Motivation

Goal: *Improve Autonomous Robot Control*

- Evolve adaptive control:
  - changes to a control signal
  - changes in the environment
  - changes in dynamics (morphology)

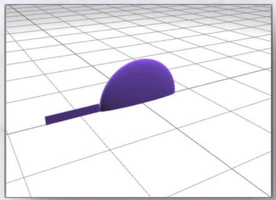
- Not behaviors

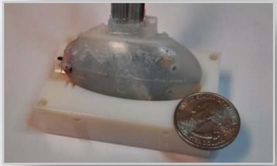
Motivation : Robotic Fish

Industrial

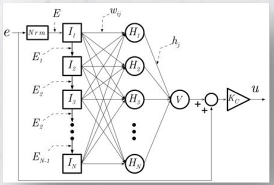
Biological

Outline

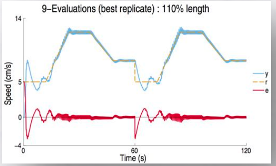


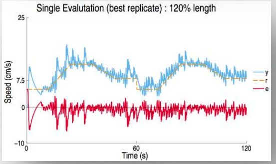


Robotic Fish Design

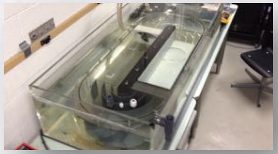


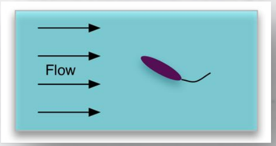
Adaptive Control



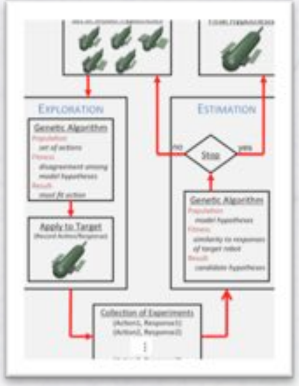


Velocity Study





Flow Tank Application



Future Work

Small Robotic Fish

- Stickleback size
  - robot : 7 cm
  - real : 4 to 6 cm
- Electrical components
  - 32-bit ARM μ-controller
  - 3-axis accelerometer
  - 3-axis gyroscope
  - 2 light sensors
  - 2.4 GHz wireless
  - magnetic motor
  - 1 hour battery life
  - **NOT** tethered

Design Process

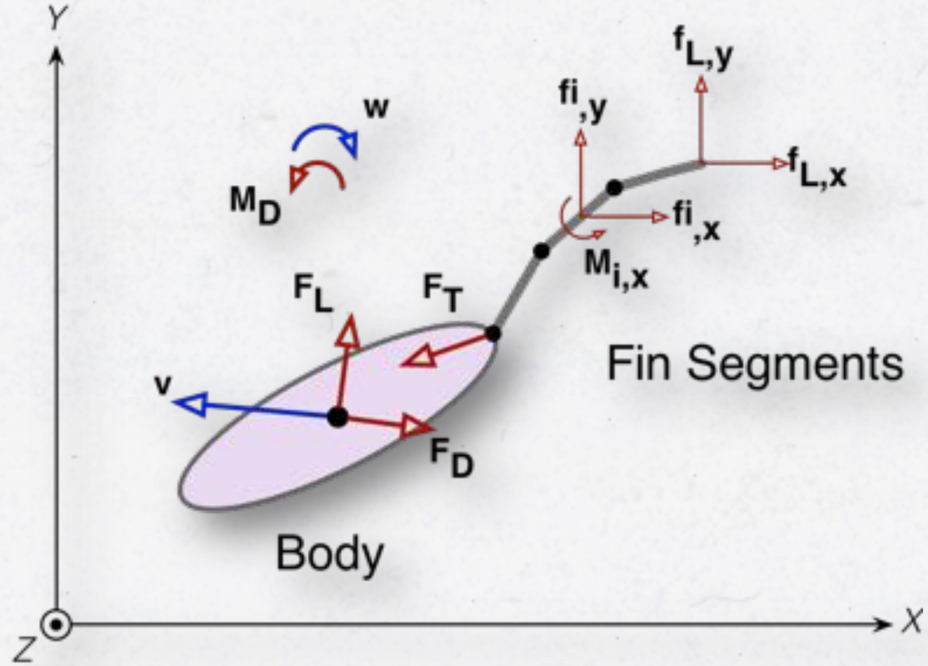
Robot Prototype

Design Process

Robot Prototype

↓

Dynamic Modeling



[Wang 2012, Clark 2012]

Design Process

Robot Prototype

↓

Dynamic Modeling

↓

Parameter Identification

Design Process

Robot Prototype

↓

Dynamic Modeling

↓

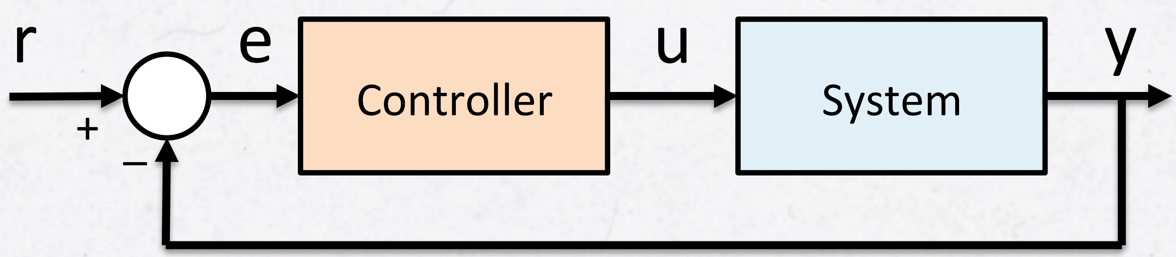
Parameter Identification

↓

Control Design

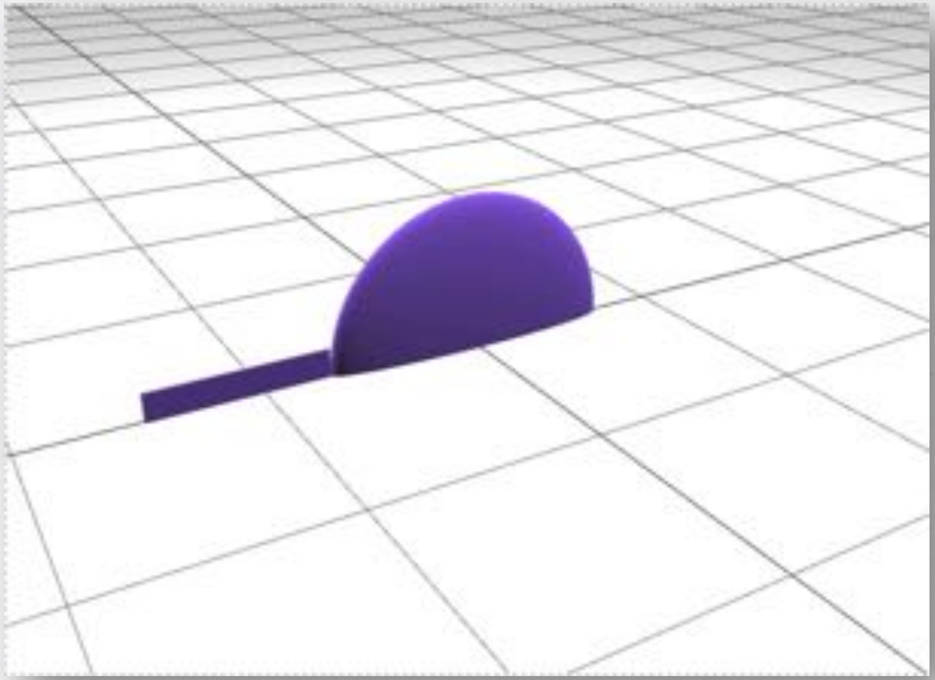
Control System

- r : desired system output
- y : actual system output
- e : system output error
- u : control signal



