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
  \[ \downarrow \]
Dynamic Modeling
  \[ \downarrow \]
Parameter Identification
  \[ \downarrow \]
Control Design

Control System
- \( r \) : desired system output
- \( y \) : actual system output
- \( e \) : system output error
- \( u \) : control signal

\[ \begin{align*}
 r & \rightarrow e \\
 + & \rightarrow - \\
 e & \rightarrow u \\
 u & \rightarrow y \\
 e & \rightarrow r
\end{align*} \]
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

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

\[
\Delta w_{ij}(n) \propto \frac{\partial E_s}{\partial w_{ij}},
\]

\[
= \frac{\partial E_s}{\partial y} \frac{\partial y}{\partial w_{ij}},
\]

\[
= \frac{\partial E_s}{\partial y} \frac{\partial y}{\partial u} \frac{\partial u}{\partial w_{ij}},
\]

\[
= \frac{\partial E_s}{\partial y} \frac{\partial y}{\partial u} \frac{\partial u}{\partial o} \frac{\partial o}{\partial w_{ij}},
\]

\[
= -\eta K_c S_f(n) e(n) q_j(n) (1 - q_j(n)) E_i(n) \sum_{k=1}^{N} h_k(n),
\]
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

<table>
<thead>
<tr>
<th>Name</th>
<th>Flexibility</th>
<th>Length</th>
</tr>
</thead>
<tbody>
<tr>
<td>sim1</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>sim2</td>
<td>200%</td>
<td>100%</td>
</tr>
<tr>
<td>sim3</td>
<td>50%</td>
<td>100%</td>
</tr>
<tr>
<td>sim4</td>
<td>100%</td>
<td>110%</td>
</tr>
<tr>
<td>sim5</td>
<td>200%</td>
<td>110%</td>
</tr>
<tr>
<td>sim6</td>
<td>50%</td>
<td>110%</td>
</tr>
<tr>
<td>sim7</td>
<td>100%</td>
<td>90%</td>
</tr>
<tr>
<td>sim8</td>
<td>200%</td>
<td>90%</td>
</tr>
<tr>
<td>sim9</td>
<td>50%</td>
<td>90%</td>
</tr>
</tbody>
</table>
Multi-trial Evolution
Changing Dynamics

9 Evaluations, low-limits (best replicate) : 10% stiffness

Control signal : u

Motor angle

Speed vs Frequency

Speed (cm/s)

Frequency (Hz)

Motor angle

Time (s)

Frequency (Hz)

Angle (degrees)

Time (s)
Outline

Robotic Fish Design

Adaptive Control

Velocity Study

Flow Tank Application

Future Work
Station Keeping

Video of new fish
SISO to MIMO

\[
\begin{align*}
MFA & \quad \text{Controller} \\
(r_1, e_1) & \quad \text{MFA Controller} \\
(u_1) & \quad \text{System} \\
(y_1) & \quad (\text{IMU x-axis}) \\
MFA & \quad \text{Controller} \\
(r_2, e_2) & \quad \text{MFA Controller} \\
(u_2) & \quad \text{System} \\
(y_2) & \quad (\text{IMU y-axis})
\end{align*}
\]
Outline

Robotic Fish Design

Adaptive Control

Velocity Study

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?

Robotic Fish Design
Adaptive Control
Velocity Study
Flow Tank Application
Future Work
References


• [Clark 2012] : *Evolutionary design and experimental validation of a flexible caudal fin for robotic fish.*


• [Rose 2013] : *Just Keep Swimming: Accounting for Uncertainty in Self-Modeling Aquatic Robots*