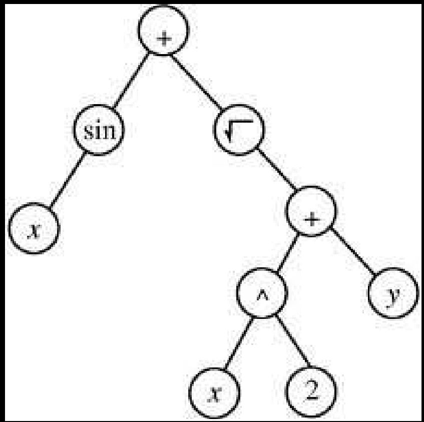
Closed-loop turbulence control using machine learning



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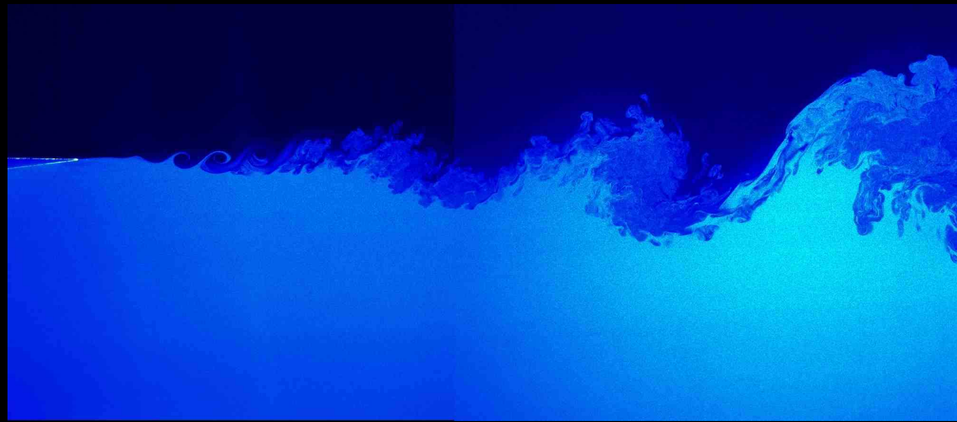

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. . . . [1]Argentinia, [2]Australia, [3]Europe & [4]USA

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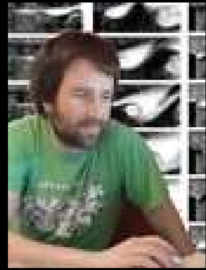
Berlin Workshop on Model Reduction for Transport-dominated Phenomena
Einstein Foundation, Berlin Institute of Technology, Germany 2015-05-19..20

Friends / core team

Machine learning

M. Abel
M. Segond
Ambrosys

Closed-loop turbulence control — theory



L. Cordier, T. Duriez, E. Kaiser,
B. Noack, M. Schlegel, et al.
P' + Berlin + Buenos Aires

Statistical physics

Robert Niven
UNSW
Australia

Control theory

S. Brunton
N. Kutz
U Washington

Closed-loop turbulence control — experimental demonstrators

V. Parezanovic
et al.
P'

Rudi King
et al.
TU Berlin

CFD + Stab.anal.

Marek
Morzyński
TU Poznań

More friends (experiments)

• **A. Spohn, V. Parezanovic, E. Kaiser** . . . . (PPRIME, Poitiers) . . . . soon: MLC in separation control over a smooth ramp
• **J. Borée, D. Barros, C. Li, Y. Cao** . . . . (PPRIME, Poitiers) . . . . MLC in drag reduction of an Ahmed body . . . . machine learning modelling in combustion engine
• **F. Harambat, T. Ruiz** . . . . (PSA, Peugeot-Citroën, Velizy) . . . . MLC in drag reduction of a realistic car model
• **N. Gautier, N., J.-L. Aider,** . . . . (PMMH Paris) . . . . MLC for mixing enhancement of backward facing step
• **M. Stanislas, C. Raibaudo, C. Cuvier,** . . . . (LML Lille) . . . . MLC for separation mitigation of a turbulent boundary layer
• **A. Kourta, A. Debien & N. Mazellier** . . . . (PRISM, Orléans) . . . . MLC for separation mitigation of a turbulent boundary layer
• **C.O. Paschereit, C.N. Nayeri, K. Oberleithner, J. Moeck** . . (TU Berlin) . . . . . combustion-related experiments, soon: MLC in wind-turbine, cars
• **R. Radespiel, R. Semaan, P. Scholz,** . . . . (TU Braunschweig) . . . . MLC in drag reduction of a d-shaped body . . . . MLC in highlift airfoil with $\sim$100 actuators and $\sim$ 500 sensors

MLC experiments in this talk

- PPRIME Poitiers : V. Parezanovic, J. Delville (t), K. Fourment (t), J.-P. Bonnet
- PMMH Paris : N. Gautier, N., J.-L. Aider
- LML Lille : M. Stanislas, C. Raibaudo, C. Cuvier
- PRISME, Orléans : A. Kourta, A. Debien & N. Mazellier

Overview

1. **An eldorado of engineering applications**
   . . . . The need for closed-loop turbulence control

2. **Weapons of choice**
   . . . . A review of turbulence control strategies

3. **Machine learning control (MLC) as magic bullet**
   . . . . . Introduction to a fool-proof method

4. **Recent MLC applications**
   . . . . Demonstrations in shear turbulence experiments

5. **Turbulence control strategies revisited**
   . . . . . MLC as paradigm shift

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Turbulence control $\mapsto$ transport vehicles

Control goals

- lift increase
- drag reduction
- acoustic noise reduction
- mixing/combustion control

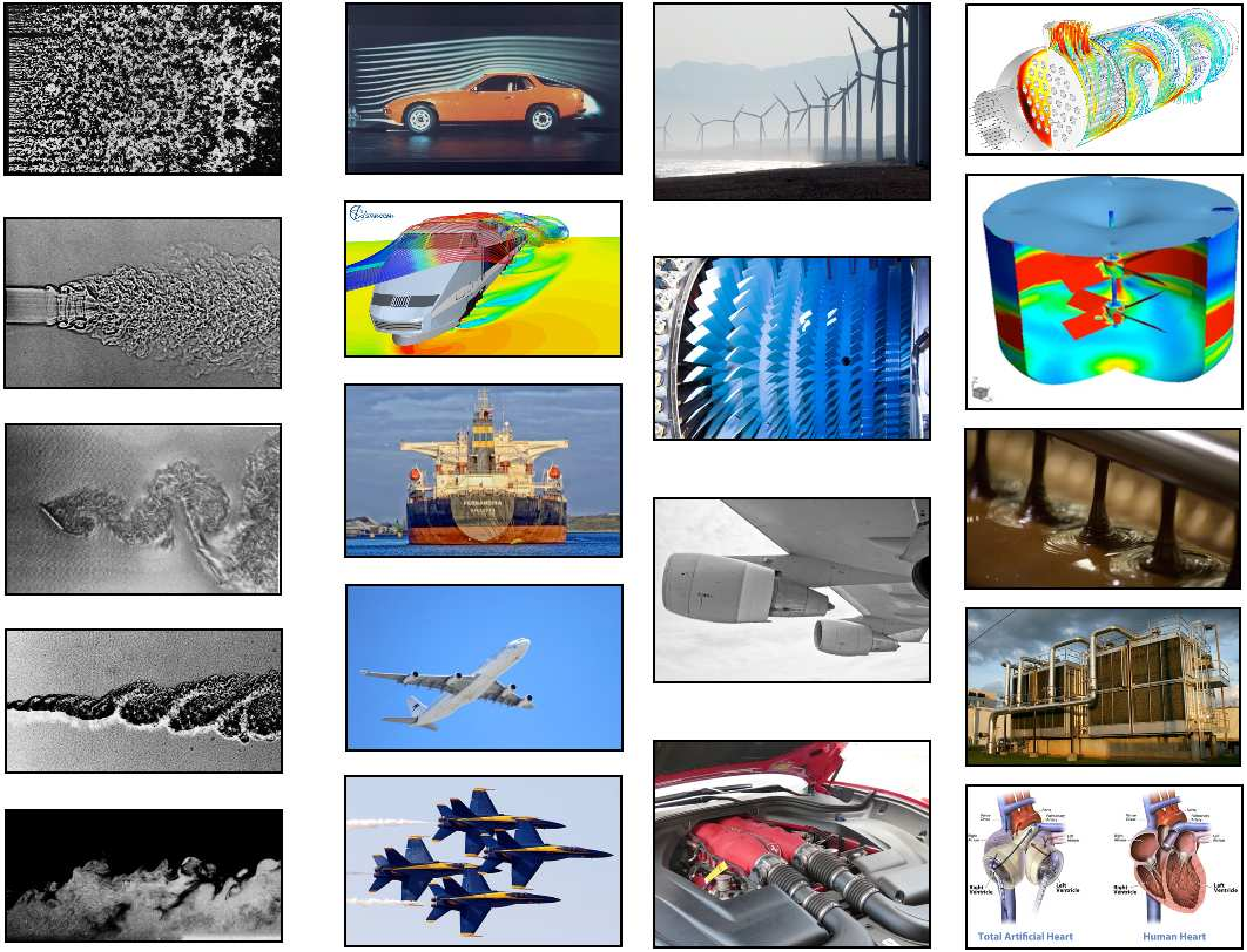
Control strategies

- aerodynamic design
- passive (e.g. riblets)
- active, open-loop
  (e.g. periodic blowing)
- active, closed-loop
  (largest opportunities!)

