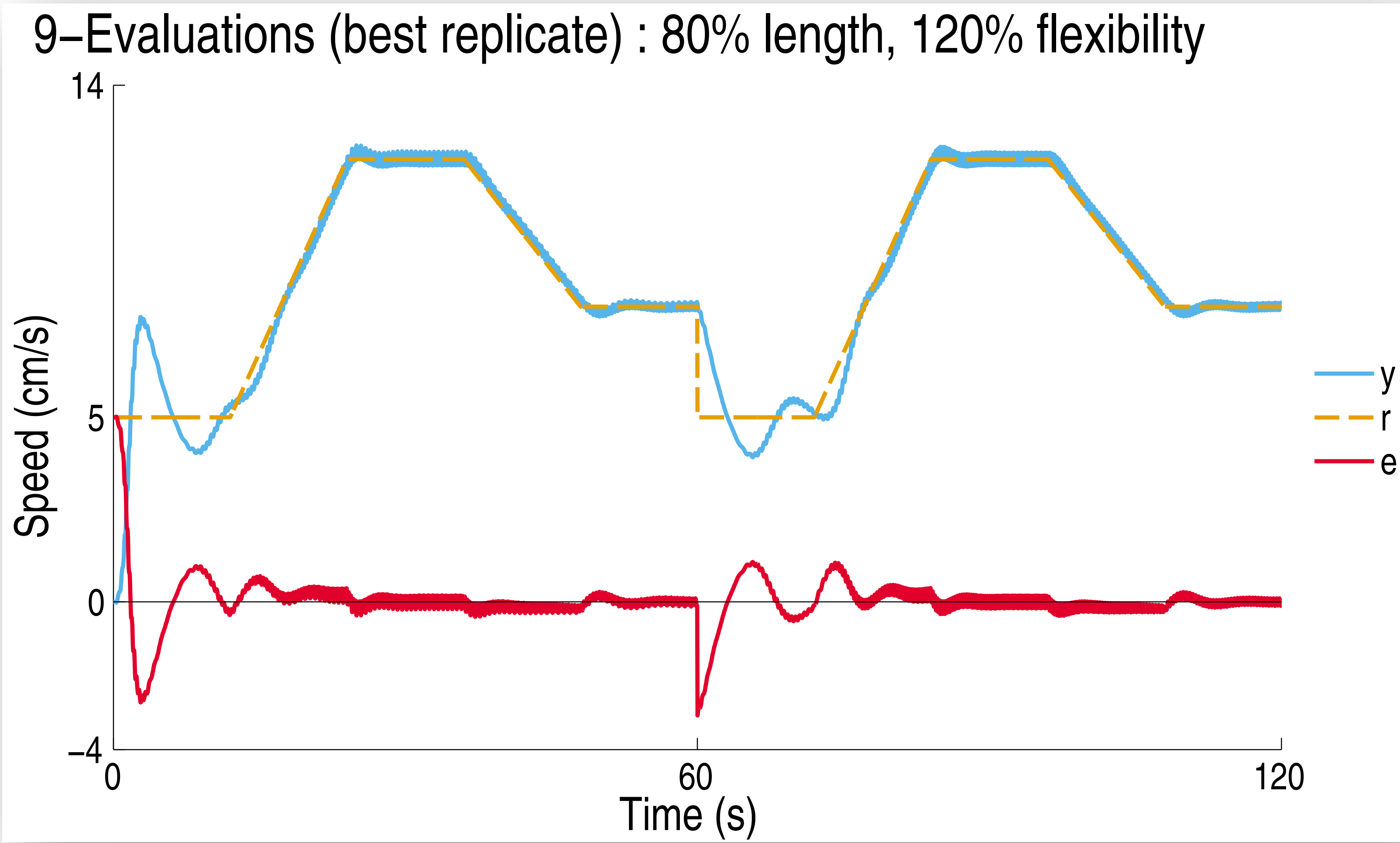
Different accelerations

Different decelerations



Flexibility of 150% compared to the nominal value

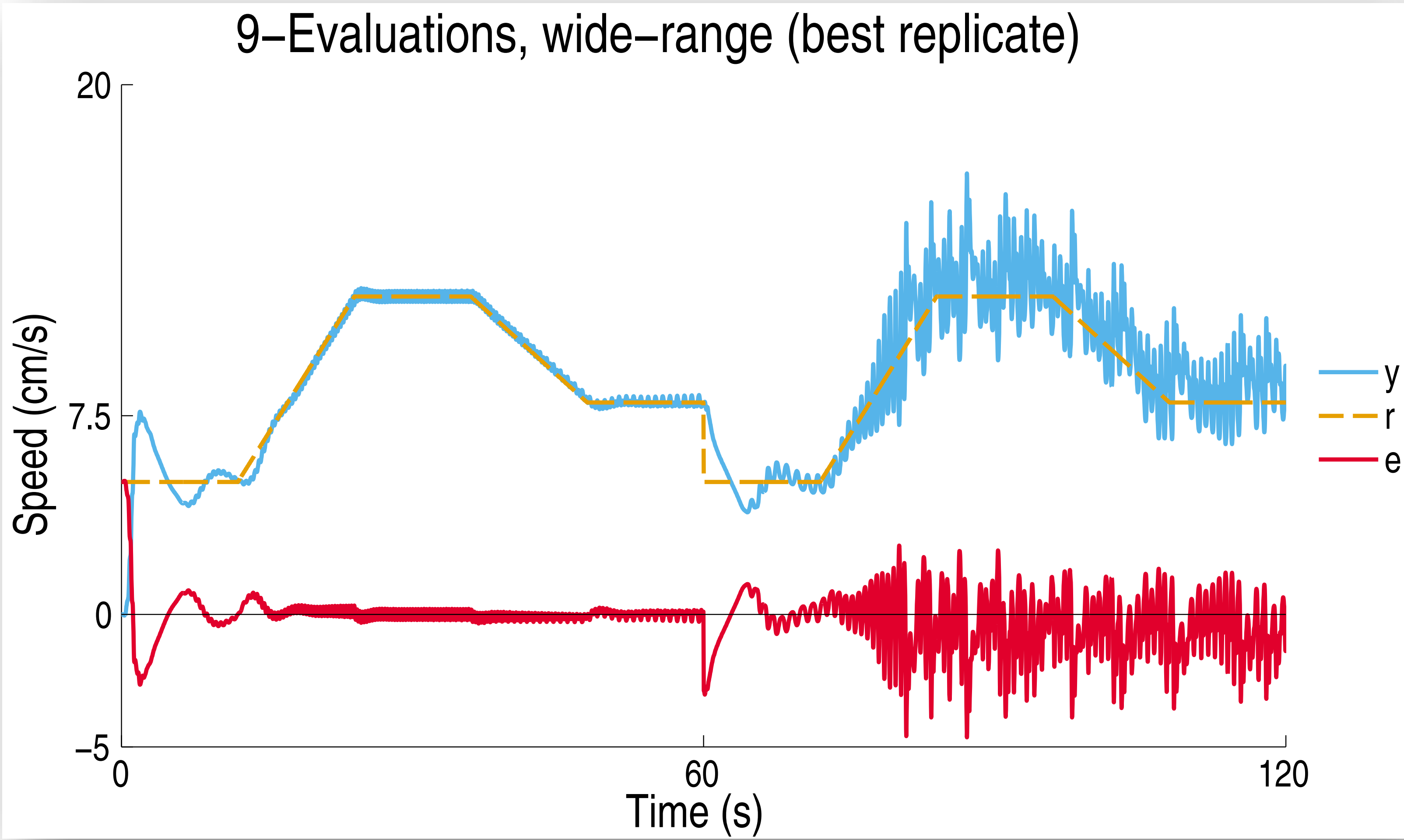
