Reverse Engineering of Self-propelled Anguilliform Swimmers

Philippe Chatelain

with : S. Kern, P. Koumoutsakos
support: Swiss National Science Foundation
Anguilliform Swimming?

- Simple geometry for swimmer: eel
- Reverse-engineering of motion
  - given a biological objective, identify and characterize a swimming mode

Approach/Assumptions
- Undulatory swimming modes dominated by flow physics
- Simple assumptions about biomechanics
Swimming modes (1)

• Efficiency
  – Long migration
  – Metabolic measurements in eels indicate high swimming efficiency

  – In contradiction with observed wake patterns: lateral jets?

• Speed
  – wake changes?
  – motion

U.K. Mueller et al. (2001), J. Exp. Biol. 204

Tytell and Lauder (2004), J. Exp. Biol. 207
Swimming modes (1)

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  – Wake changes
  – Motion

Investigation of Efficient and Fast modes

Tytell and Lauder (2004), J. Exp. Biol. 207
Swimming modes (2)

• Acoustics
  – Sensing in fishes
    • Predator evasion/Prey detection
    • orientation
    • communication
  – Acoustic far-field of swimmers
    • little knowledge: monopole or dipole
    • experimental challenges
    • models needed to estimate detection distances
Swimming modes (2)

• Acoustics
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Find **Quiet** mode
How close is it to **Efficient**?
(Reverse) engineering

Swimming mode
• as the solution of optimization problem in search space = motion
• characterized in terms of
  – Kinematics
  – Dynamics
  – Fluid mechanics
    • wake
    • noise generation
  – Motion generation
(Reverse) engineering

Function
- Efficiency
- Speed
- Stealth

Identification
- Motion
- Wake
- Dynamics
- Noise
(Reverse) engineering

Function
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Optimization

Identification
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Optimization

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Objective function
Motion parameterization
Numerical simulation
(Reverse) engineering

Optimization

Objective function
Motion parameterization
Numerical simulation
Evolutionary strategy

Identification

Motion
Wake
Dynamics
Noise

Function
Efficiency
Speed
Stealth
Geometry and Motion Parameterization

- Eel-like body with ellipsoid cross sections
- Motion determined by 2D deformation of centerline: **wave of curvature**

\[ \kappa(s, t) = \mathcal{K}(s) \sin \left[ 2\pi \left( \frac{t}{T} - \tau(s) \right) \right] \]
Geometry and Motion Parameterization

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**cubic spline** through

\[ \mathcal{K}_i, \ i = 1, \ldots, 4 \]
Geometry and Motion Parameterization

• Eel-like body with ellipsoid cross sections

• Motion determined by 2D deformation of centerline: \textbf{wave of curvature}

\[
\kappa(s,t) = \left[ \mathcal{K}(s) \right] \sin \left[ 2\pi \left( \frac{t}{T} - \tau(s) \right) \right]
\]

cubic spline through \( \mathcal{K}_i, i = 1, \ldots, 4 \)

linear phase shift
\[
\tau(s) = \frac{s}{L} \tau_{\text{tail}}
\]
Geometry and Motion Parameterization

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\[ \kappa(s, t) = \kappa_i(s) \sin \left[ 2\pi \left( \frac{t}{T} - \tau(s) \right) \right] \]

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- cubic spline through \( \kappa_i, i = 1, \ldots, 4 \)
- linear phase shift \( \tau(s) = \frac{s}{L} \tau_{tail} \)

=> 5 parameters to be optimized

\( \kappa_1, \ldots, 4, \tau_{tail} \)
Computational setup (1)

- **Fluid-Structure Problem**
  - **Self-propelled** undulating body
  - \( \text{Re}_L = \frac{UL}{\nu} \approx 30000 \)
- **Handled with**
  - 3D viscous unsteady DNS with STAR-CD v. 3.150A (ALE FV solver)
  - Sequential staggered **coupling of fluid and body physics** (user subroutines)
  - Moving & deforming structured grid
    - 300k cells (optimization cases: 70k)
    - follows center of mass
    - pressure boundary conditions
  - \( \text{Re}_L = \frac{UL}{\nu} \approx 4000, \text{Re}_a = \frac{a^2}{Tv} \approx 100 \)
Computational setup (2)

- **Acoustics problem**
  - Moving object
  - Deforming object
  - Far-field
  - Low Mach number