Turbulence control $\mapsto$ other applications

Turbulence control $\mapsto$ even more applications

Simple prototype flows | Transport vehicles | Energy systems | Production etc.



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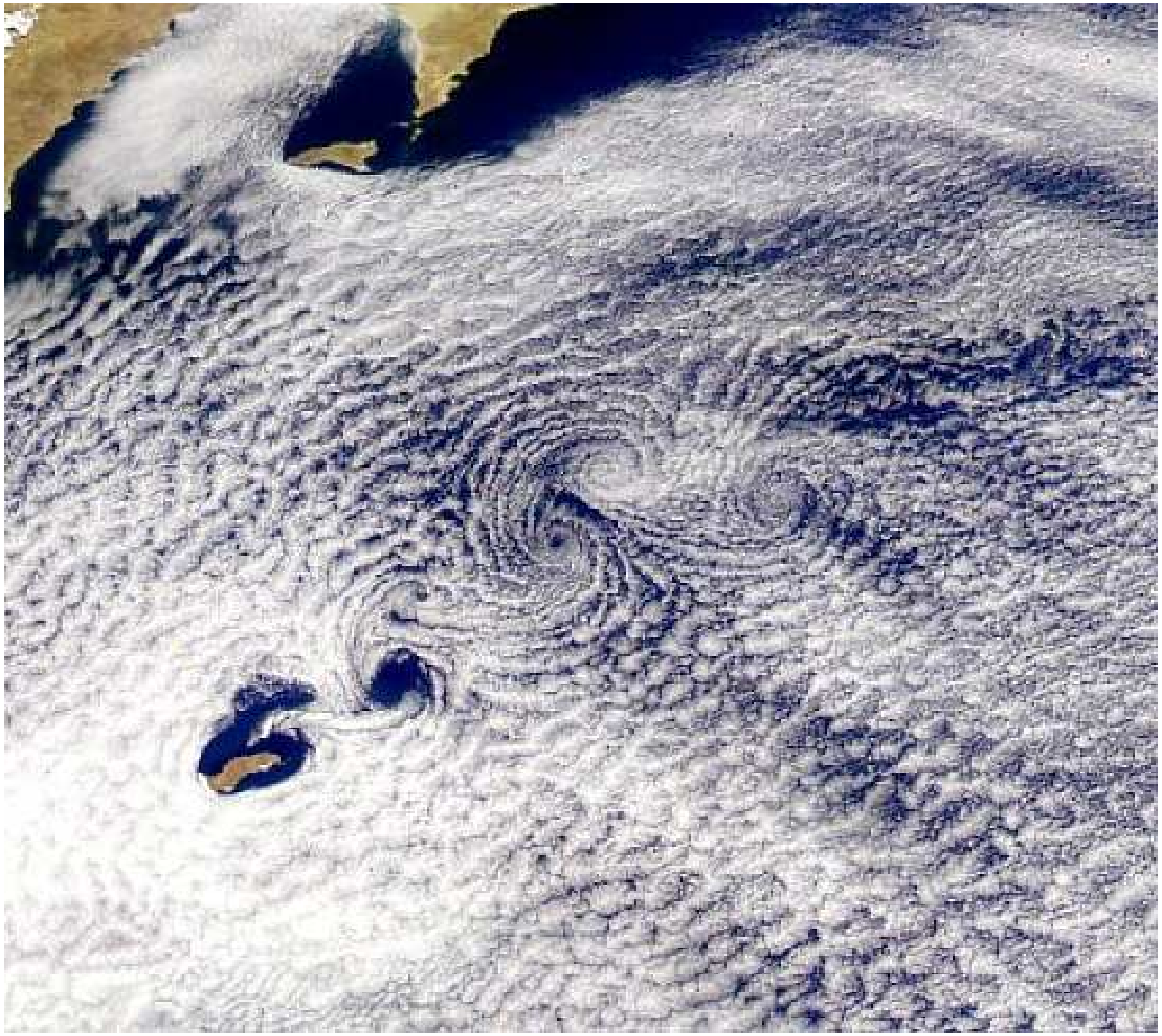
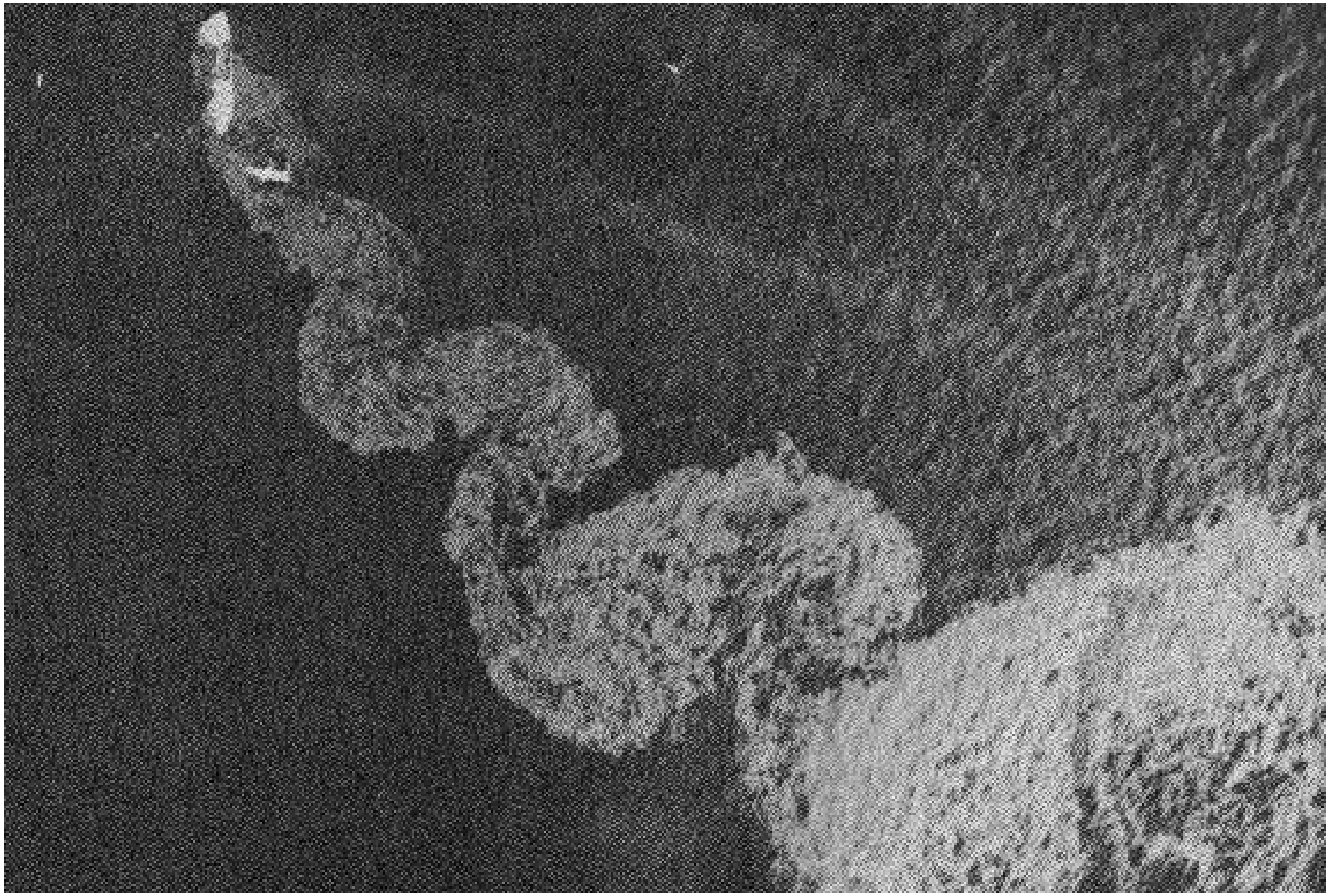
von Kármán vortex street in nature