Design Process

Robot Prototype
↓
Dynamic Modeling
↓
Parameter Identification
↓
Control Design
↓
Simulation



[Clark 2013]

Design Process

Robot Prototype

↓

Dynamic Modeling

↓

Parameter Identification

↓

Control Design

↓

Simulation

↓

Physical Experiments

Design Process

Robot Prototype
↓
Dynamic Modeling
↓
Parameter Identification
↓
Control Design
↓
Simulation
↓
Physical Experiments

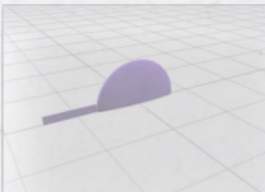
Repeat to refine

- reduce modeling error
- improve parameter estimates
- model noisy sensors

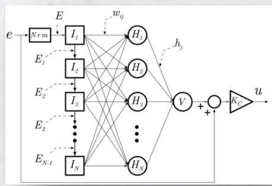
Repeat for new robot

- different parameters
- different sensors

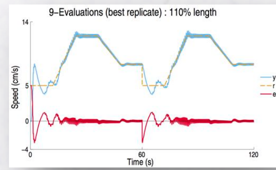
Outline

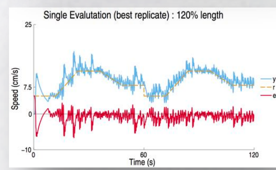