Simultaneous Changes



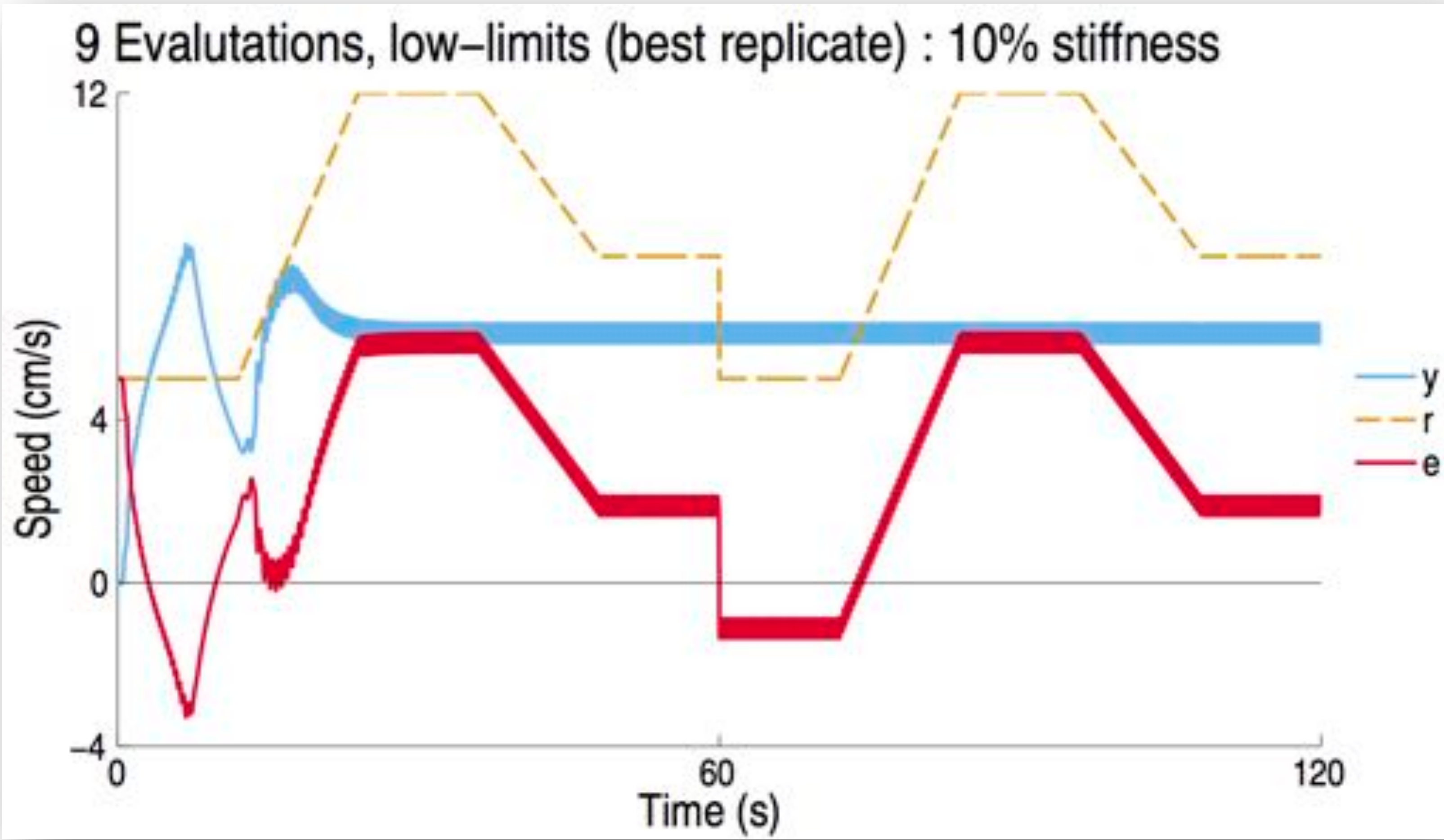
Extended Multiple Evaluations

Trial	Flexibility	Length
sim1	100 %	100 %
sim2	200 % → 1000 %	100 %
sim3	50 % → 10 %	100 %
sim4	100 %	110 % → 200 %
sim5	200 % → 1000 %	110 % → 200 %
sim6	50 % → 10 %	110 % → 200 %
sim7	100 %	90 % → 67 %
sim8	200 % → 1000 %	90 % → 67 %
sim9	50 % → 10 %	90 % → 67 %