Rear side of the island Guadalupe (20 Aug. 1999)

von Kármán vortex street in technology

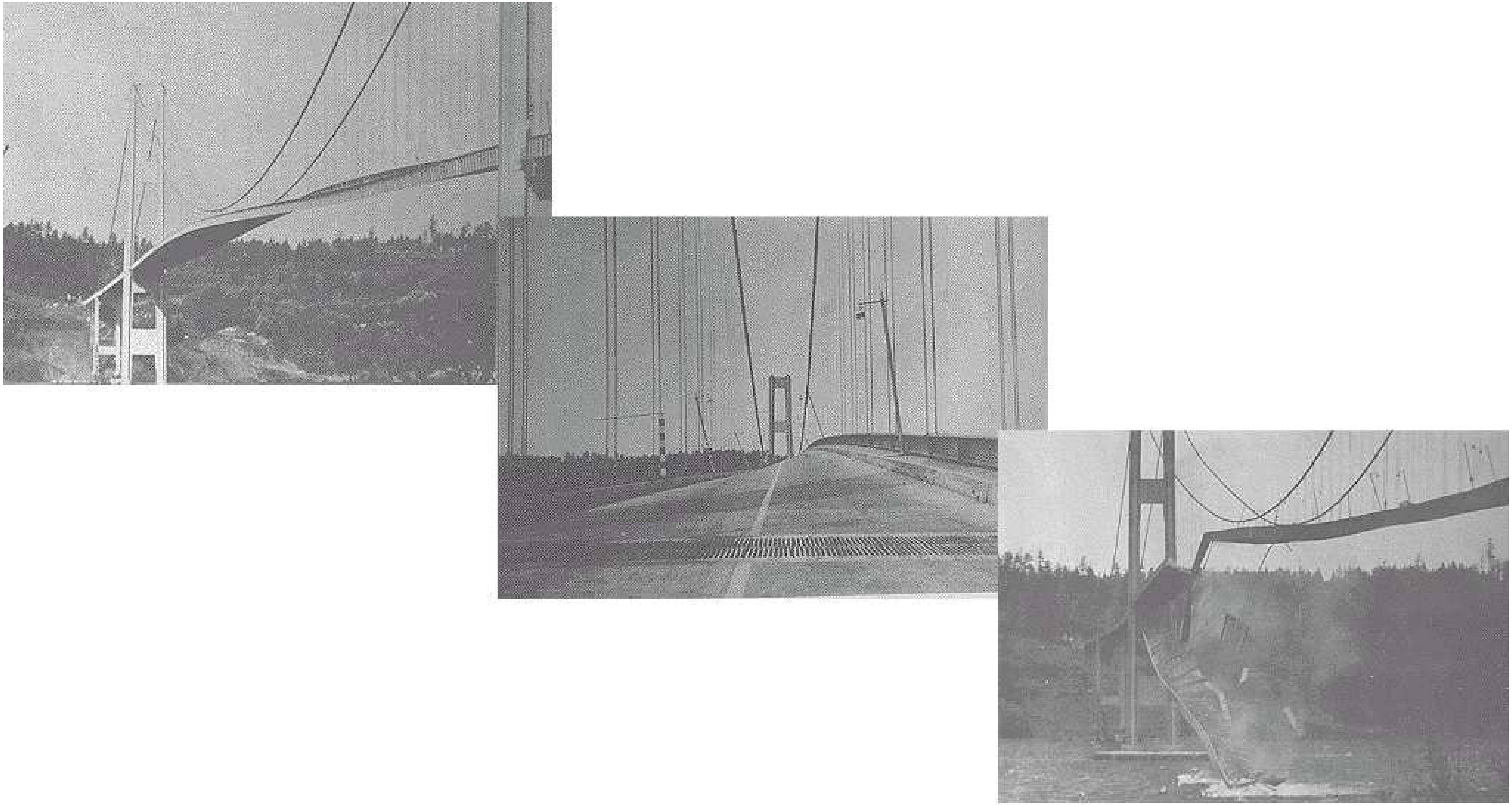
Damaged tanker — oil visualization



Van Dyke (1982), page 100

von Kármán vortex street in technology

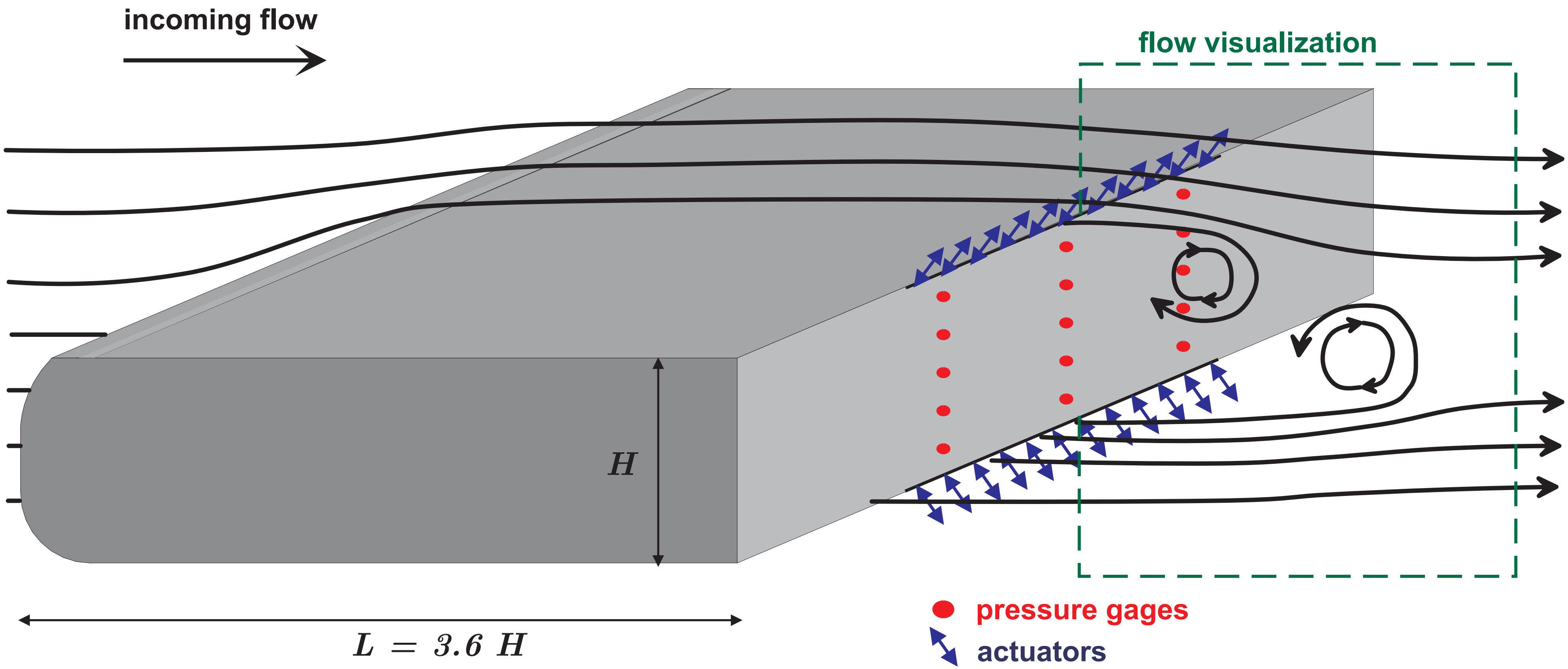
Tacoma Narrows Bridge (7 Nov. 1940)



