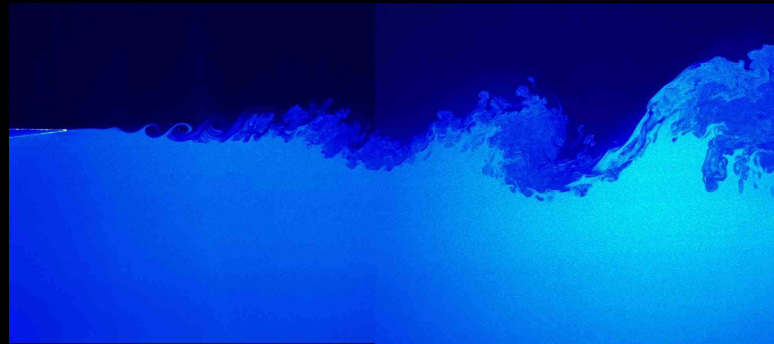
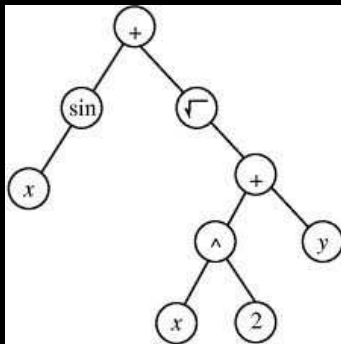


Closed-loop turbulence control using machine learning

Stop thinking and let your PC and experiment do the hard work!



B. Noack³, T. Duriez^{1,3}, L. Cordier³, K. von Krbek³,
E. Kaiser^{3,4}, V. Parezanovic³, **J.-P. Bonnet**³,
M. Segond³, M. Abel³, N. Gautier³, J.-L. Aider³,
C. Raibaud³, C. Cuvier³, **M. Stanislas**³, A. Debien³,
N. Mazellier³, A. Kourta³, **S. Brunton**¹, R. Niven² &

.....¹Argentina, ²Australia, ³Europe & ⁴USA

— supported by ANR, DFG, ERC & ADFA@UNSW —

Friends / core team

Complex systems



M. Abel
M. Segond
Ambrosys

Closed-loop turbulence control — theory



**L. Cordier, T. Duriez, E. Kaiser,
B. Noack, K. von Krbek, C.
Pivot, M. Schlegel, et al.**

Statistical physics



Robert Niven
UNSW
Australia

Control theory



S. Brunton
U Washington

Closed-loop turbulence control — experimental demonstrators

D. Barros
J.-P. Bonnet
J. Borée
R. Li
V. Parezanovic
P'

R. Semaan
R. Radespiel
Braunschweig
R. King
TU Berlin

CFD + Stab.anal.



M. 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)
..... soon: 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. Raibaud, 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, 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 ~ 100 actuators and ~ 500 sensors

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

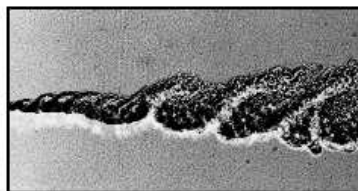
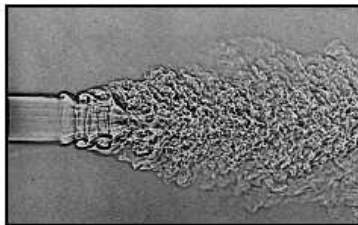
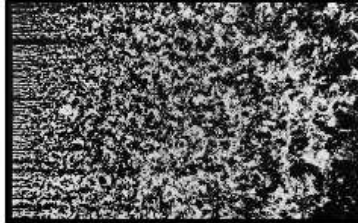
- aerodynamic design
- passive (e.g. riblets)
- active, open-loop
(e.g. periodic blowing)
- active, closed-loop
(largest opportunities!)

Turbulence control \mapsto other applications

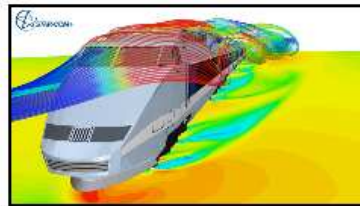


Turbulence control \mapsto even more applications

Simple prototype flows



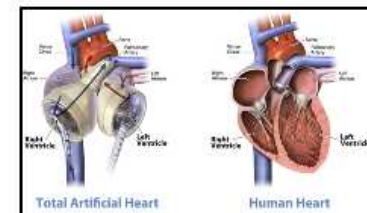
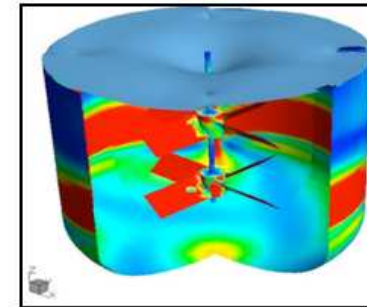
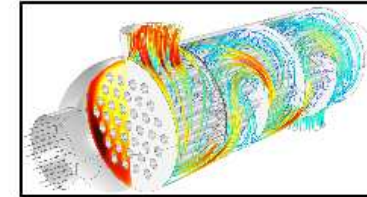
Transport vehicles



Energy systems



Production etc.