- Handled with
  - Ffowcs Williams & Hawkings acoustic analogy
  - Source terms computed from incompressible flow solution

\[
\left( \frac{1}{c^2} \frac{\partial^2}{\partial t^2} - \nabla^2 \right) p'(x, t) = \frac{\partial}{\partial t} \left\{ [\rho_0 v_n + \rho (u_n - v_n)] \delta(f) \right\} - \frac{\partial}{\partial x_i} \left\{ [P_{ij} \hat{n}_j + \rho u_i (u_n - v_n)] \delta(f) \right\} + \frac{\partial^2}{\partial x_i \partial x_j} [T_{ij} H(f)]
\]

“thickness noise”

“loading noise”

“quadrupole noise”
Computational setup (2)

- **Acoustics problem**
  - **Moving** object
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\[
+ \frac{\partial^2}{\partial x_i \partial x_j} [T_{ij} H(f)]
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- "thickness noise"
- "loading noise"
- "quadrupole noise"

neglected
Computational setup (2)

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\]

- Control surface brought to swimmer surface
- Solved in integral form, Green’s function with advanced time

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Casalino, J. Sound Vib., 2003
(Reverse) engineering

- Function
  - Efficiency
  - Speed
  - Stealth

- Optimization
  - Objective function
  - Motion parameterization
  - Numerical simulation
  - Evolutionary strategy

- Identification
  - Motion
  - Wake
  - Dynamics
  - Noise

Objective function

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CIMTEC 2008, June 10
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Optimization: Objective Functions
Optimization: Objective Functions

1. Migration: Optimize swimming efficiency

\[ f_\eta = \frac{m \bar{U}^2}{2 W_{cycle}} \quad W_{cycle} = \int_t^{t+T} \int_S -\bar{\sigma} \cdot n \cdot u \ dS \ dt \]
Optimization: Objective Functions

1. **Migration**: Optimize *swimming efficiency*

\[
 f_\eta = \frac{m\bar{U}^2}{2W_{cycle}} \quad \quad W_{cycle} = \int_t^{t+1} \int_S -\bar{\sigma} \cdot n \cdot u \, dS \, dt
\]

2. **Burst swimming**: Maximize *swimming velocity* with constraints on input power

\[
 f_U = U - c_1 R_{\text{mean}} - c_2 R_{\text{peak}},
\]

\[
 R_{\text{mean}} = H(\bar{P}_{\text{total}} - \bar{P}_{\text{max}}) \cdot (\bar{P}_{\text{total}} - \bar{P}_{\text{max}})^2
\]

\[
 R_{\text{peak}} = H(P_{\text{total}} - P_{\text{max}}) \cdot (P_{\text{total}} - P_{\text{max}})^2 \quad \Rightarrow \quad \text{Penalty terms}
\]
Optimization: Objective Functions

1. Migration: Optimize swimming efficiency

\[ f_\eta = \frac{m\overline{U}^2}{2W_{cycle}} \quad W_{cycle} = \int_t^{t+1} \int_S -\sigma \cdot n \cdot u \ dS \ dt \]

2. Burst swimming: Maximize swimming velocity with constraints on input power

\[ f_U = U - c_1 R_{mean} - c_2 R_{peak} \]
\[ R_{mean} = H(\overline{P}_{total} - \overline{P}_{max}) \cdot (\overline{P}_{total} - \overline{P}_{max})^2 \]
\[ R_{peak} = H(P_{total} - P_{max}) \cdot (P_{total} - P_{max})^2 \] Penalty terms

3. Quiet swimming: Minimize sound pressure signature while achieving swimming velocity of efficient mode

\[ f_{p'} = \frac{1}{2\pi r} \int_{|x|=r} \sqrt{\left( \frac{1}{T} \int p'(x,t) - \overline{p}'(x) \ dt \right)^2} \ dx + cR_{eff} \]
\[ R_{eff} = H(\overline{U}_{eff} - \overline{U}) (\overline{U}_{eff} - \overline{U})^2 \]
Optimization: Evolutionary Strategy

- **black box** approach, $\nabla f$ not readily available
- **iterative methods** operating with **populations** of candidate solutions
- Here: Covariance Matrix Adaptation - ES

![Diagram of evolutionary strategy process]

Optimization: Evolutionary Strategy

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\[ \text{Stopping criteria fulfilled?} \]
\[ \text{yes} \quad \text{no} \]
\[ g = g + 1 \]

Parents
\[ \{ x_k \}_k^\mu \]

Selection

Evaluation

Recombination

Mutation

Offspring
\[ \{ x_k \}_k^\lambda \]

\[ x_1 \]
\[ x_2 \]


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**Diagram:**

1. **Selection**
2. **Evaluation**
3. **Recombination**
4. **Mutation**

- **Parents** $\{x_k\}_{k=1}^\mu$
- **Offspring** $\{x_k\}_{k=1}^\lambda$

Stopping criteria fulfilled? yes $\Rightarrow$ stop

$g = g + 1$ no

$g = 0$

Start with initial offspring population

---

Optimization: Evolutionary Strategy

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![Diagram of evolutionary strategy process](image)

Optimization: Evolutionary Strategy

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![Diagram](attachment:image.png)

**Selection**

**Evaluation**

**Recombination**

**Mutation**

**Offspring**


stop

no

$g=g+1$

$f$ fulfills stopping criteria?