D-shaped body: Experimental setup

Pastoor, Henning, Noack, King & Tadmor 2008 JFM

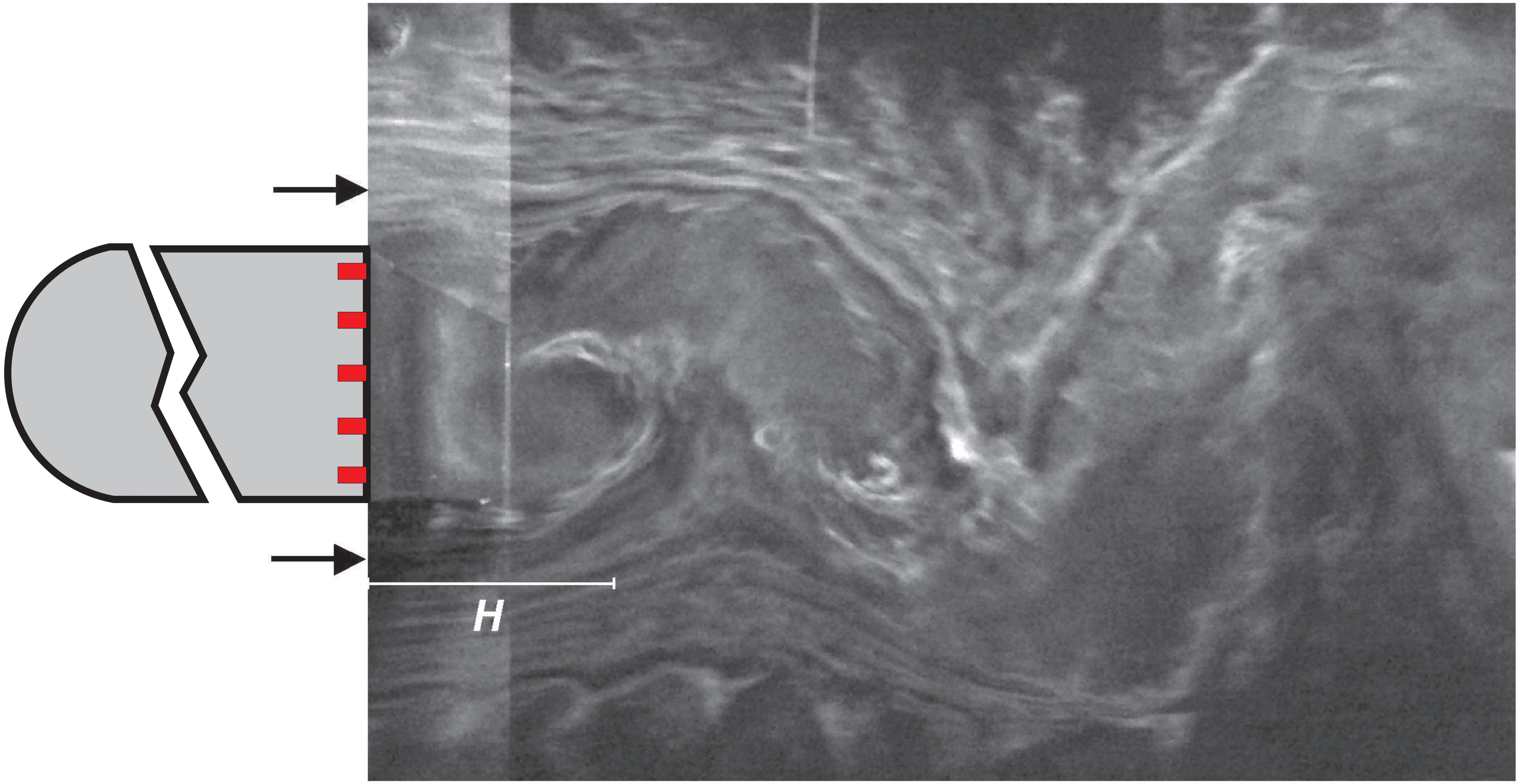
$$Re_H = 20\,000 \ldots 60\,000$$



D-shaped body: Un-actuated flow

Pastoor, Henning, Noack, King & Tadmor 2008 JFM

smoke visualization, $Re_H = 40\,000$



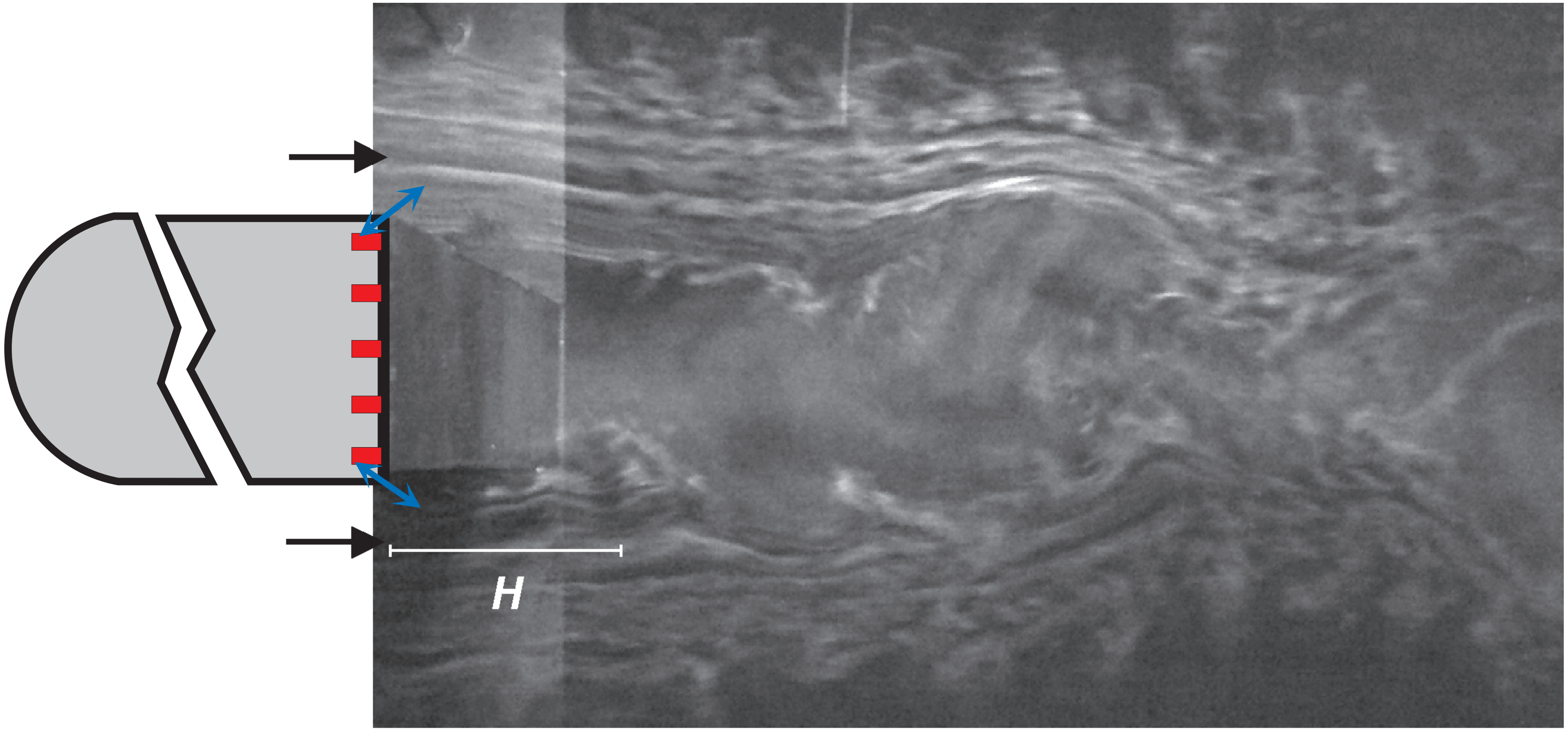
$St_n = 0.20 \quad c_{D,0} = 1.2 \quad \bar{c}_{P,0} = -0.5$

D-shaped body: Open-loop control

Pastoor, Henning, Noack, King & Tadmor 2008 JFM

Symmetric actuation $St_a = 0.63 St_n$ . . . . . . *suggested by ROM*

J.-L. Aider et al. $\mapsto$ backward facing step $Re_H = 40\,000$



$c_\mu = 0.015$ $St_a = 0.126$ $c_D/c_{D,0} = 0.85$ $\overline{c_D}/|\bar{c}_{P,0}| = -0.6$