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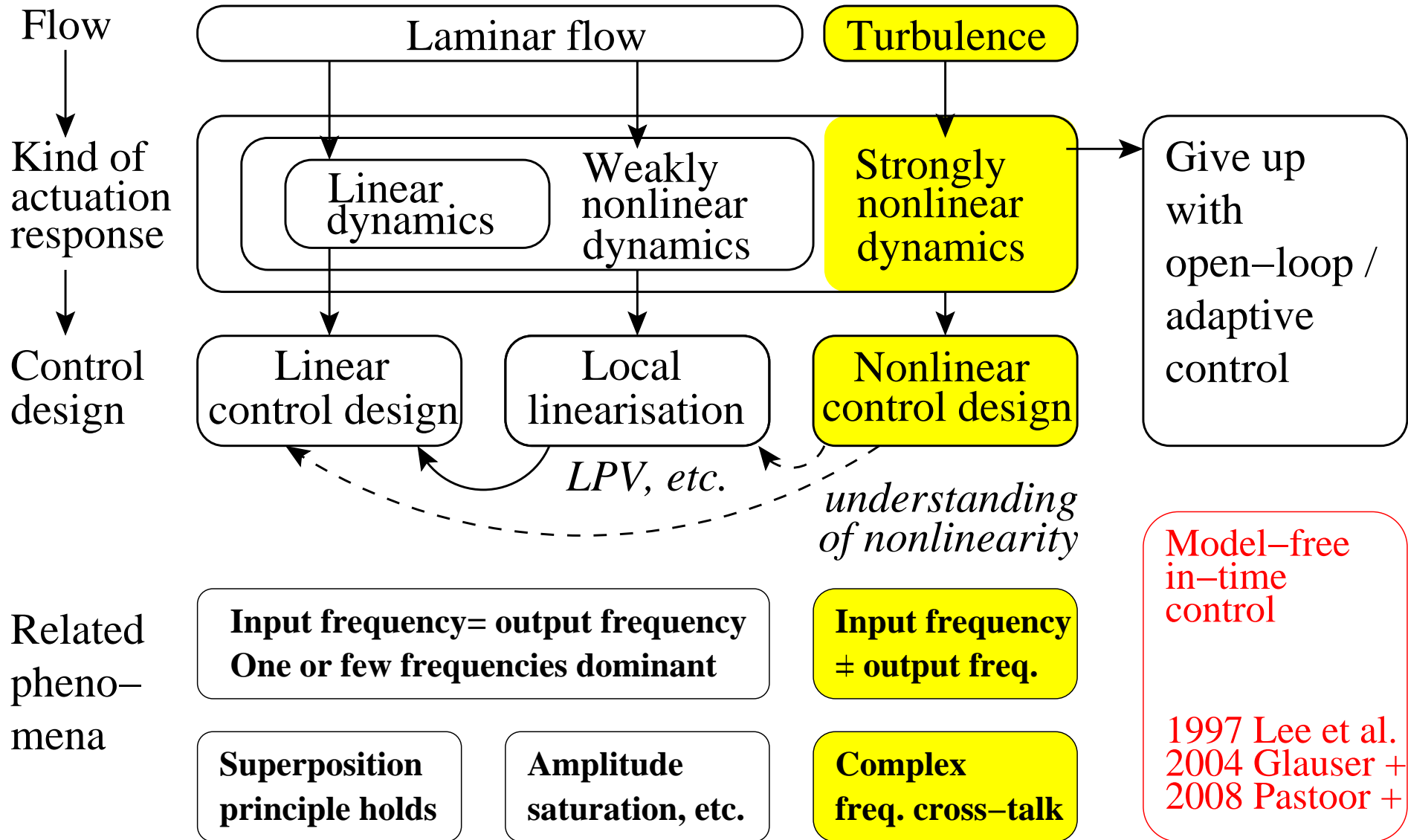
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Turbulence control → nonlinearity challenge

☰ Duriez et al. 2014 AIAA



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

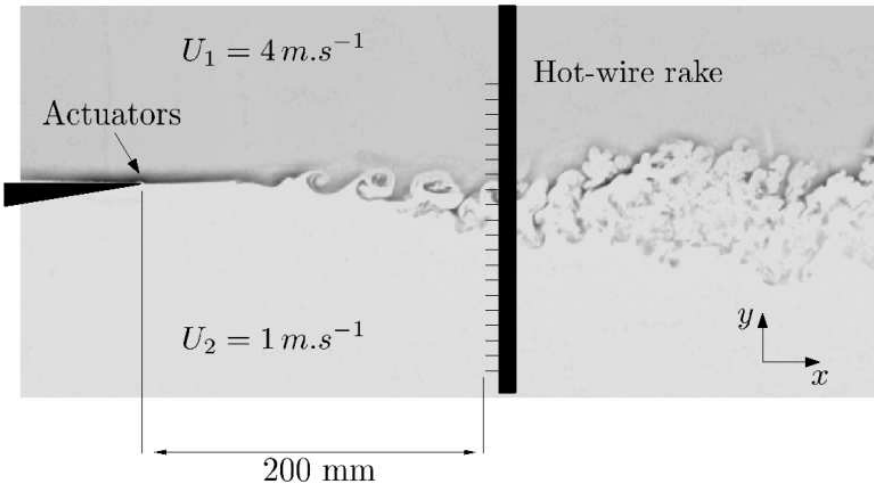
- **High frequency forcing**

can mitigate the dominant frequency

☐ Glezer+ 2005 AIAA-J, ☐ Luchtenburg+ 2009 JFM, ...

- **Low-frequency forcing** too

☐ Aider+ 2014, ☐ Pastoor+ 2008 JFM, ...



