

# Stabilization of the fluidic pinball and control of the open cavity with gradient-enriched machine learning control

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and Bernd R. Noack<sup>2</sup>

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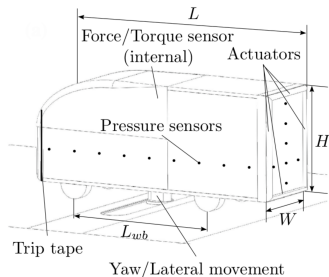
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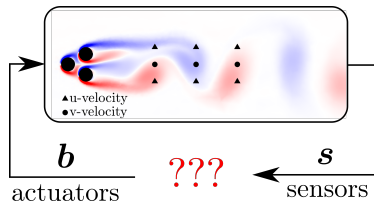


**Acknowledgement** : ANR-17-ASTR-0022, FLOWCON project : Contrôle d'écoulements turbulents en boucle fermée par apprentissage automatique

# A methodology for MIMO control



**Truck model @TU-B with 18 pressure sensors and 5 actuators**  
(from Pfeiffer & King 2018 *Exp. Fluids*)



The **fluidic pinball** with **3 actuators** and **9 sensors**.

## An optimization problem—a model-free approach

$$\mathbf{b}(t) = \mathbf{K}(\mathbf{h}(t), \mathbf{s}(t))$$

$$\mathbf{K}^* = \arg \min_{\mathbf{K} \in \mathcal{K}} J(\mathbf{K})$$

$\mathbf{h}$  : periodic functions

$\mathbf{s}$  : sensors

$\mathcal{K}$  : control law space

# The fluidic pinball - a nonlinear system for control benchmark

$$\text{Reynolds number } Re = \frac{U_\infty D}{\nu} = 100$$



## Fluidic pinball community

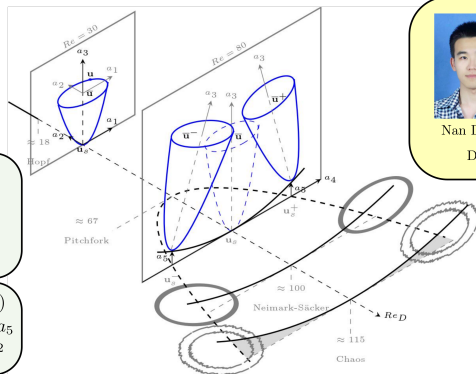
- **Deep reinforcement learning control**  
Thibaut Guégan & Laurent Cordier (Institut Pprime)
- **Experiment** in University of Calgary Robert Martinuzzi (Raibaudo 2020 *Physics of Fluids*)
- **Myriad of regimes** (Chen 2020 *JFM*)

**Hopf** ( $Re \approx 18$ )

$$\begin{aligned} da_1/dt &= \sigma a_1 - \omega a_2 \\ da_2/dt &= \sigma a_2 + \omega a_1 \\ da_3/dt &= \sigma_3 a_3 + \beta_3 r^2 \end{aligned}$$

+ **Pitchfork** ( $Re \approx 68$ )

$$\begin{aligned} da_4/dt &= \sigma_4 a_4 - \beta_4 a_4 a_5 \\ da_5/dt &= \sigma_5 a_5 + \beta_5 a_4^2 \end{aligned}$$



Nan Deng



Luc Pastur

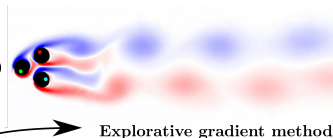
Deng 2020 *JFM*

# The fluidic pinball - a hierarchy of stabilization mechanisms

Distance to the symmetric steady solution

$$J_a = \frac{1}{T_{ev}} \int_{t_0}^{t_0+T_{ev}} \|\mathbf{u}_b(t) - \mathbf{u}_s\|_{\Omega}^2 dt \quad -72\% \quad J_a/J_0$$

$$J_b = 0.12$$



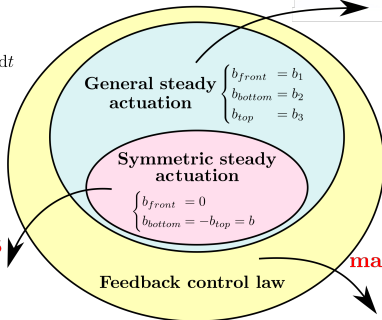
Explorative gradient method

Y. Li 2020 *JFM* (arXiv)

$$\begin{cases} b_{front} = 1.11 \\ b_{bottom} = -0.20 \\ b_{top} = -0.16 \end{cases}$$

Actuation power

$$J_b(\mathbf{b}) = \frac{1}{T_{ev}} \int_{t_0}^{t_0+T_{ev}} \sum_{i=1}^3 \mathcal{P}_{act,i} dt$$



General steady actuation

$$\begin{cases} b_{front} = b_1 \\ b_{bottom} = b_2 \\ b_{top} = b_3 \end{cases}$$