Robotic
Fish Design

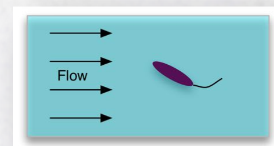


Adaptive
Control

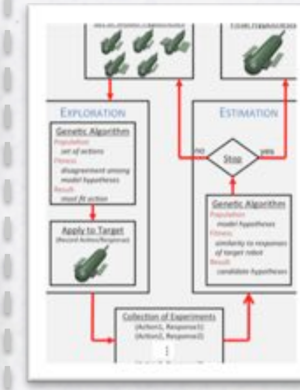




Velocity
Study

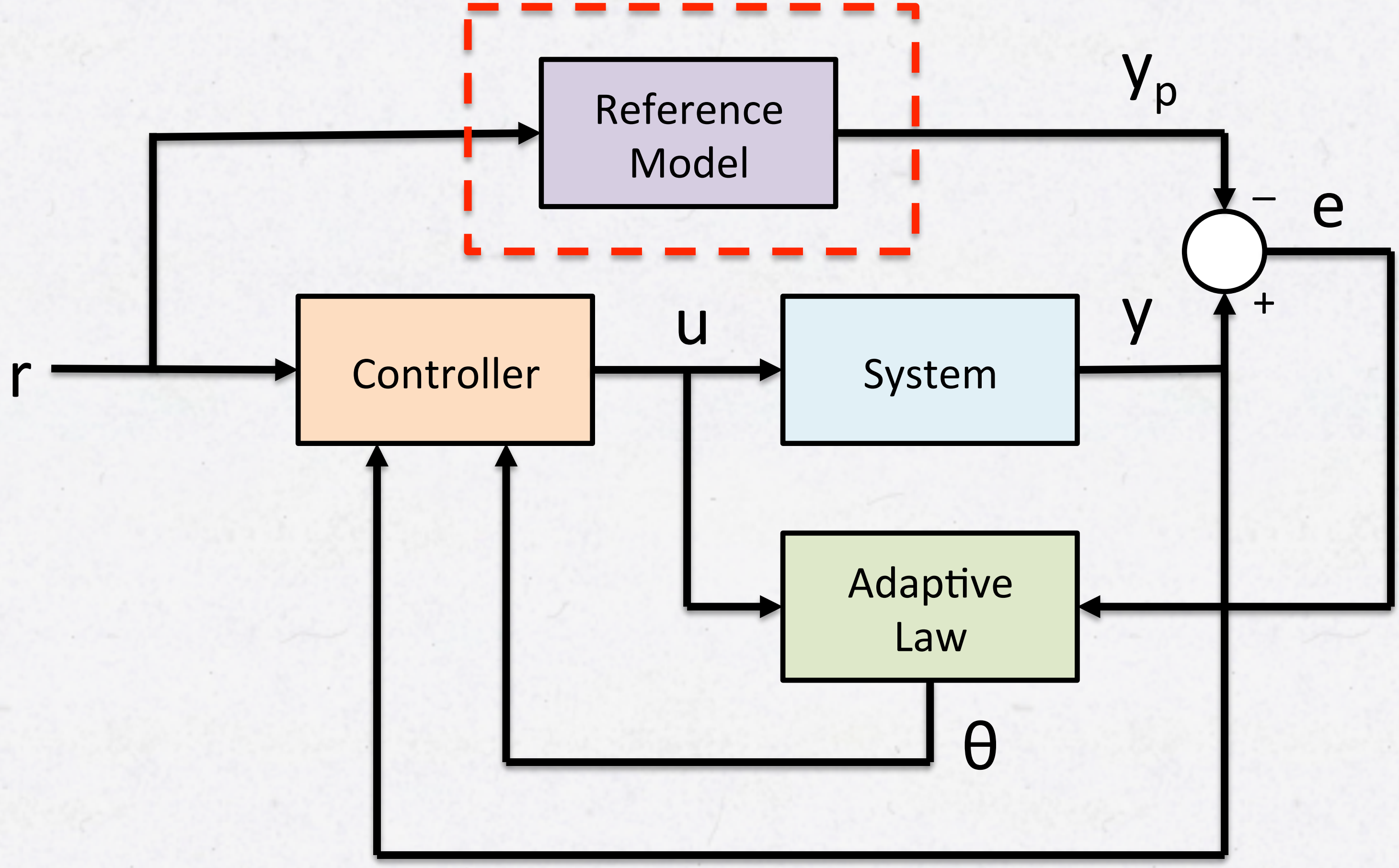


Flow Tank
Application

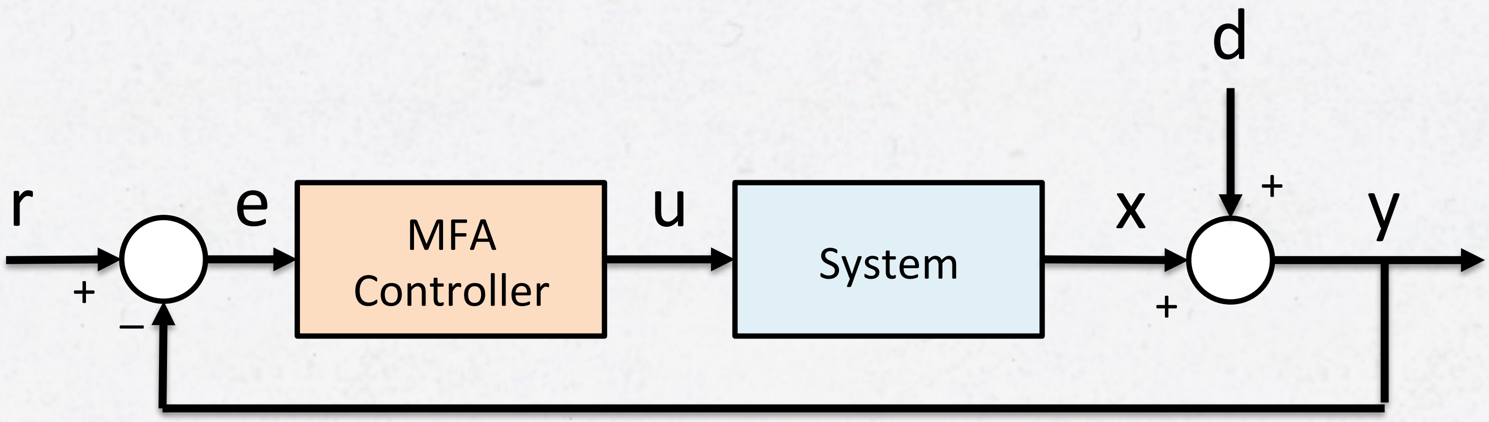


Future
Work

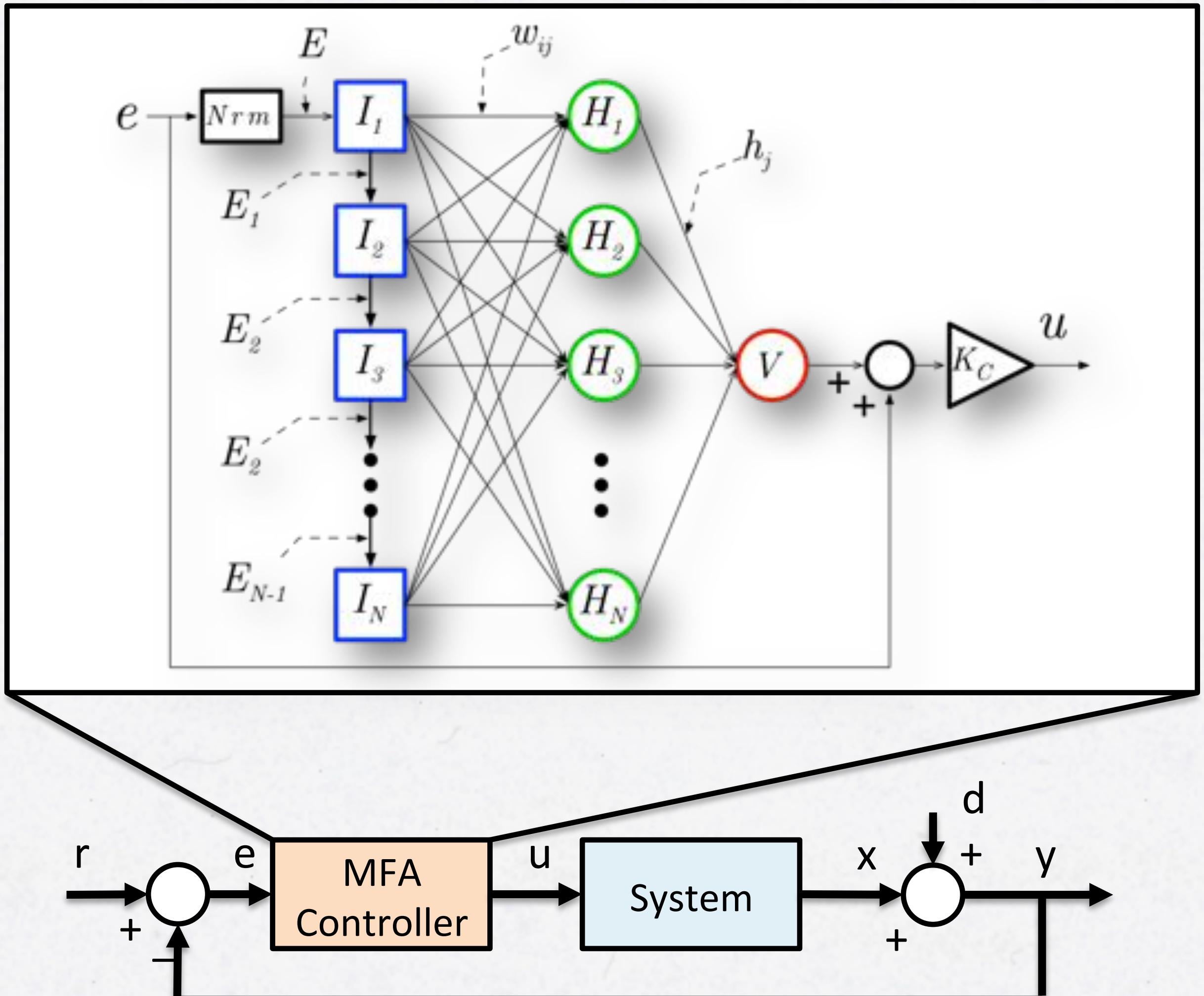
Adaptive Control : MRAC



Model-Free Adaptive Control



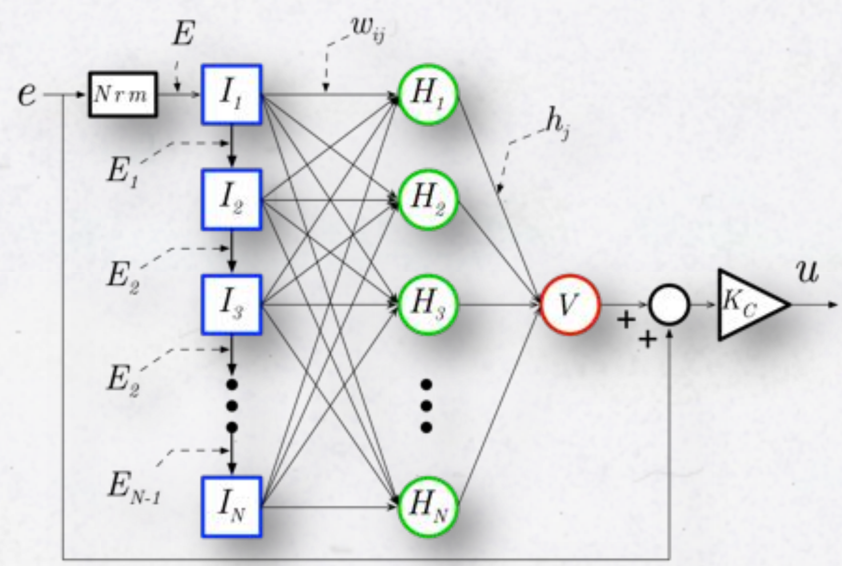
Model-Free Adaptive Control



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

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

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

Parameters

Network values

- hidden layer bias
- hidden layer bias weights
- output layer bias
- output layer bias weight