$\{x_k\}_{k=1}^{\mu}$

$\{x_k\}_{k=1}^{\lambda}$

start with initial offspring population

$g=0$

$x_1$

$x_2$
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**Diagram:**
- **Parents** $\{x_k\}_{k=1}^\mu$
- **Selection**
- **Evaluation**
- **Recombination**
- **Mutation**
- **Offspring** $\{x_k\}_{k=1}^\lambda$

Probability distribution $x_k \sim P(\theta(g))$

Stopping criteria fulfilled? yes no

Stop

$g = g + 1$

$x_k$ start with initial offspring population
Optimization: Evolutionary Strategy

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\begin{align*}
\text{stop} \quad \text{if stopping criteria fulfilled?} \quad \text{g}=g+1 \\
\text{Selection} \quad \text{Parents} \quad \{\bm{x}_k\}_{k=1}^\mu \\
\text{Evaluation} \quad \text{Recombination} \\
\text{Offspring} \quad \{\bm{x}_k\}_{k=1}^\lambda \\
\text{Mutation} \quad \text{g}=0 \\
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![Evolutionary Algorithm Diagram](image)

- Efficient: learn from prior information to adapt **mutation pdf** $P$


\[ x_k \sim P(\theta^{(g)}) \]
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\[
\begin{align*}
\text{Parents } & \{x_k\}_{k=1}^\mu \\
\text{Selection} & \\
\text{Evaluation} & \\
\text{Offspring} & \\
\text{Recombination} & \\
\text{Mutation} & \\
g = 0 & \\
\text{Stopping criteria fulfilled?} & \\
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\text{yes} & \\
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- Efficient: learn from **prior** information to adapt **mutation pdf** $P$
- Popular because of their **flexibility** and **robustness**

Optimization: Evolutionary Strategy

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- Efficient: learn from **prior** information to adapt **mutation pdf** $P$
- Popular because of their **flexibility** and **robustness**
- Main **disadvantage**: Need **large number of objective function evaluations**
Example: Efficient swimming
Convergence, manually stopped
Single evaluation ~ 2.5 CPU hours

Optimization: History

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(Reverse) engineering

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Identification
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- Wake
- Dynamics
- Noise

Objective function

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Kinematics

Reference motion

\[ y(s, t) = \frac{(s + 0.025)}{1.025} \sin[2\pi(s - t)] \]

\[ U_\parallel = 0.4 \]
Kinematics

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\[ y(s, t) = \frac{(s + 0.025)}{1.025} \sin[2\pi(s - t)] \]

\[ \mathbf{K} = (3.34, 1.67, 6.28, 6.28) \]
\[ \tau_{\text{tail}} = 1.72 \]

Efficient swimming

\[ \mathbf{K} = (1.51, 0.48, 5.74, 2.73) \]
\[ \tau_{\text{tail}} = 1.44 \]

Fast swimming

\[ \mathbf{K} = (6.28, 0.17, 6.28, 4.10) \]
\[ \tau_{\text{tail}} = 1.92 \]

Quiet swimming

\[ \bar{U}_\parallel = 0.33 \]

\[ \bar{U}_\parallel = 0.47 \]

\[ \bar{U}_\parallel = 0.4 \]

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Energy/distance:

- Efficient swimming: 1.55
- Fast swimming: 1
- Quiet swimming: 1.64
- Reference motion: 1.15

Slip \( U_{\parallel} / V \):

- Efficient swimming: 0.55
- Fast swimming: 0.55
- Quiet swimming: 0.63
- Reference motion: 0.57
**Kinematics**

**Reference motion**  

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**Efficient swimming**
- 2 times more efficient than prescribed motion pattern
- Has increased curvature, but smaller max tail angle
- Smaller acceleration/deceleration in cycle