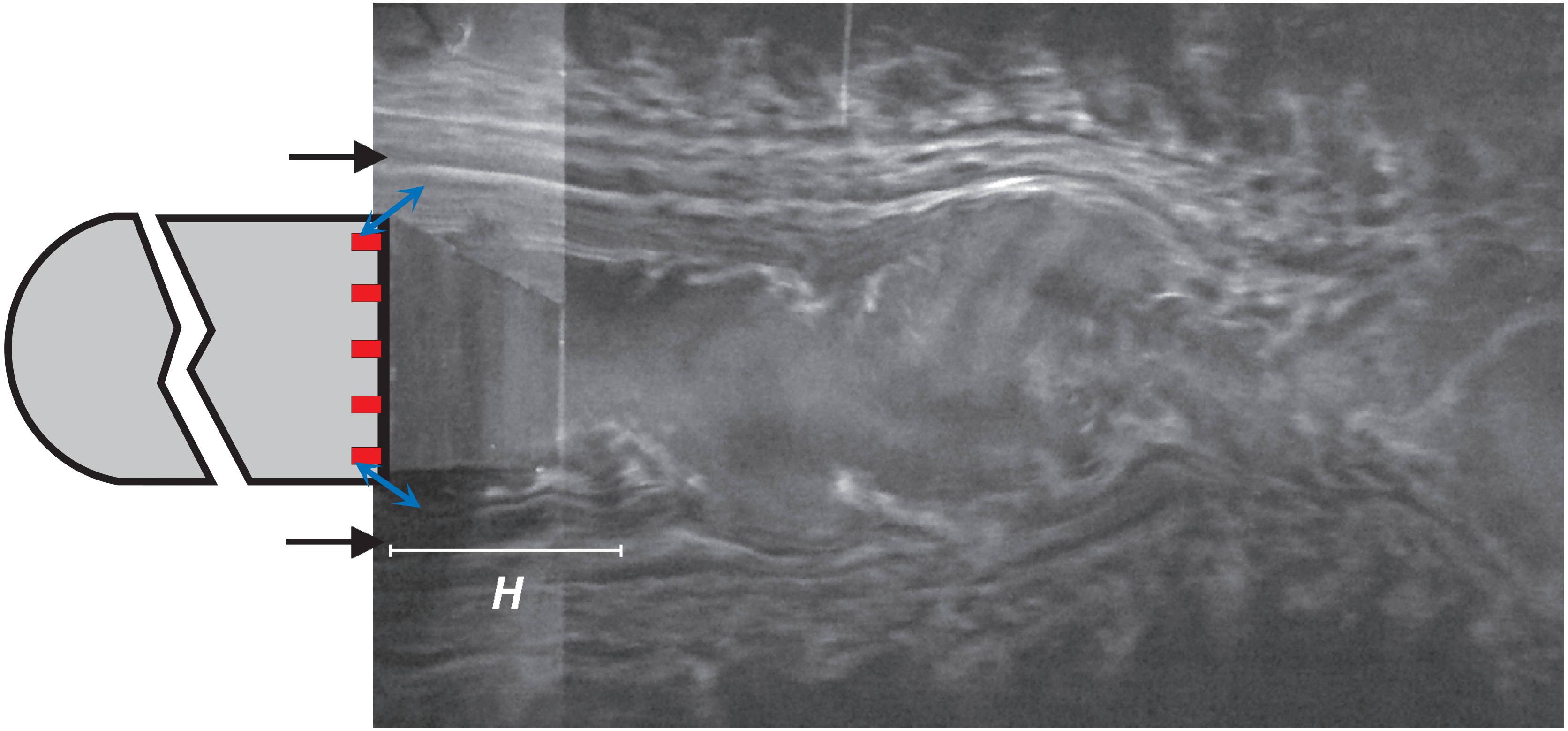
- **40% increase in base pressure.**
- **20% decrease in drag.**

D-shaped body: Closed-loop control

Pastoor, Henning, Noack, King & Tadmor (2008) JFM

Phase control . . . . *derived from ROM*

$Re_H = 40\,000$



$c_\mu = 0.015 \quad St_A = 0.17 \quad c_D/c_{D,0} = 0.85 \quad \overline{c_D}/|\bar{c}_{P,0}| = -0.6$

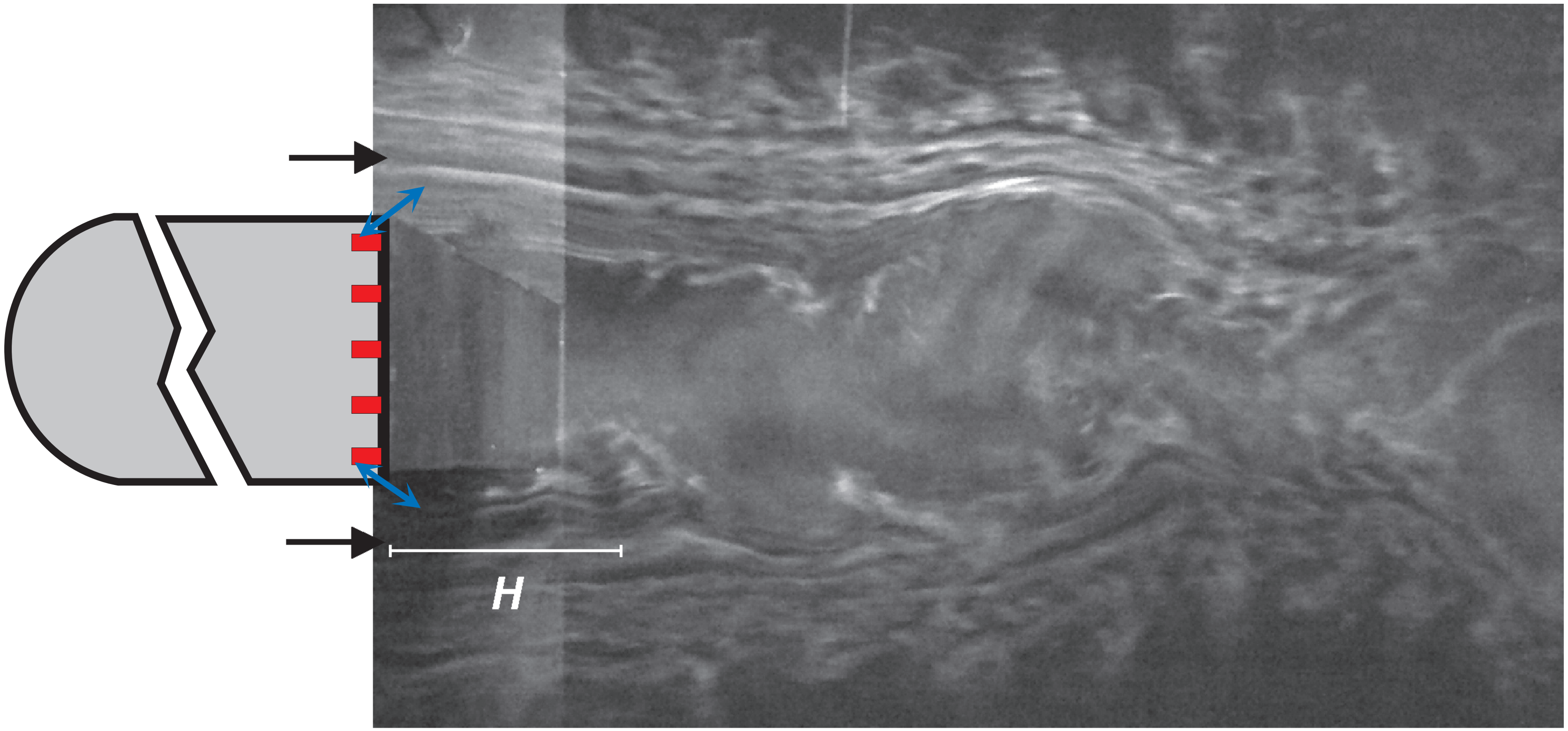
- Same drag reduction, **but at all Re [20000,60000]** ...
- **... and with 40% less actuation energy.**

D-shaped body: Closed-loop control II

Pastoor, Henning, Noack, King & Tadmor 2008 JFM

Phase control .... derived from ROM

$Re_H = 40\,000$



$c_\mu = 0.015 \quad St_A = 0.126 \quad c_D/c_{D,0} = 0.85 \quad \overline{c_D}/|\bar{c}_{P,0}| = -0.6$

- Same drag reduction at same actuation energy.
- **But only one (!) actuator.**

Generalized mean field model

Luchtenburg et al. 2009 JFM & Aleksić et al. 2010 AIAA

Dynamical system structure:

$$\frac{d}{dt}\begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \end{bmatrix} = \begin{bmatrix} \tilde{\sigma}^n & -\tilde{\omega}^n & 0 & 0 \\ \tilde{\omega}^n & \tilde{\sigma}^n & 0 & 0 \\ 0 & 0 & \tilde{\sigma}^a & -\tilde{\omega}^a \\ 0 & 0 & \tilde{\omega}^a & \tilde{\sigma}^a \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ \kappa & -\lambda \\ \lambda & \kappa \end{bmatrix} \mathbf{b}.$$

with state-dependent coefficients

$$\begin{aligned} \tilde{\sigma}^n &= \sigma^n - \sigma^{n,n}\,(A^n)^2 - \sigma^{n,a}\,(A^a)^2, \\ \tilde{\omega}^n &= \omega^n + \omega^{n,n}\,(A^n)^2 + \omega^{n,a}\,(A^a)^2, \\ \tilde{\sigma}^a &= \sigma^a - \sigma^{a,n}\,(A^n)^2 - \sigma^{a,a}\,(A^a)^2, \\ \tilde{\omega}^a &= \omega^a + \omega^{a,n}\,(A^n)^2 + \omega^{a,a}\,(A^a)^2, \\ a_5 &= c + c^n\,(A^n)^2 + c^a\,(A^a)^2, \end{aligned}$$

with $A^n = \sqrt{a_1^2 + a_2^2}$, $A^a = \sqrt{a_3^2 + a_4^2}$ and $\mathbf{b} = (b, \dot{b}/\tilde{\omega}^a)$