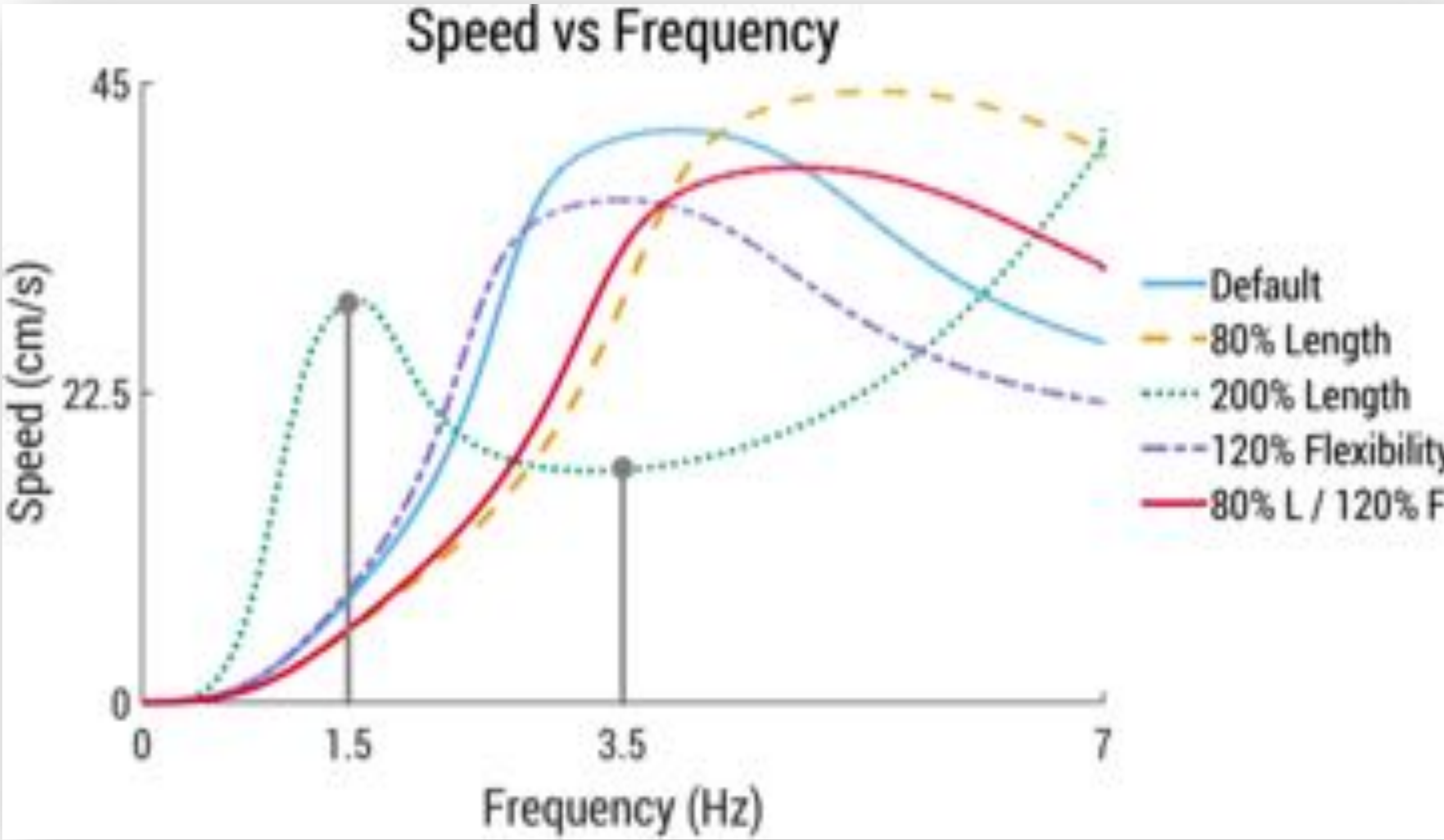
Increase Simulation Ranges



When Adaptation Breaks-Down



When Adaptation Breaks-Down



Key Points

1. Attained adaptability
   – to varying parameters for the robotic fish

2. Performance was easily better than expert chosen values

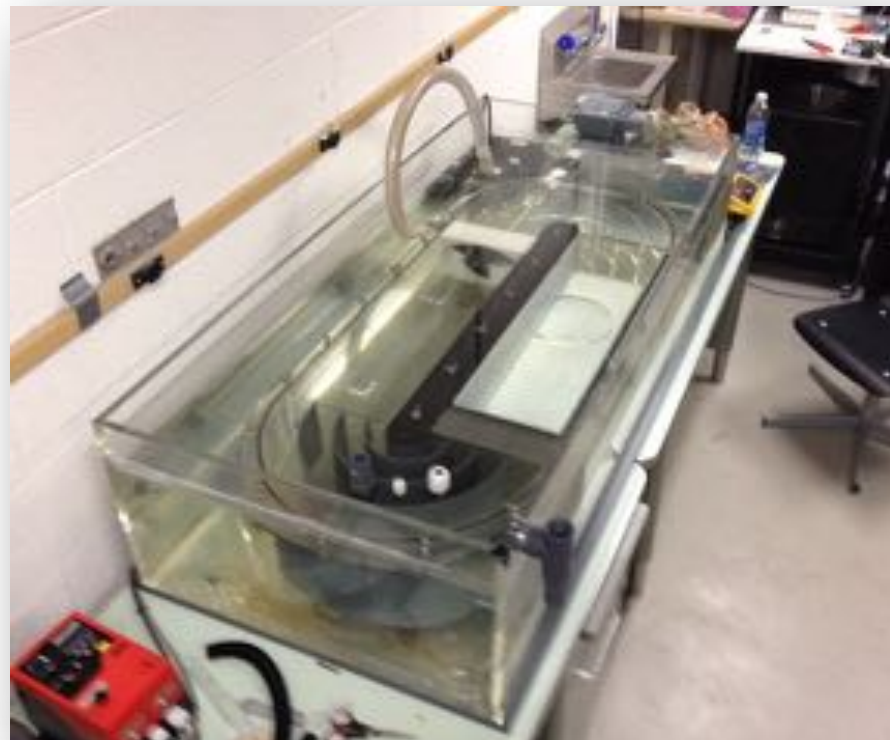
1. Envelope of adaptability
   – for evolution (tested values)
   – for operation (range of adaptability)

Ongoing Work

1. Integrate with high-level control
   – self-modeling takes over when adaptation fails

1. Multiple-input, Multiple-output
   – regulate speed and direction

1. Physical testing
   – perform adaptation online