Learning Values

- learning rate

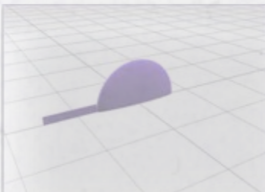
Network topology

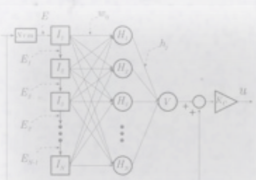
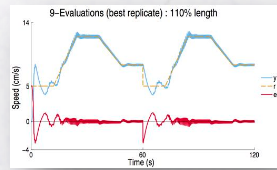
- number of input nodes
- number of hidden nodes

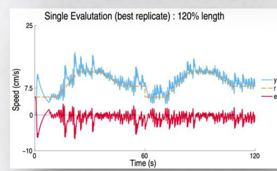
Control values

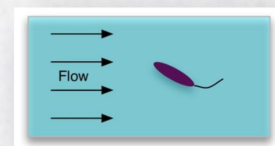
- gain
- error bounds
- activation period

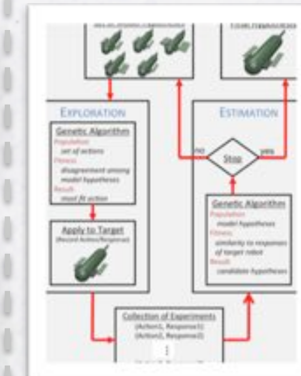
Outline







Robotic Fish Design

Adaptive Control

Velocity Study

Flow Tank Application

Future Work

Simulation Study

Swim at a given (changing) speed

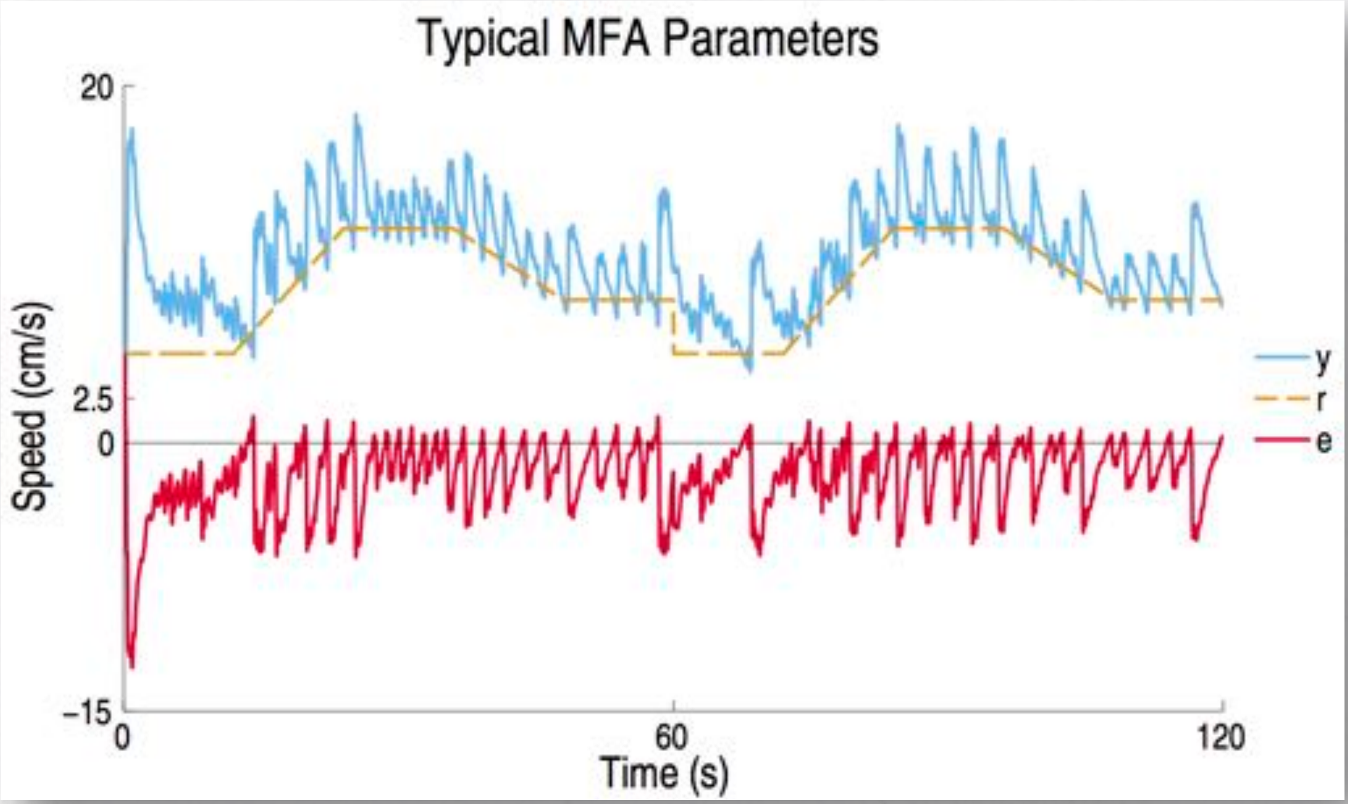
Adapt to:

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

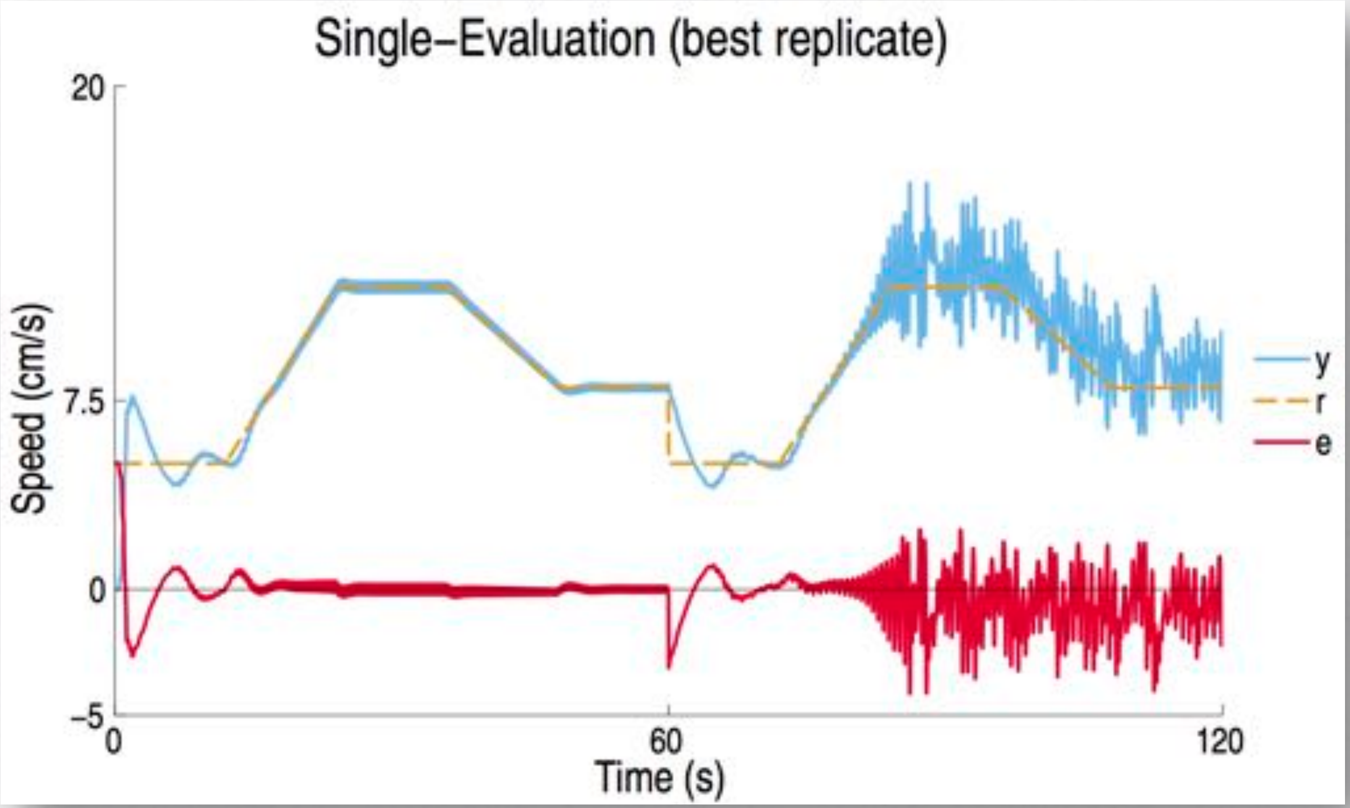
Evaluation

- simulate for 60 seconds with a varying control signal
- fitness = mean absolute error

Un-tuned Parameters



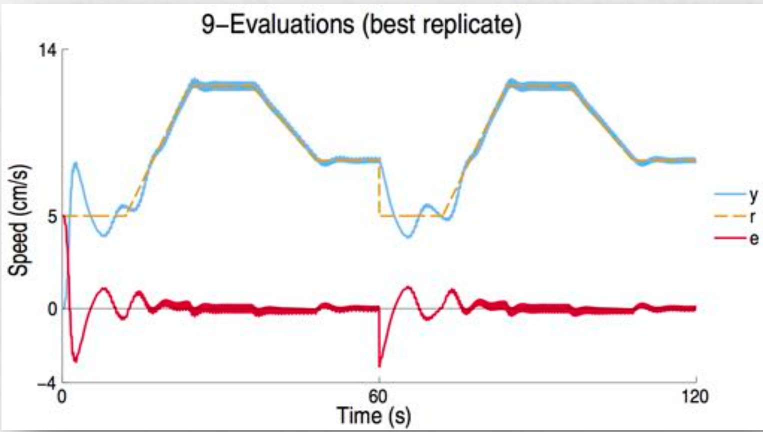
Single Trial Evolution

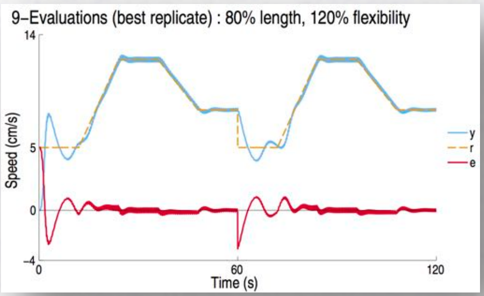


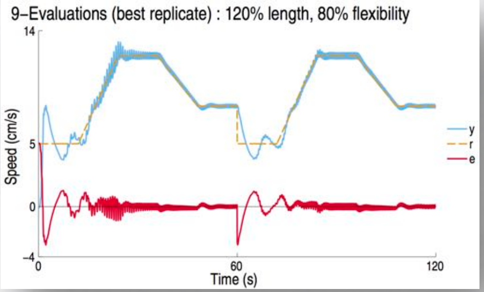
Multi-trial Evolution

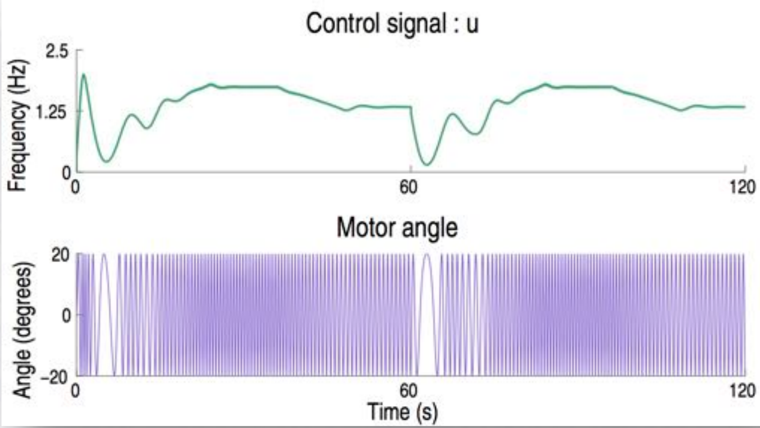
Name	Flexibility	Length
sim1	100%	100%
sim2	200%	100%
sim3	50%	100%
sim4	100%	110%
sim5	200%	110%
sim6	50%	110%
sim7	100%	90%
sim8	200%	90%
sim9	50%	90%