Prototypic model of frequency cross-talk

Luchtenburg et al. 2009 JFM & Aleksić et al. 2010 AIAA

Simplified generalized mean-field model:

$$\frac{d}{dt}\begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \end{bmatrix} = \begin{bmatrix} \sigma_1 & -1 & 0 & 0 \\ 1 & \sigma_1 & 0 & 0 \\ 0 & 0 & -0.1 & -10 \\ 0 & 0 & 10 & -0.1 \end{bmatrix}\begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ b \end{bmatrix}$$

$$\sigma_1 = 0.1 - a_1^2 - a_2^2 - a_3^2 - a_4^2$$

Goal = mitigate instability $J = \overline{a_1^2 + a_2^2} + 0.01\overline{b^2} \stackrel{!}{=} \min$

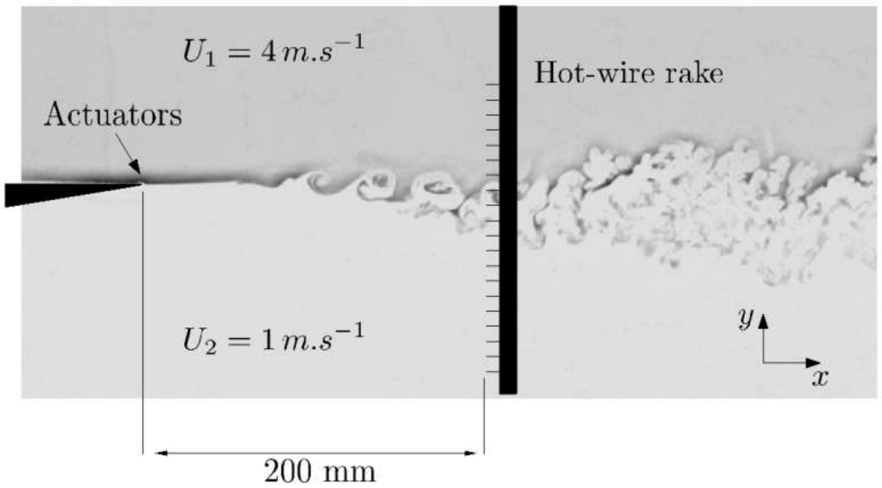
Linear control ⇒ first oscillator uncontrollable!

- **Fixed point** . . . . $a_1 = a_2 = a_3 = a_4 = 0$
- **Linearized system around fixed point** . . . . $\sigma_1 = 0.1$

Nonlinear control: Excite 2nd osc. $a_3^2 + a_4^2 > 0.1 \Rightarrow \sigma_1 < 0$

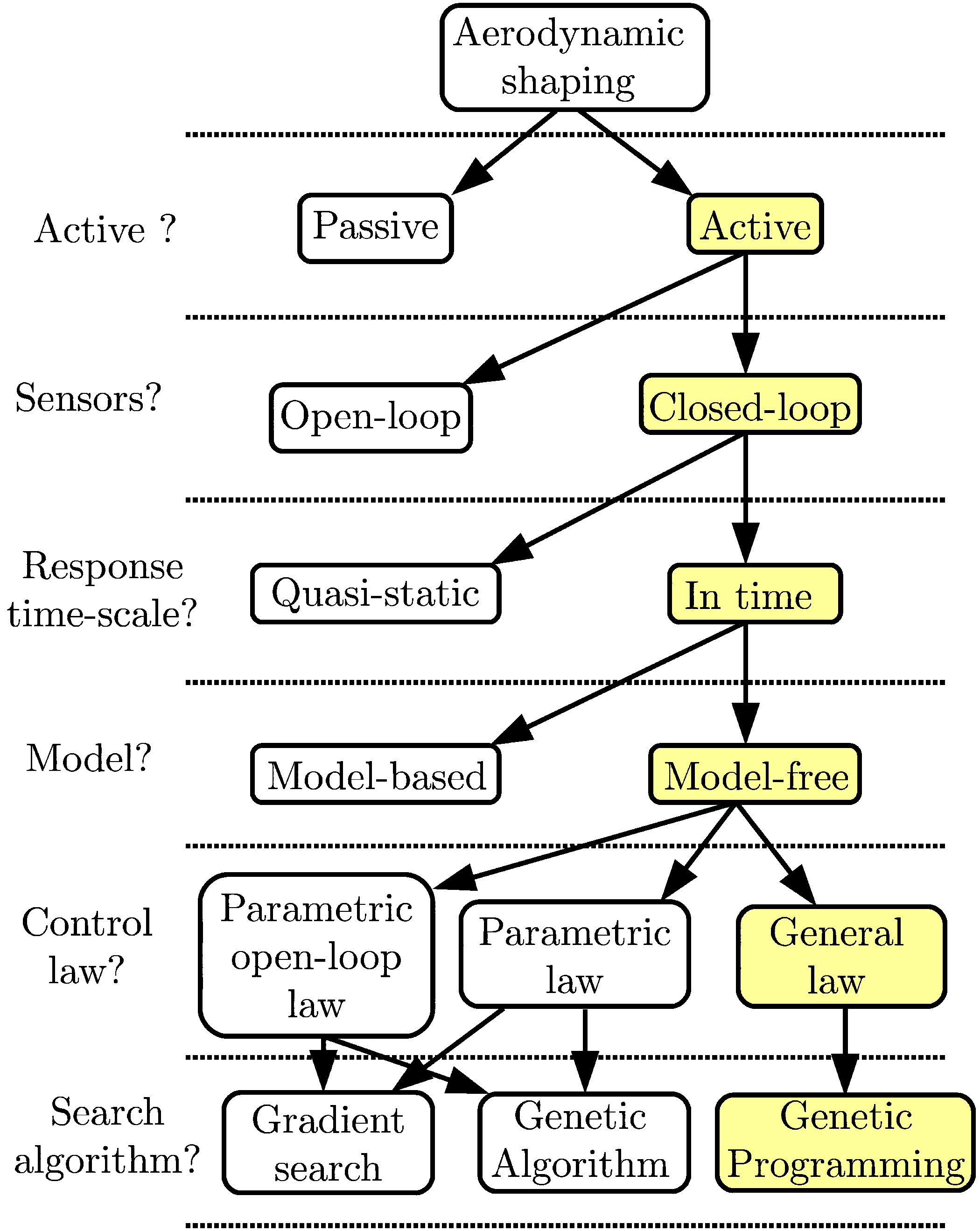
Frequency cross-talk
= show stopper for model-based control

- **Reynolds stress**
  at any frequency
  changes mean flow
  ☰ Reynolds + Hussain 1972 JFMs



- **Normal turbulence cascade**
  Dominant $\mapsto$ high frequencies
- **Inverse turbulence cascade**
  Dominant $\mapsto$ lower frequencies
- **High frequency forcing**
  can mitigate the dominant frequency
  ☰ Glezer+ 2005 AIAA-J, ☰ Luchtenburg+ 2009 JFM, ...
- **Low-frequency forcing** too
  ☰ Aider+ 2014, ☰ Pastoor+ 2008 JFM, ...