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

Linear control \Rightarrow 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. $a_3^2 + a_4^2 > 0.1 \Rightarrow \sigma_1 < 0$

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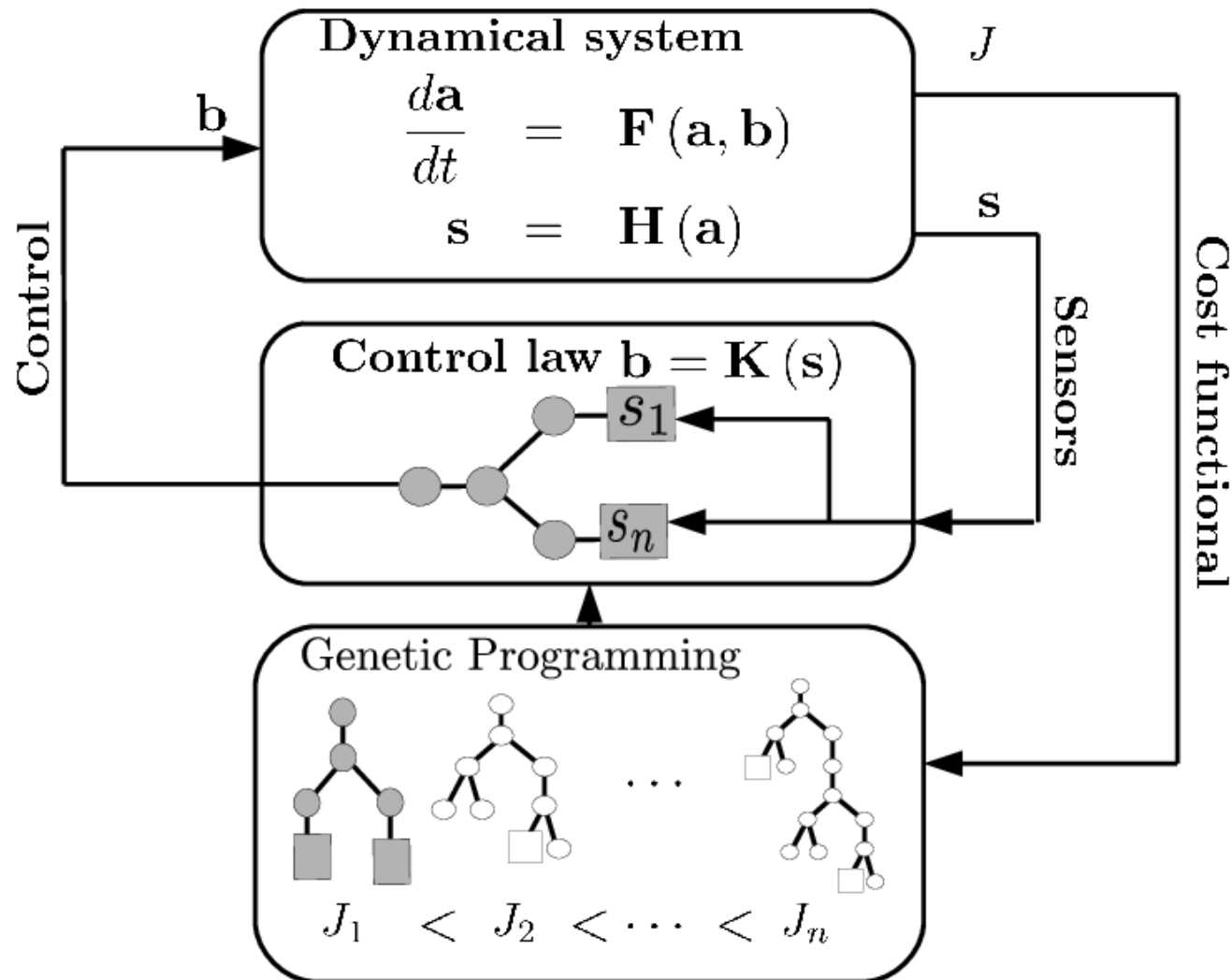
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Machine learning control I