**Energy/distance:**

<table>
<thead>
<tr>
<th></th>
<th>1.55</th>
<th>1</th>
<th>1.64</th>
<th>1.15</th>
</tr>
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</table>

**Slip \( U_{\parallel}/V: \)**

|        | 0.55 | 0.55 | 0.63 | 0.57 |
Kinematics

Reference motion

Efficient swimming
\[ y(s, t) = \frac{(s + 0.025)}{1.025} \sin[2\pi(s - t)] \]
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- front part of body remains essentially straight
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**Fast swimming**

- front part of body remains essentially straight

**Quiet swimming**

- High curvature in front
- Reduced amplitude of tail angle
- 15% less efficient

Energy/distance:

- Efficient swimming: 1.55
- Fast swimming: 1.64
- Quiet swimming: 1.15

Slip \( U_{\parallel}/V \):

- Efficient swimming: 0.55
- Fast swimming: 0.57
- Quiet swimming: 0.55
Wake Structure

Efficient swimming

Fast swimming

\[ \omega_z, u \]

\[ |\omega| \equiv 2, \omega_y \]
Wake Structure

Efficient swimming

\[ |\omega| \equiv 2, \quad \omega_y \]

Fast swimming

\[ \omega_z, u \]
Wake Structure

\[ \omega_z, u \]

\[ |\omega| \equiv 2, \omega_y \]

- **Efficient swimming**
  - both swimming modes: characteristic lateral jets
  - both swimming modes: weak streamwise flow

- **Fast swimming**
  - vortex rings elongated in swimming direction
  - stronger secondary structures
Wake Structure

Secondary flow structures:
• $\omega_x$, a signature of undulations
• Production and convection in the wake

Efficient swimming

Fast swimming
Dynamics

Mean drag and thrust forces along the body

- Piecewise integration of viscous and pressure forces
  \[ F = \oint_S \bar{\sigma} \cdot n \, dS \]

- 5 Segments

- Efficient and Quiet: Thrust from middle segment
- Fast: Thrust from tail
Dynamics

Unsteady drag and thrust forces along the body

- **Efficient** and **Quiet**: Curvature in middle segment provides thrust
- **Fast**: Thrust at tail
- Similarity between **Efficient** and **Quiet**
- Inefficiency: suction past rounded tail edge, lack of fin?
Acoustics

How *contradictory* are quiet and efficient modes?

![Diagram showing the relationship between various angles and directions](image)

\[ r = 75 \]
How **contradictory** are quiet and efficient modes?

**Quiet:** Efficiency degradation of 15%... just how *quieter* is it?
Acoustics

How **contradictory** are quiet and efficient modes?

**Quiet**: Efficiency degradation of 15%... just how **quieter** is it?

- Sound pressure level reduce by ~17dB
- Loading noise is actually **increased** in Quiet
- Main Gain: **Thickness** noise is **strongly** reduced
Acoustics

How **contradictory** are quiet and efficient modes?

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Motion generation and actuation

From kinematics, fluid stresses, mass distribution,...
Motion generation and actuation

From kinematics, fluid stresses, mass distribution,...
discretization along centerline
Motion generation and actuation

From kinematics, fluid stresses, mass distribution,...

discretization along centerline
reconstruct **torque** histories at ideal joints
Motion generation and actuation

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Motion generation and actuation

From kinematics, fluid stresses, mass distribution,... discretization along centerline reconstruct **torque** histories at ideal joints

**Efficient swimming**

**Fast swimming**

**Quiet swimming**

Torque ~ standing wave
Motion generation and actuation

Differentiate modes for motion generation
Motion generation and actuation

Differentiate modes for motion generation and hints for Pattern Generation/Neural Circuits to lock onto swimming mode?
Motion generation and actuation

Differentiate modes for motion generation and hints for Pattern Generation/Neural Circuits to lock onto swimming mode?

E.g. assuming oscillators for the torque and curvature signals, compute gain/transfer function Torque/curvature

![Graphs showing different modes of motion generation](image-url)
Motion generation and actuation

Differentiate modes for motion generation and hints for Pattern Generation/Neural Circuits to lock onto swimming mode?

E.g. assuming oscillators for the torque and curvature signals, compute gain/transfer function Torque/curvature

Control phase-shift?
Summary

• Highly optimized anguilliform swimming modes discovered using Evolutionary Optimization

• Results support hypothesis that eels can modify their propulsive mode
  – difference in flow structures depending on swimming mode

• Novel insight to unsteady drag and thrust production of the undulating body

• Acoustic signature mainly due to thickness noise, can be reduced at moderate cost in efficiency

• Motion generation