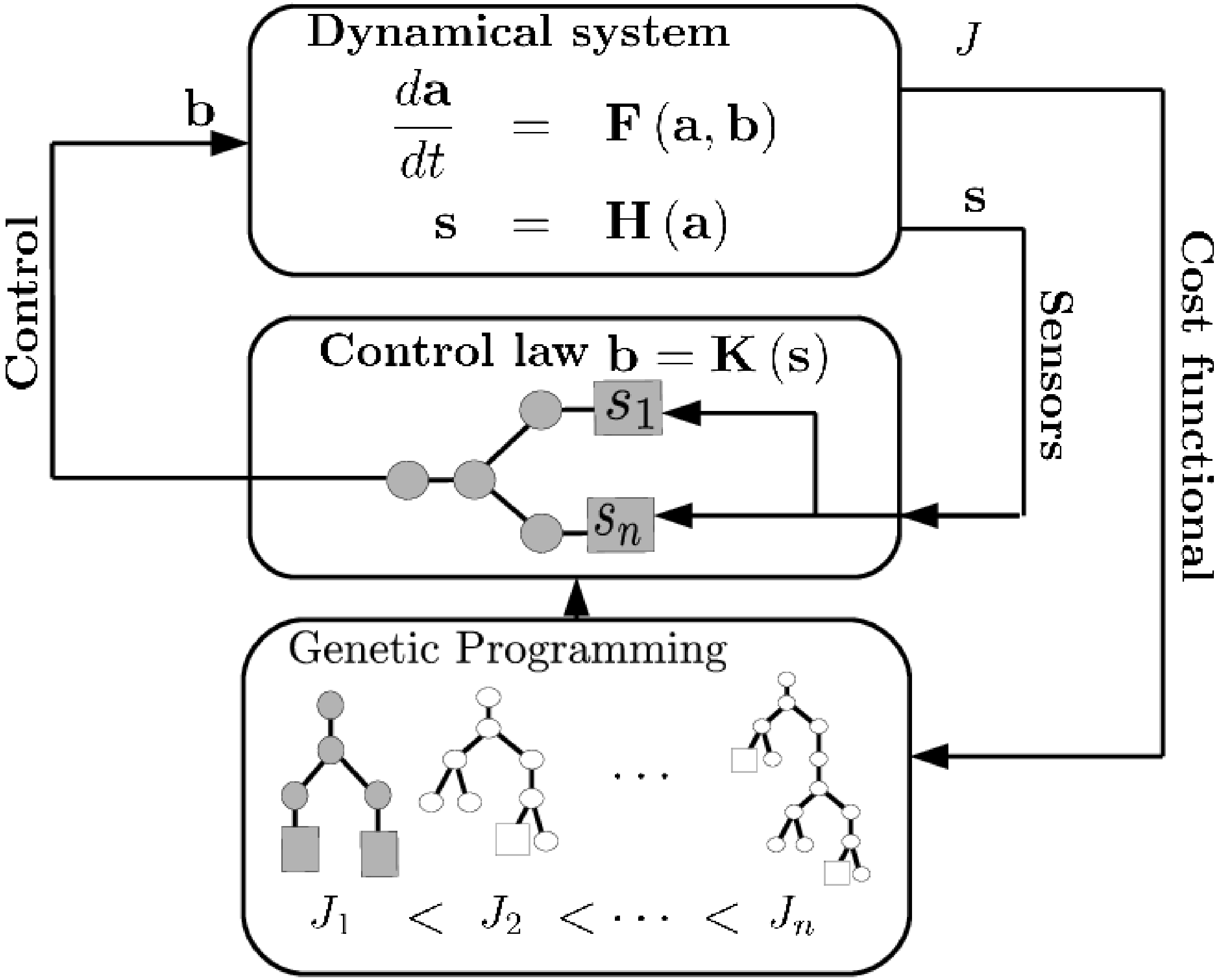
Turbulence control → decision tree



Overview

Machine learning control I

Duriez et al. 2014 AIAA, Wahde 2008



MLC = model-free optimization of control laws

Similar approaches exist for robotic missions, etc.

Machine learning control II

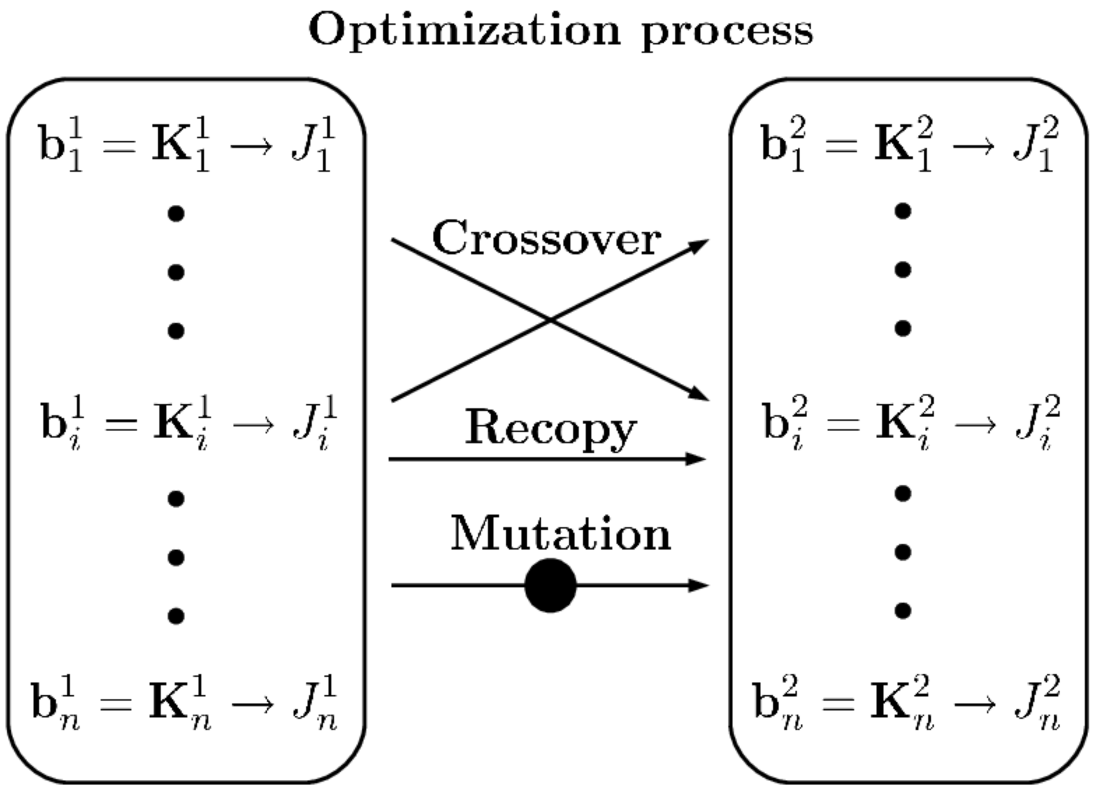
Duriez et al. 2014 AIAA

Step 1: 1st generation with random nonlinear control laws

$b_m^1 = K_m^1(s), m = 1, ..., 100$

Step 2–50:

Biologically inspired optimization of the control laws based on the 'fitness grades' $J\,[b = K(s)]$



J.R. Koza 1992 Genetic Programming, The MIT Press

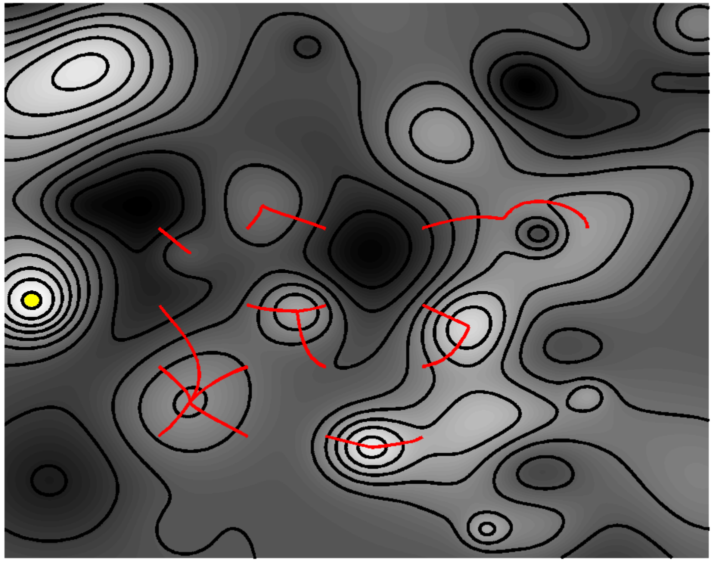
Detailed description

Machine learning control III

Duriez et al. 2014 AIAA, Gautier et al. 2015 JFM

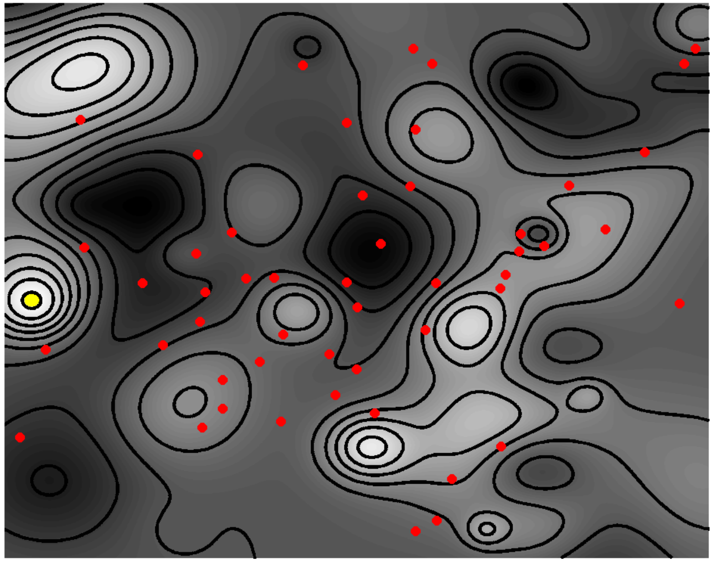
Gradient search

requires structure identification of the control law and yields parameter identification
(local minimization)



Genetic algorithm/programming

= evolutionary algorithm for regression with parameter/structure identification of the control law
(global minimization)