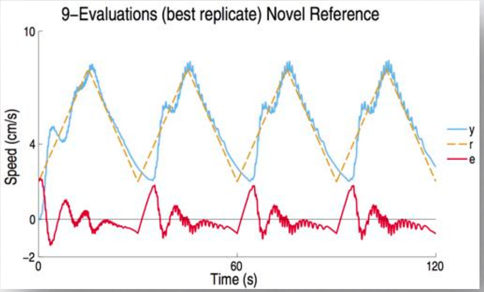
Multi-trial Evolution



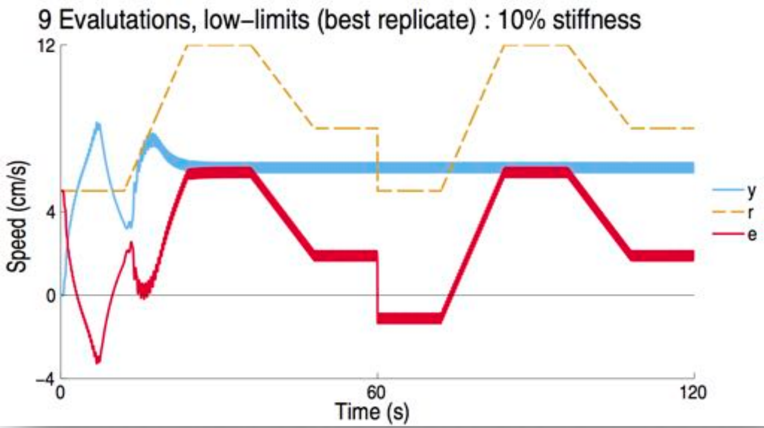


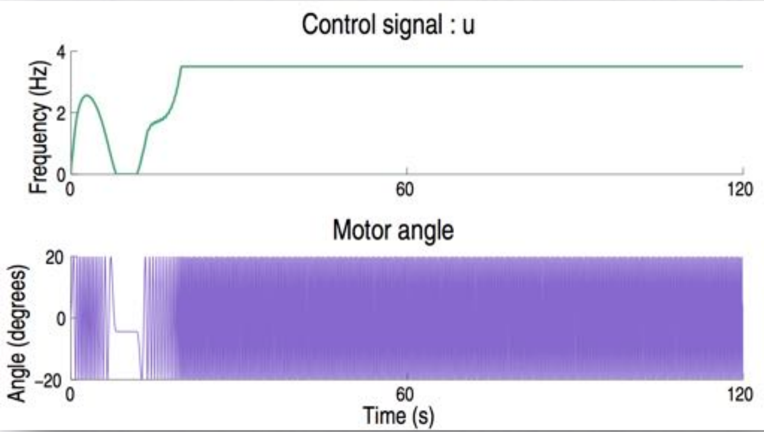


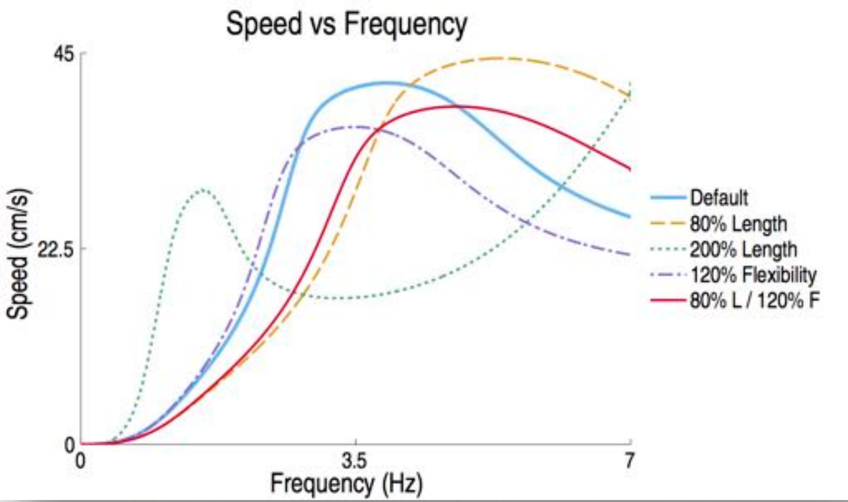




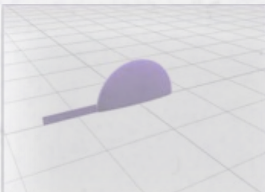
Changing Dynamics

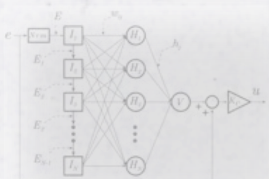


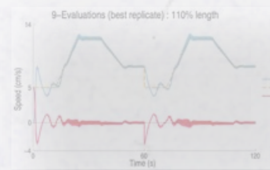


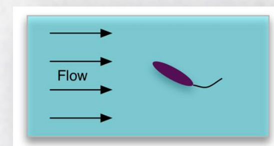


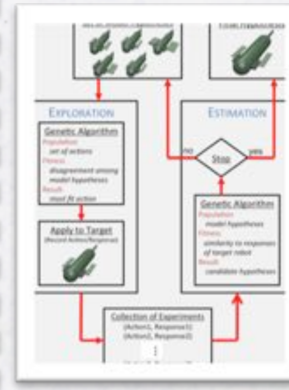
Outline











Robotic Fish Design