Symmetric steady actuation

$$\begin{cases} b_{front} = 0 \\ b_{bottom} = -b_{top} = b \end{cases}$$

Parametric study

$$\begin{cases} b_{front} = 0 \\ b_{bottom} = -b_{top} = -0.375 \end{cases}$$

$$-49\% \quad J_a/J_0$$

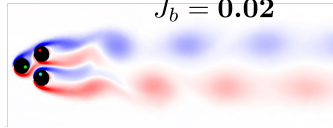
$$J_b = 0.03$$



gradient-enriched machine learning control

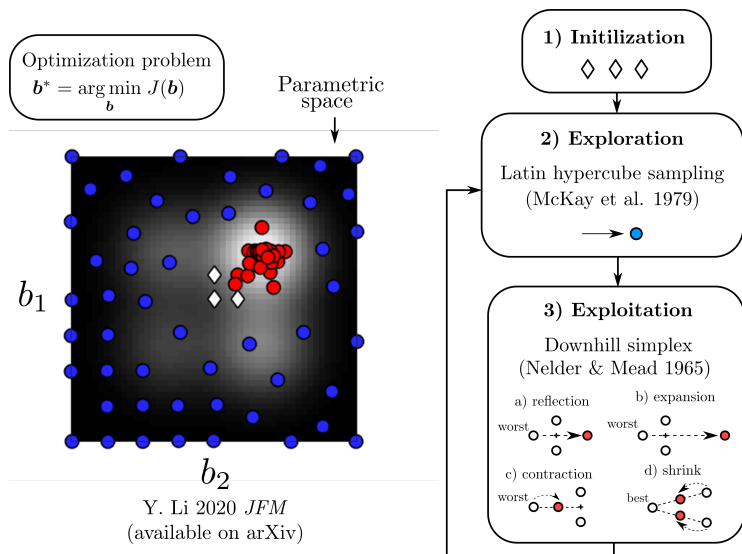
$$-80\% \quad J_a/J_0$$

$$J_b = 0.02$$



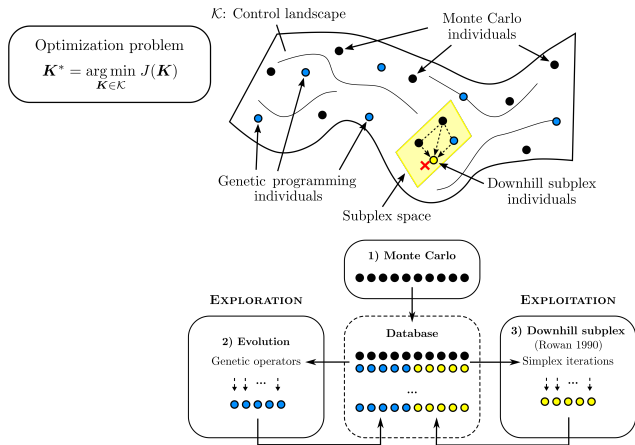


# Explorative gradient method (EGM)



**A parametric optimization algorithm balancing wide exploration and quick convergence of gradient methods.**

# The gradient-enriched machine learning control (gMLC) algorithm



An automated self-learning algorithm for feedback control law optimization.

# Stabilization of the fluidic pinball with aMLC

## Control landscape

- $h(t) = 0$
- $\mathbf{s}(t)$  : 9 sensors + delays = 36 sensor signals

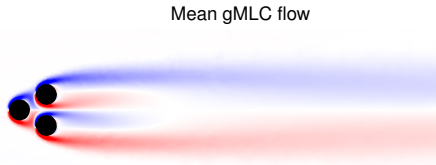
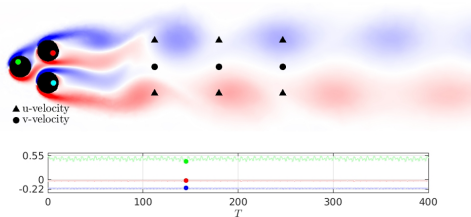
## gMLC performance

gMLC = asymmetric steady forcing + phasor control

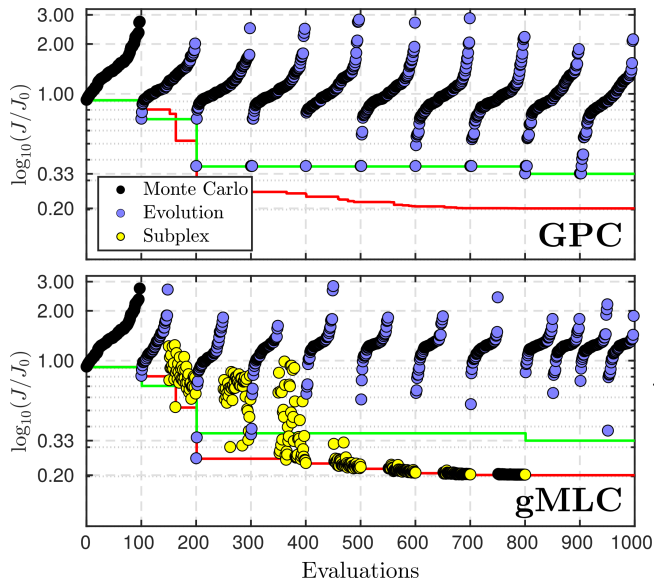
- $-80.0\%$   $J_a/J_0$  !
- Only **0.02** actuation power!