≡ 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

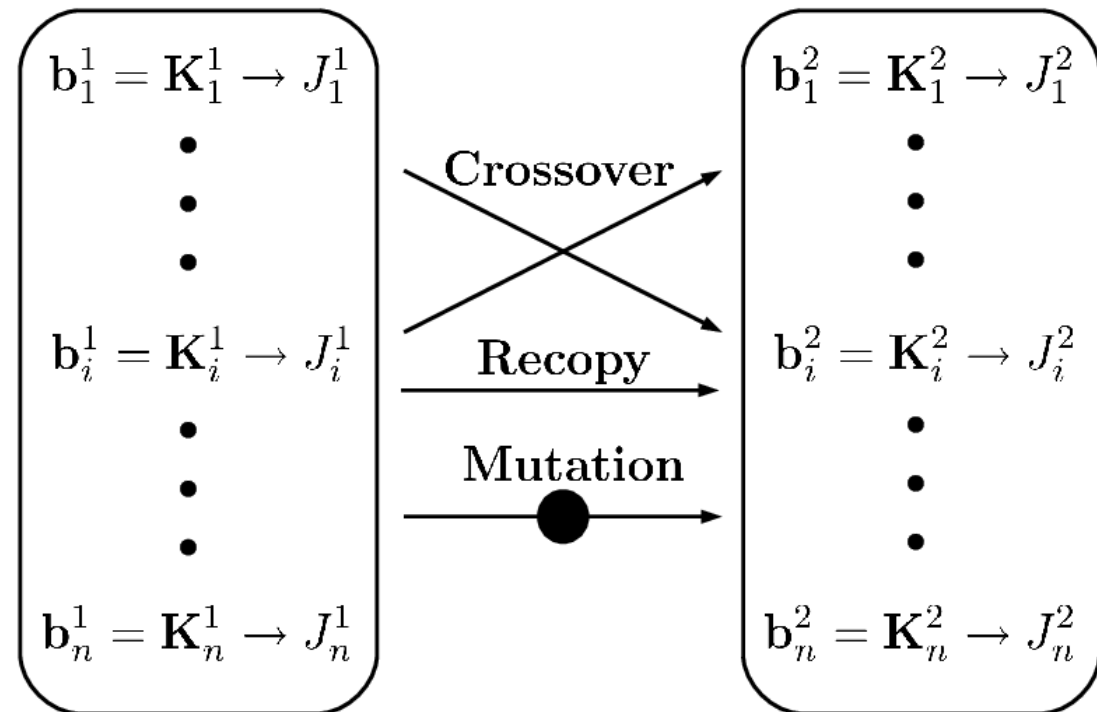
$$b_m^1 = K_m^1(s), m = 1, \dots, 100$$

Step 2–50:

Biologically inspired optimization of the control laws based on the 'fitness grades'

$$J[b = K(s)]$$

Optimization process



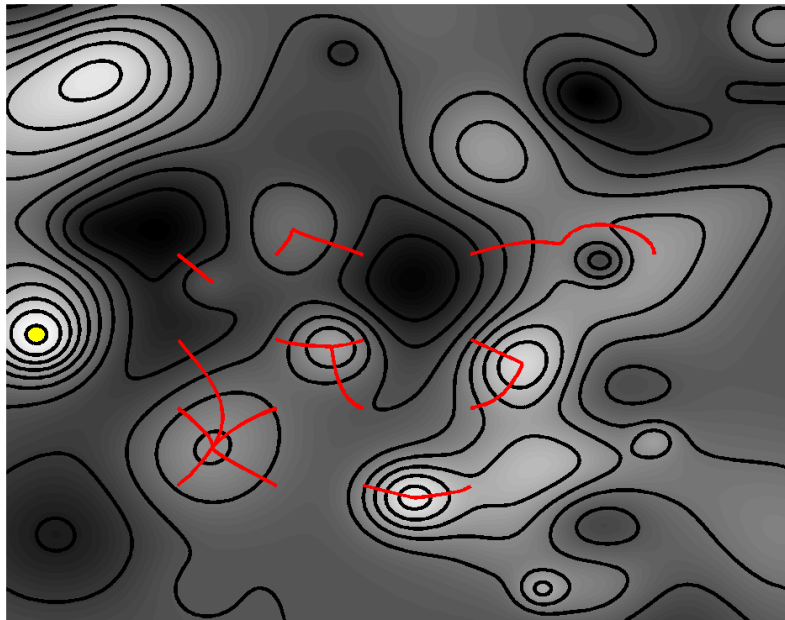
☰ J.R. Koza 1992 Genetic Programming, The MIT Press

Machine learning control *III*

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

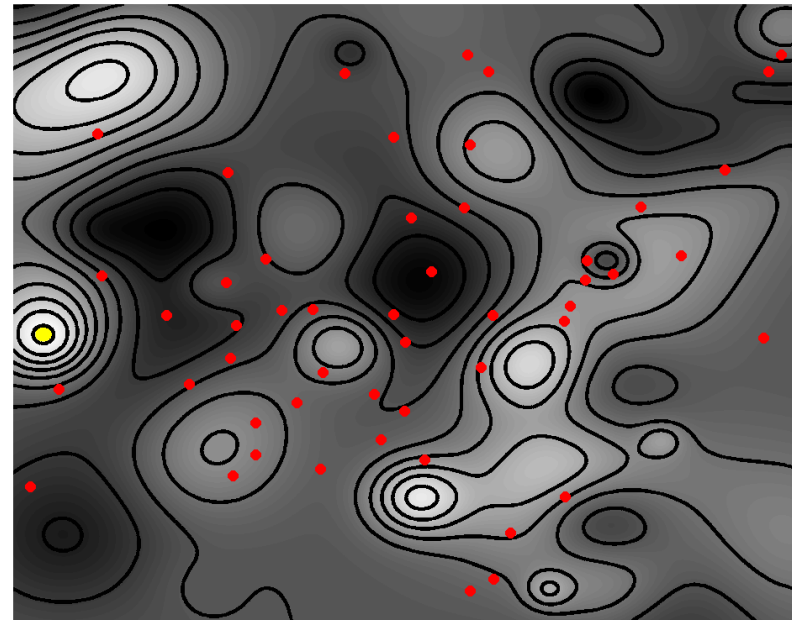
Gradient search

requires structure identification of the control law and parameter identification based on local minimization



Genetic programming

= evolutionary algorithm for regression with structure identification of control law