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An NSF Center for the Study of Evolution in Action

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Uncertainty in Robotics

Materials

- materials changing with temperature
- flexibility changing due to water absorption

Hardware

- motors becoming less efficient

Environment

- transitioning from smooth to rough terrain

Address Uncertainty (1)

Mimicking biology

- biomimetic / bioinspired design
  - soft / flexible materials
- evolutionary design
  - evolutionary robotics and optimization
- evolving / learning behaviors
  - artificial neural networks (ANNs)
  - central pattern generators (CPGs)

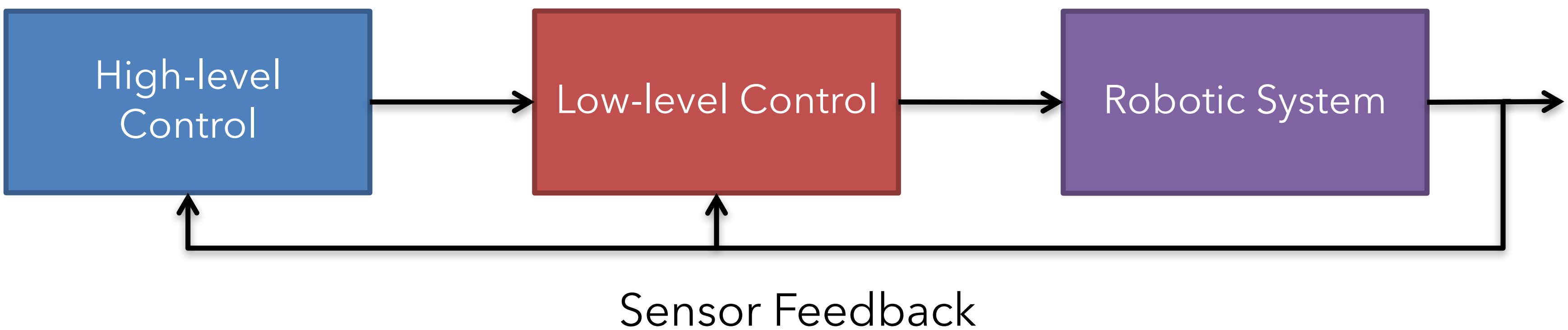
Address Uncertainty (2)