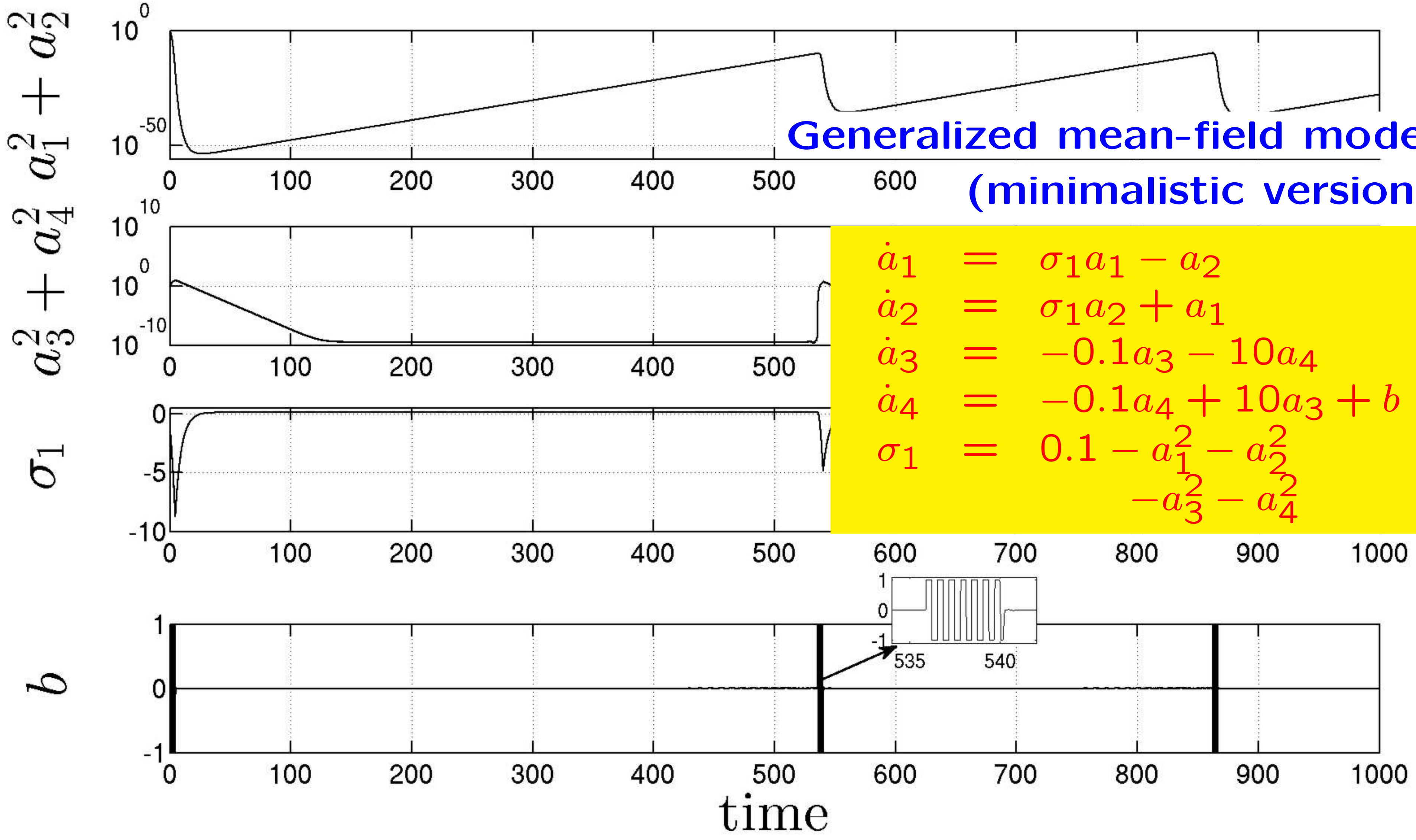


Example of an evolutionary minimization

MLC $\mapsto$ generalized mean-field model

Luchtenburg, Günther, Noack, King & Tadmor 2009 JFM & Duriez et al. 2014 AIAA

MLC goal: $b(\boldsymbol{a})$ with $J = \frac{1}{T}\int_0^T dt\,\left[a_1^2 + a_2^2 + 0.01 b^2\right] = min$



Generalized mean-field model (minimalistic version)

$$
\begin{aligned}
\dot{a}_1 &= \sigma_1 a_1 - a_2 \\
\dot{a}_2 &= \sigma_1 a_2 + a_1 \\
\dot{a}_3 &= -0.1 a_3 - 10 a_4 \\
\dot{a}_4 &= -0.1 a_4 + 10 a_3 + b \\
\sigma_1 &= 0.1 - a_1^2 - a_2^2 \\
&\quad - a_3^2 - a_4^2
\end{aligned}
$$

MLC $\mapsto$ Lorenz equation

Duriez et al. 2014 AIAA

Forced Lorenz system

$$\frac{da_1}{dt} = \sigma\left(a_2 - a_1\right),$$
$$\frac{da_2}{dt} = a_1\left(\rho - a_3\right) - a_2,$$
$$\frac{da_3}{dt} = a_1 a_2 - \beta a_3 + b,$$
$\sigma = 10$, $\beta = 8/3$ and $\rho = 20$

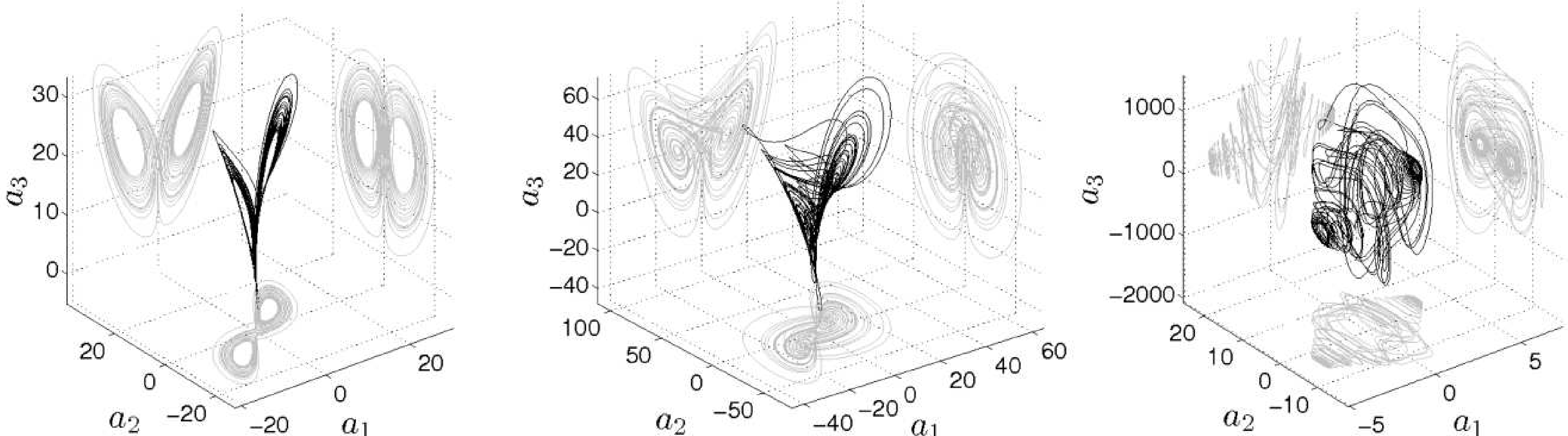
MLC goal:

Find a control law $b(\boldsymbol{a})$ with mimimizes the max. Lyapunov exponent

$$J = \exp(-\lambda_1) + \frac{\gamma}{T}\int_0^T dt\, b^2$$

Controlled Lorenz attractors

$\gamma = 1$ $\lambda_1 = 0.715$, $\gamma = 0.01$ $\lambda_1 = 2.072$, $\gamma = 0$ $\lambda_1 = 17.613$



Overview

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Conclusions

≡ *Noack+ 2011 Springer (↦ROM); Kaiser+ 2014 JFM (↦CROM); Gautier+ 2015 JFM (↦MLC)*

- **Turbulence control = attractor control**

  Physics mechanisms are strongly nonlinear.

- **Model-based control design**

  → **one or two frequencies**

- **Model-free machine learning control design**

  → **broadband turbulence**

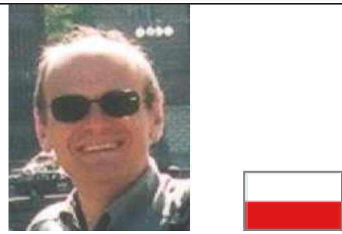
  - shear turbulence control, drag reduction, ...
  - MLC consistently outperformed best open-loop forcing
  - Even when a linear dynamics was invalidated.

- **In Progress: Cluster-based control (CROM, RL, ...)**

  → **model-based alternative for MLC** . . . . More info

More information or any ideas

Call 24h/7d

				
+61-2-62688330	+1-206-543-7124	+49-17682001688	+48-61-6652778	+33-549-366015

... or read

Kaiser+ 2014 JFM . . . . *CROM*	**Gautier+ 2015 JFM** . . . *machine learning control*
Pastoor+ 2008 JFM . . . . *bluff-body control*	**Luchtenburg+ 2009 JFM** . . . . *airfoil control*

... or ask now!!!

In any case, stay tuned in for news + publications:

- http://MachineLearningControl.com
- http://ClusterModelling.com