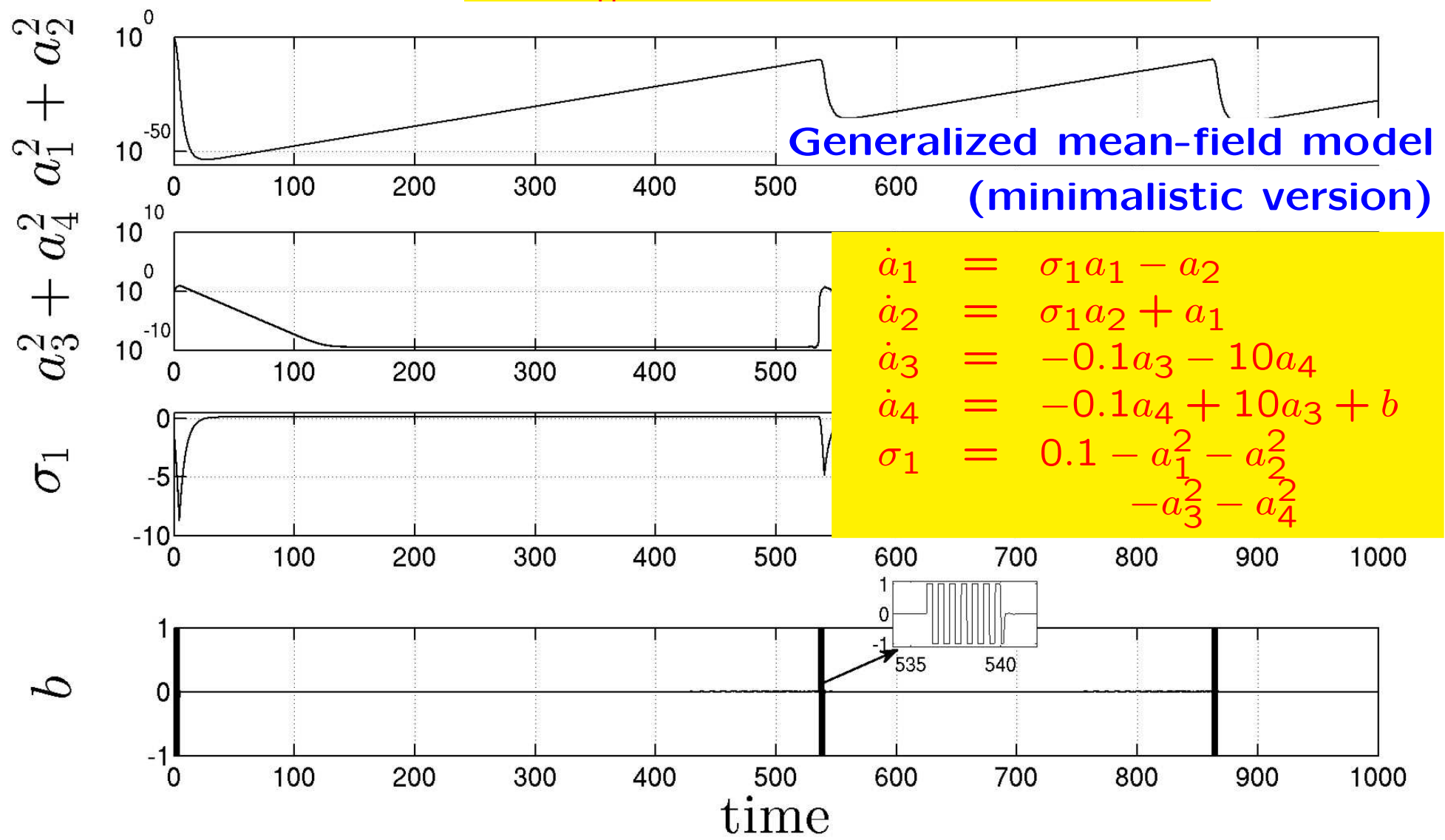


Example of an evolutionary minimization.

MLC \mapsto generalized mean-field model

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

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



MLC \mapsto Lorenz equation

 Duriez et al. 2014 AIAA

Forced Lorenz system

$$\begin{aligned}\frac{da_1}{dt} &= \sigma(a_2 - a_1), \\ \frac{da_2}{dt} &= a_1(\rho - a_3) - a_2, \\ \frac{da_3}{dt} &= a_1a_2 - \beta a_3 + b, \\ \sigma &= 10, \beta = 8/3 \text{ and } \rho = 20\end{aligned}$$

MLC goal:

Find a control law $b(a)$ with minimizes the max. Lyapunov exponent

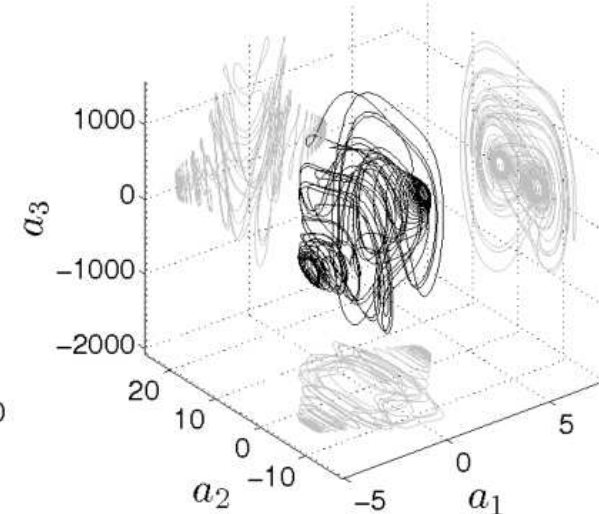
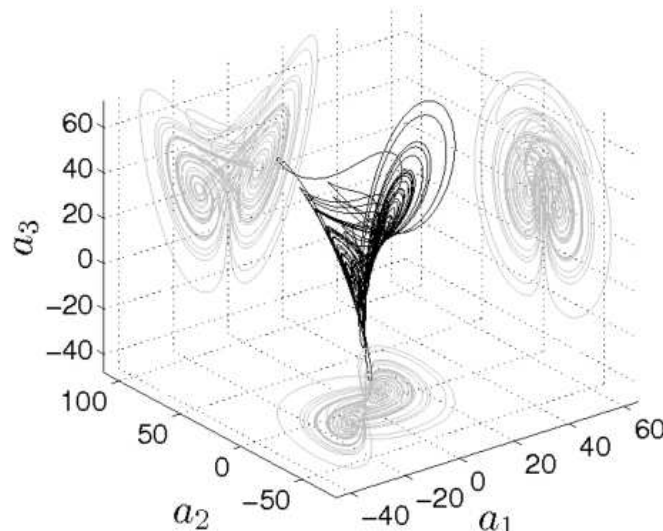
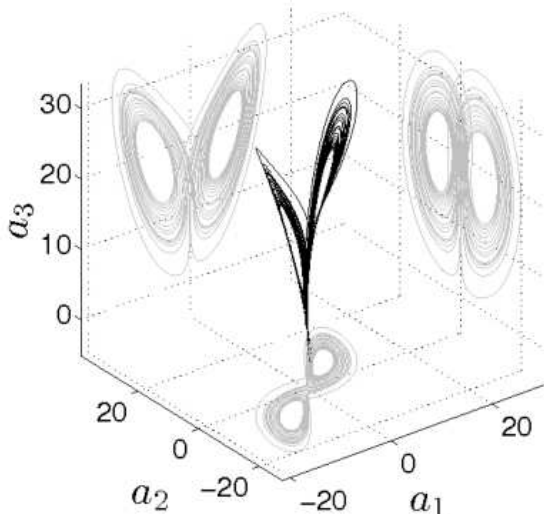
$$J = \exp(-\lambda_1) + \frac{\gamma}{T} \int_0^T dt b^2$$

Controlled Lorenz attractors

$$\begin{aligned}\gamma &= 1 \\ \lambda_1 &= 0.715,\end{aligned}$$

$$\begin{aligned}\gamma &= 0.01 \\ \lambda_1 &= 2.072,\end{aligned}$$

$$\begin{aligned}\gamma &= 0 \\ \lambda_1 &= 17.613\end{aligned}$$



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TUCOROM wind-tunnel

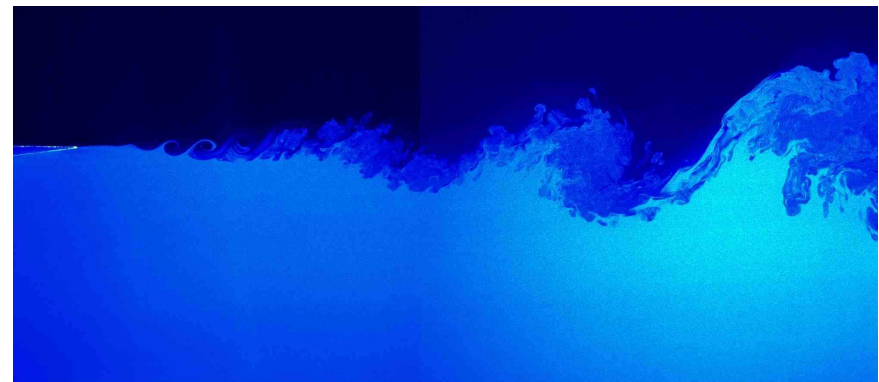
☰ Parezanović et al. 2014 FTC & ☰ Duriez et al. 2014 AIAA