## Comparison with genetic programming

- Genetic programming:  
100 × 10 →  $-67\%$   $J_a/J_0$
- gMLC: after **250** evaluations  
 $-74\%$   $J_a/J_0$



## gMLC and GPC comparison



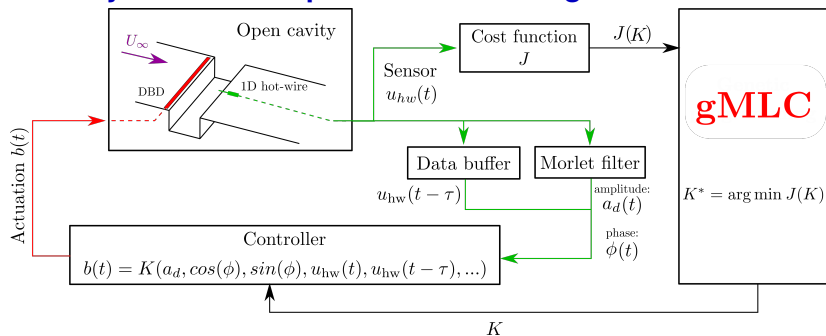
-73% cost reduction

-80% cost reduction!

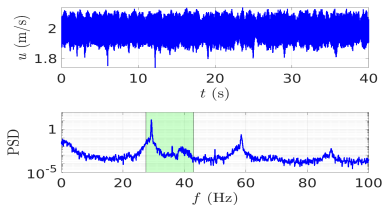
**We converged not only to a BETTER solution but also FASTER!**

**gMLC applied to an experiment:  
the open cavity @LIMSI**

# Open cavity control set-up and control with gMLC



Hot-wire velocity and PSD of the unforced natural flow.



Hot-wire velocity and PSD of the unforced natural flow.

$$\text{Cost function : } J(b) = J_a(b) + \gamma_b J_b(b)$$

$$\text{amplitude : } J_a(b) = \frac{\langle a_d(u_{hw})^2 \rangle_T}{\langle a_d(u_0)^2 \rangle_T}$$

$$\text{actuation : } J_b(b) = \frac{\langle (E - E_0)^2 \rangle_T}{(E_{max} - E_0)^2}$$

# Open cavity control— GP control versus gMLC

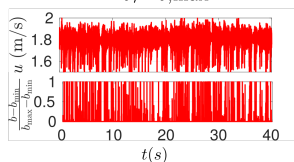
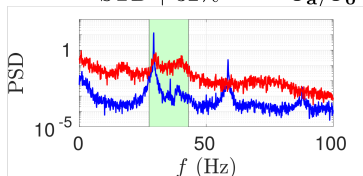
$$\text{Cost function : } J = J_a + J_b$$

Genetic programming control: after 1500 evaluations

STD  $\uparrow$  32%

$J_a/J_0 \downarrow$  73%

$J_b/J_{b,\max} \approx 3\%$

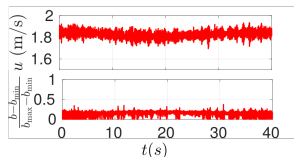
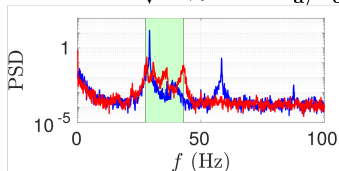


**gMLC: after  $\approx$  250 evaluations !**

STD  $\downarrow$  52%

$J_a/J_0 \downarrow$  94%

$J_b/J_{b,\max} \approx 3\%$



**gMLC outperforms genetic programming control in an experiment!**

# Summary and perspectives

## Summary

- **gMLC**: A new model-free self-learning algorithm capable of broad **exploration** and **exploitation** of local gradients in the control landscape
- **Outperformed** genetic programming in terms of **speed** (**4× faster**) and **final solution** (**+20% better**).
- **Fluidic pinball**: revealed a feedback control law combining **asymmetric forcing** and **phasor control**  
  
→ **Cornejo Maceda 2020 *J. Fluid Mech.*** (submitted and soon on arXiv)
- **Open cavity @LIMSI** : gMLC **outperformed** genetic programming (**6× faster** and **3× reduction of the PSD peak**)

## Perspectives → MIMO experiments

- Drag reduction on a **MIMO** truck model (@TU-BS with Philipp Oswald & Richard Semaan)
- **Robustness** of the control laws for **varying conditions** (Re, yaw angle, variability of the actuators)



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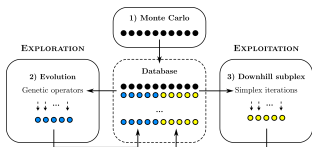
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Thank you for your attention  
Questions?



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