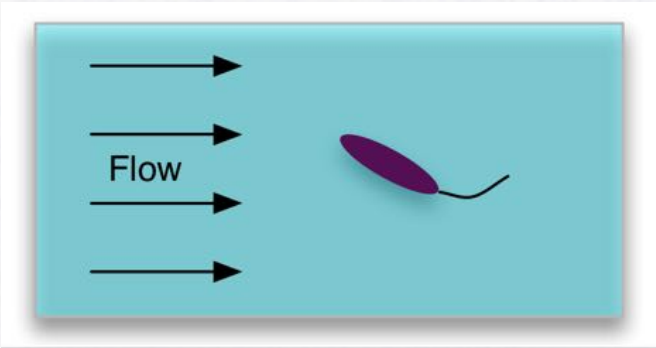
Adaptive Control

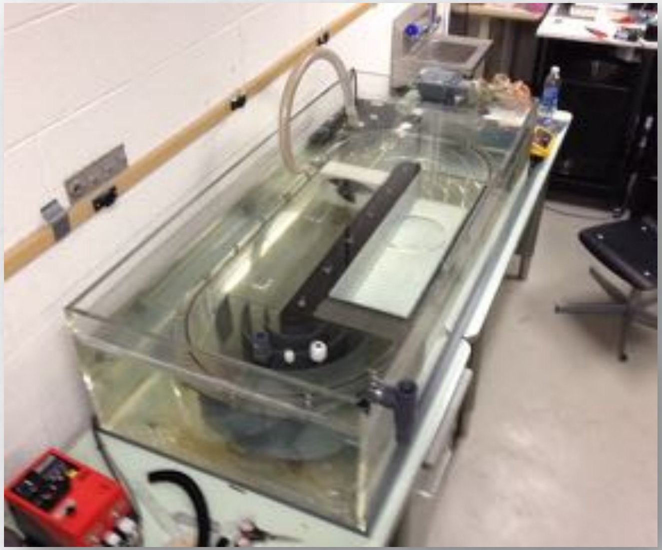
Velocity Study

Flow Tank Application

Future Work

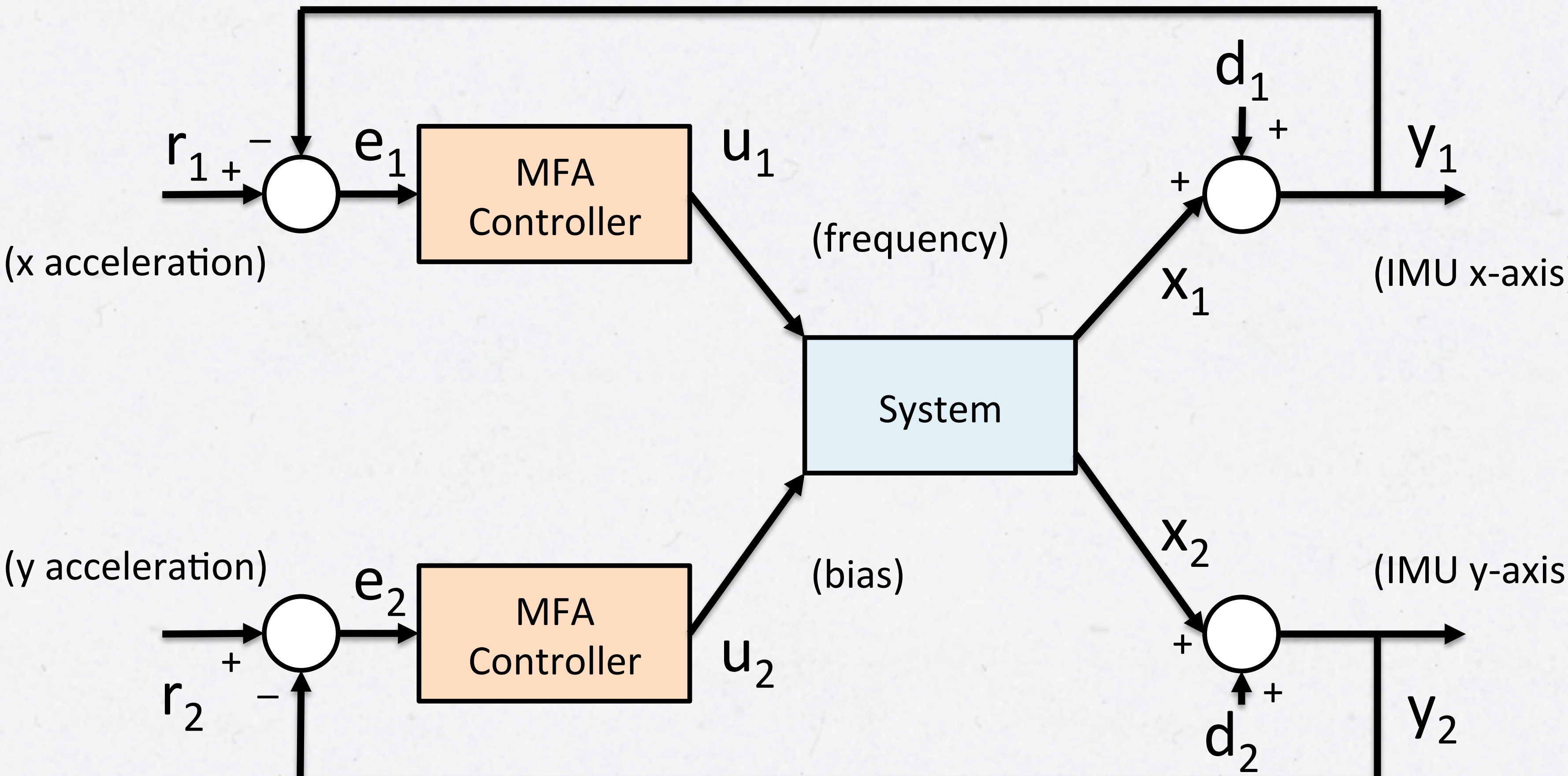
Station Keeping





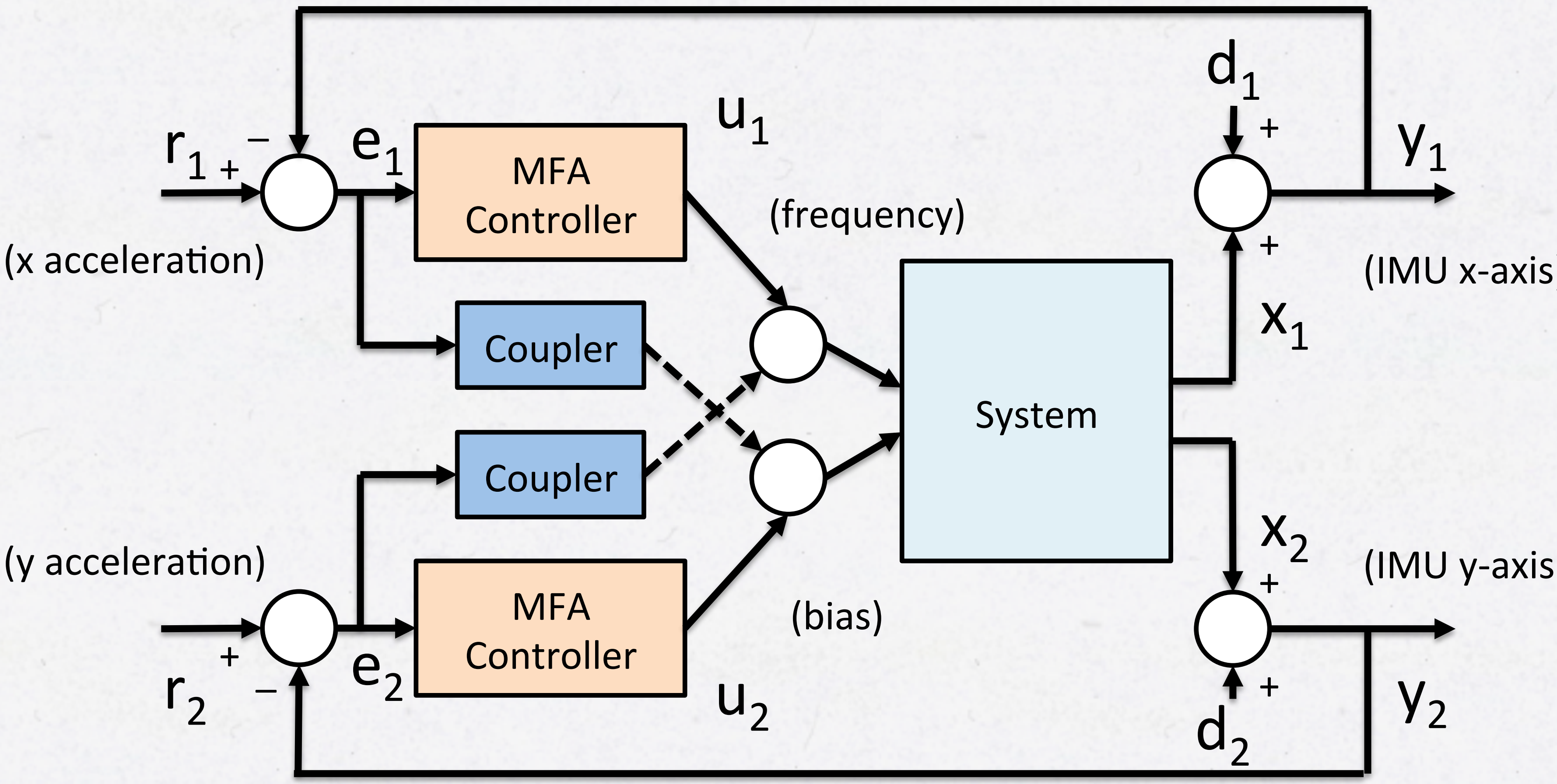
Video of new fish

SISO to MIMO



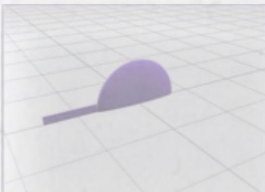
r1 +
−
e1
MFA Controller
u1
d1
+
+
y1
(x acceleration)
(frequency)
x1
(IMU x-axis)
System
(y acceleration)
e2
MFA Controller
x2
(bias)
(IMU y-axis)
+
+
r2
−
u2
+
d2
y2