New
turbulence control
wind-tunnel at P' →

Control team
at control desk

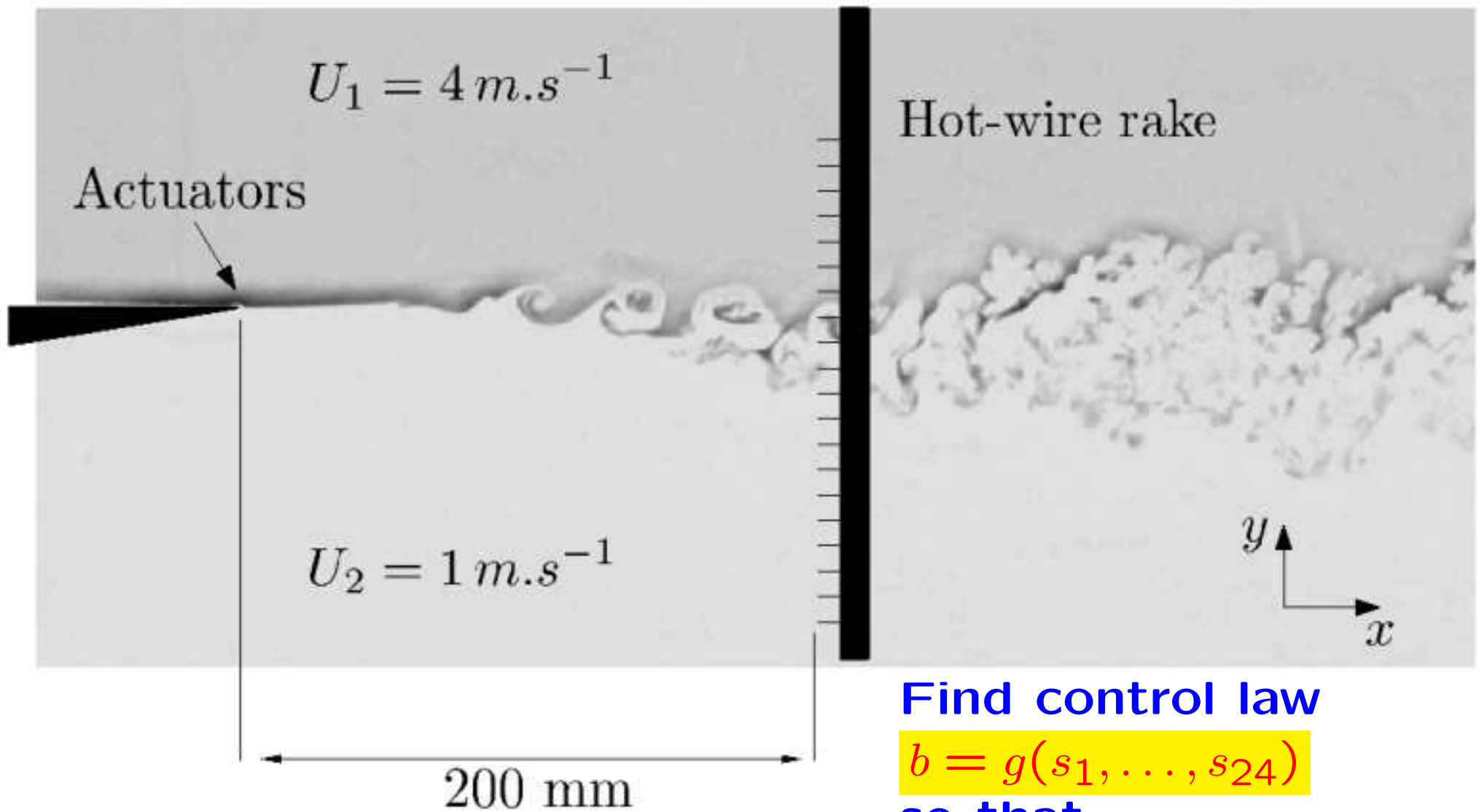


Flow visualization



TUCOROM mixing layer demonstrator

☰ Parezanović et al. 2014 FTC



Find control law

$$b = g(s_1, \dots, s_{24})$$

so that

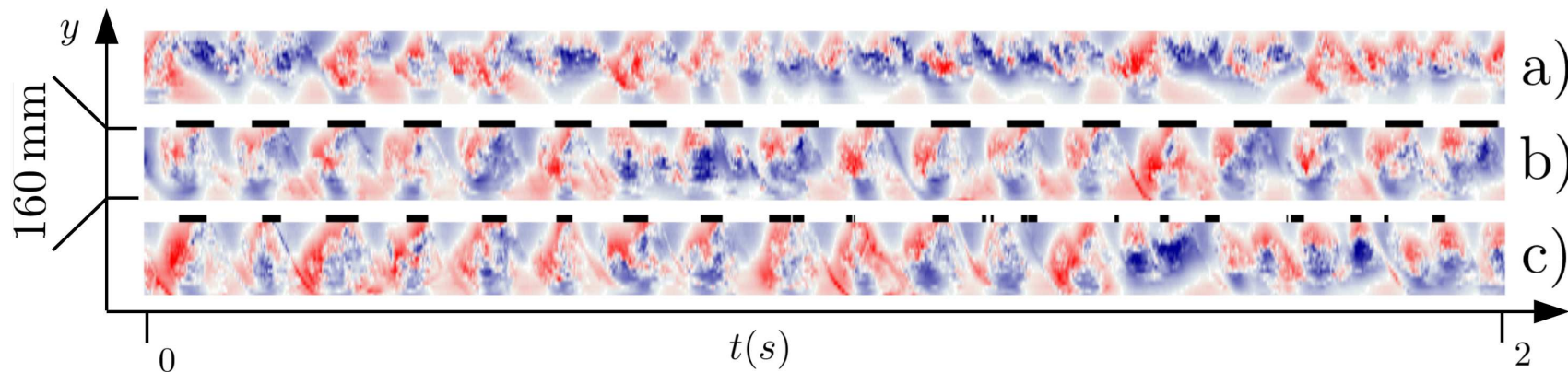
$$J = \sum_{i=1}^{24} \overline{(s'_i)^2} = \max$$

TUCOROM mixing layer control experiment

☰ *Duriez et al. 2014 AIAA* & ☰ *Parezanović et al. 2014 FTC*

set-up	actuation Q	width W
a) unactuated flow	0%	100%
b) best periodic forcing	100%	155%
c) MLC closed loop forcing	54%	167%
MLC vs open-loop	-46%	+12%

Pseudo visualizations from 24 hot-wire sensors



MLC has found a very effective nonlinear low-frequency resonance mechanism!