Complex (feedback) control strategies

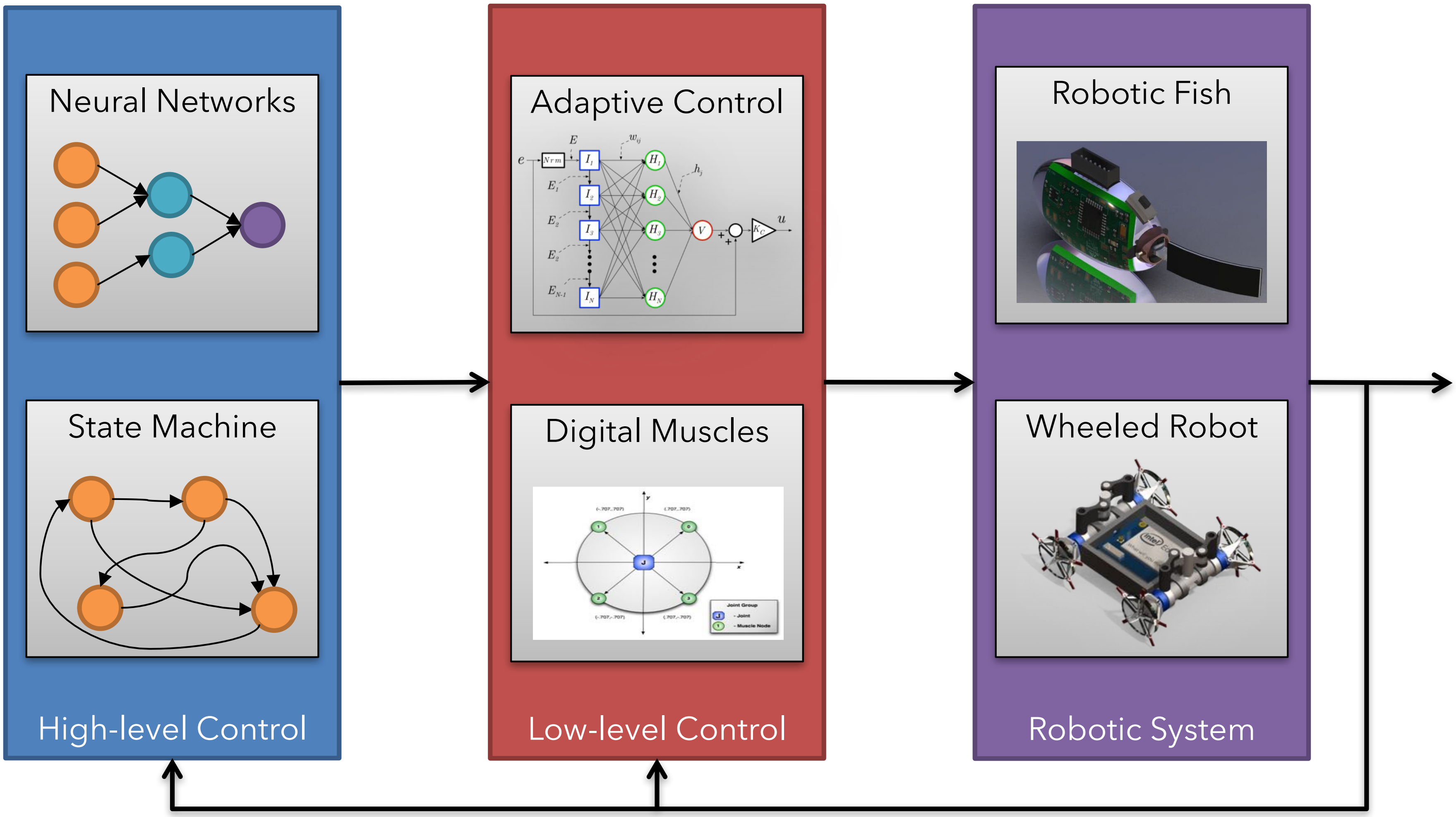
- robust control
  - handle a static range of uncertainty
  - robust to a noisy environment
- adaptive control
  - adapting to varying parameters
  - explicitly changes the controller's dynamics

Our Research

- Autonomous behaviors
- Feedback motor control
- Biomimetic robots



Our Research



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