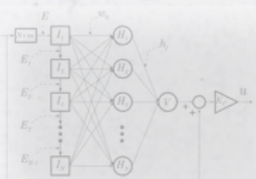
SISO to MIMO

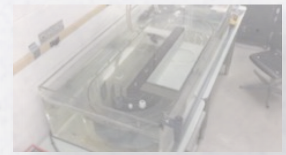


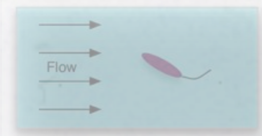
r1
+
–
e1
MFA Controller
u1
(frequency)
(x acceleration)
Coupler
Coupler
System
d1
+
+
y1
(IMU x-axis)
x1
x2
+
+
(IMU y-axis)
(y acceleration)
+
–
r2
e2
MFA Controller
(bias)
u2
d2
y2

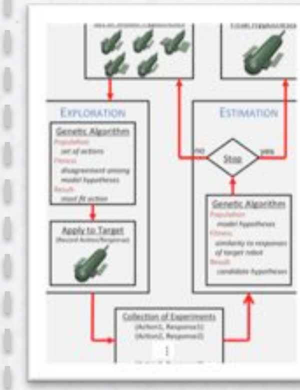
Outline











Robotic Fish Design

Adaptive Control

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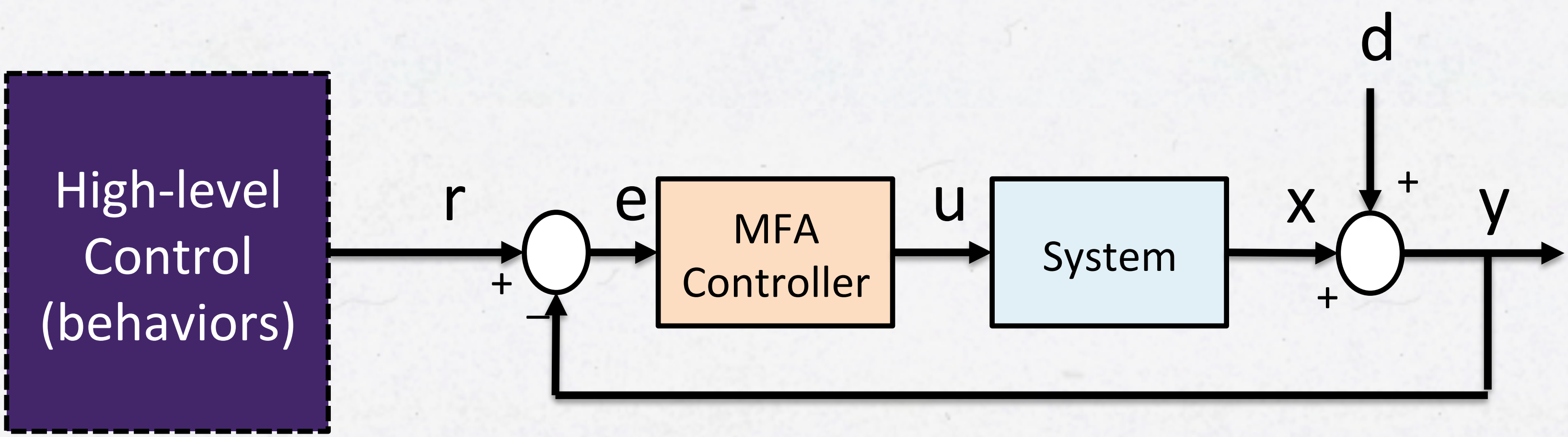
Flow Tank Application

Future Work

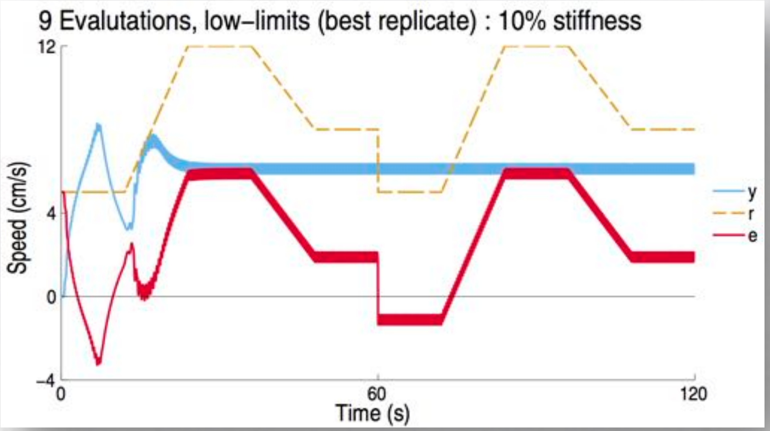
Future Work : High-level Control

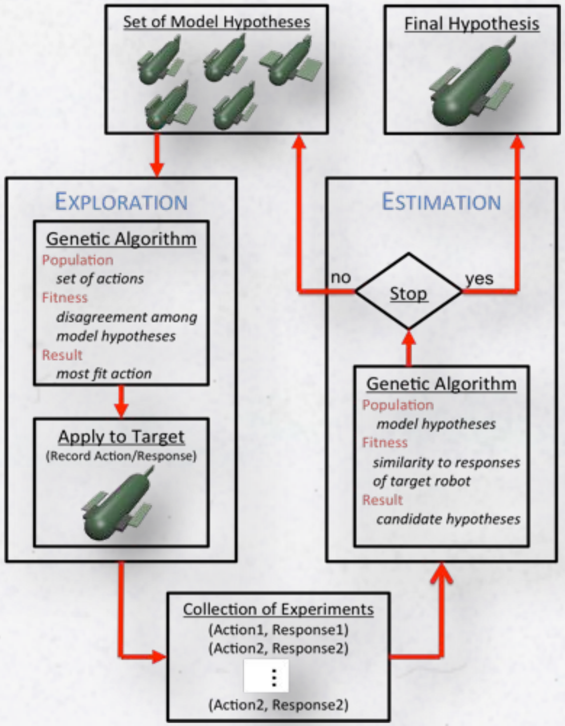
- Higher level control
  - FSM
  - ANN



Future Work : Failure

- When MFA fails
  - the error signal gets to high
  - combine with Self-modeling





[Rose 2013, Bongard 2006]

Conclusions

- Increase adaptability of autonomous robots
  – control signals, morphology, noise
- Decrease modeling effort
  – evolve online/onboard
- Help cross the reality gap in traditional ER
  – handle disparity between simulation and reality
- Requires higher-level control for behaviors

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Thank You

Questions?

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