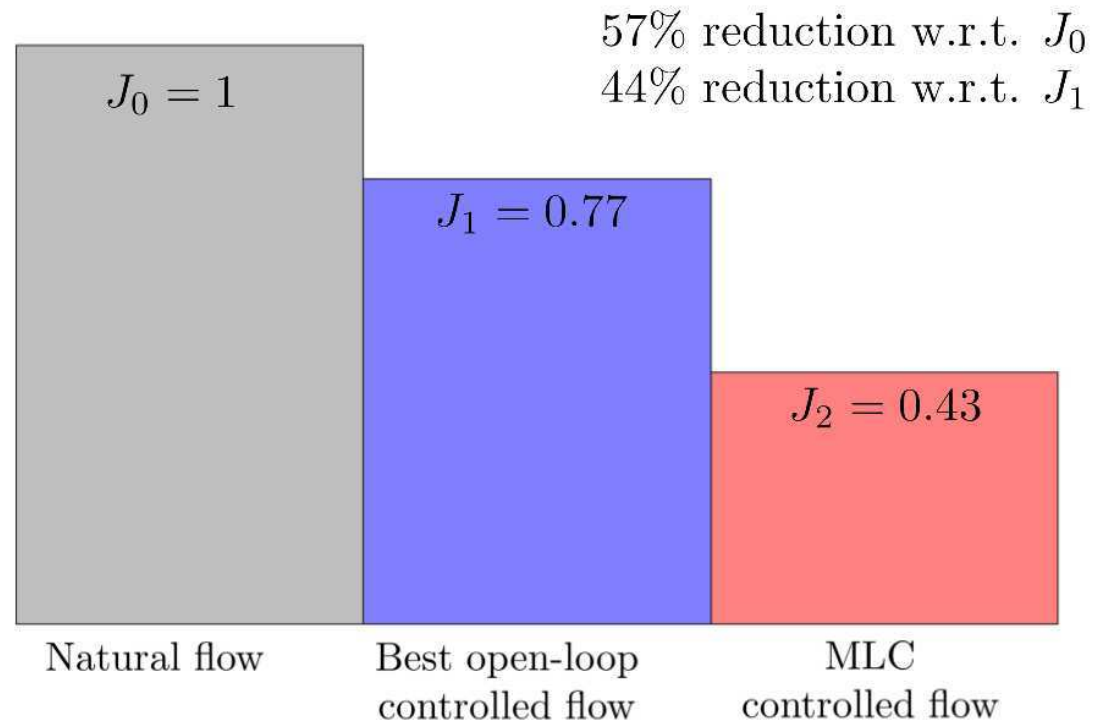
MLC in water tunnel experiment (PMMH)

☰ Gautier, Aider, Duriez, Noack, Segond & Abel 2015 JFM (accepted)

Mixing enhancement (BFS)

$$J = \bar{s} + \frac{3}{2}|\bar{b}|^2 = \min!$$

s : normalized recirculation zone; b : normalized actuator velocity



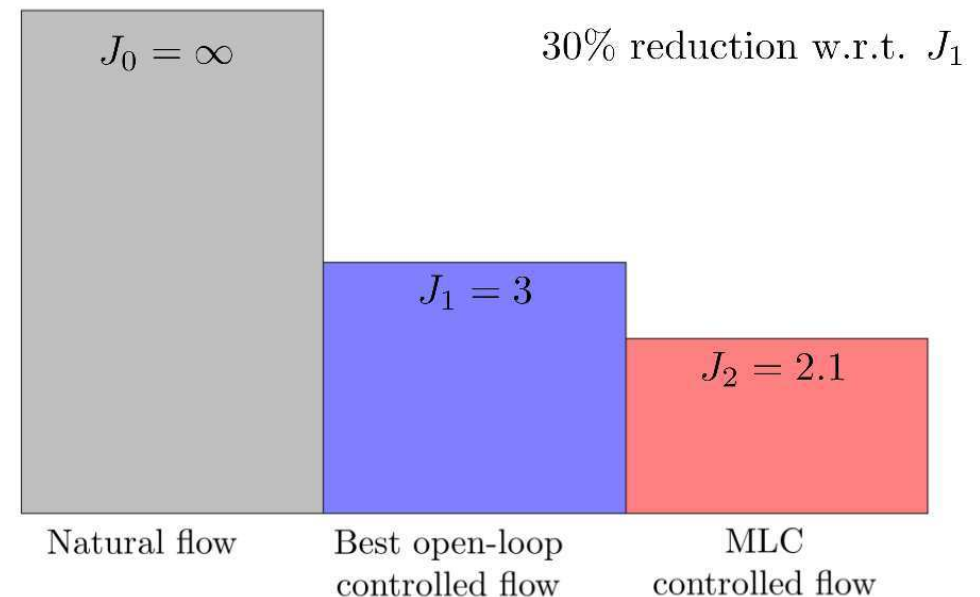
MLC has found a very effecting flapping mode mechanism for decreasing the recirculation zone!

MLC in a boundary layer experiment (LML)

☰ Duriez, Parezanović, Laurentie, Fourment, Delville, Bonnet, Cordier, Noack, Segond, Abel, Gautier, Aider, Raibaud, Cuvier, Stanislas & Brunton 2014 AIAA

Separation control of a turb. boundary layer over a ramp

J = measure of attachment + actuation penalty = min!



MLC outperformed the best open-loop forcing

by finding periods where blowing is not efficient!

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Conclusions

☰ Noack+ 2011 Springer (\mapsto ROM); Kaiser+ 2014 JFM (\mapsto CROM); Gautier+ 2015 JFM (\mapsto 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 information **or any ideas**

Call 24h/7d

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

 Kaiser+ 2014 JFM <i>CROM</i>	 Gautier+ 2015 JFM ... <i>machine learning control</i>
 Pastoor+ 2008 JFM <i>bluff-body control</i>	 Luchtenburg+ 2009 JFM <i>airfoil control</i>

... or ask now!!!

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

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