Toward real-time embedded observer of unsteady fluid flow environment

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ABSTRACT

For monitoring and actively controlling hydrodynamic and aerodynamic systems (e.g. aircraft wing), it can be necessary to estimate in real-time and predict the flow around those systems. We propose here a new method which combines data, physical models and measurements for this purpose. Very good numerical results have been obtained on 2- and 3-dimensional wake flows at moderate Reynolds, even 16 vortices shedding cycles after the learning window.

Physics-driven simulations · Reduced order models · Data-driven simulations · Data assimilation · **Our approach** · Data assimilation · On-board measurements

APPLICATIONS

Source : DG Group https://www.dg-flugzeugbau.de/en/library/flutter-resistance-of-the-dg-1000

Robust and ultra-fast aerodynamic and aeroelastic short-time prediction for better active control loops.

- active flutter suppression
- Passengers comfort
- Drag reduction
- Fuel economy

Estimation and prediction:
- Flow
- Lift, drag
- …

Controller (Simple model) → Flaps, slats; Fluidic actuators; … → Plane aerodynamism / aeroelasticity → Plane sensors → Observer (Simple model) → Controller

Which simple model? How to combine model & measurements?

METHODOLOGY

1. Ultra-fast CFD simulations with intrusive reduced order models (ROM)

- Principal Component Analysis (PCA) on a *dataset* to reduce the degrees of freedom (dof) :

Off-line simulation → Snapshots $(v(x,t_i))_i$ → PCA → PCA residual

- Approximation (at small dof n):

$$v(x,t) \approx \sum_{i=0}^{n} b_i(t)\,\phi_i(x)$$

Spatial modes $(\phi_i(x))_i$ — Learned and set up once for all

- Projection of the "physics" onto the spatial modes : (POD-Galerkin)

$\int_\Omega dx\, \phi_i(x) \cdot$ (*Physical equation* (e.g. Navier-Stokes))

We get a n coupled ordinary differential equations for very fast simulation of temporal modes $b_i(t)$

2. Measurement-simulation coupling (data assimilation)

Numerical simulations (ROM)
- Globally in space
- Erroneous

Data assimilation (particle filter + tempering)
More accurate estimation globally in space
$(p(x|y) \propto p(y|x)p(x))$

On-line measurements
- Sparse
- Possibly noisy

$p(x)$ · $837\ km.h^{-1}$ · $p(y|x)$ · $830\ km.h^{-1}$ · $840\ km.h^{-1}$ · Example of estimation: relative velocity

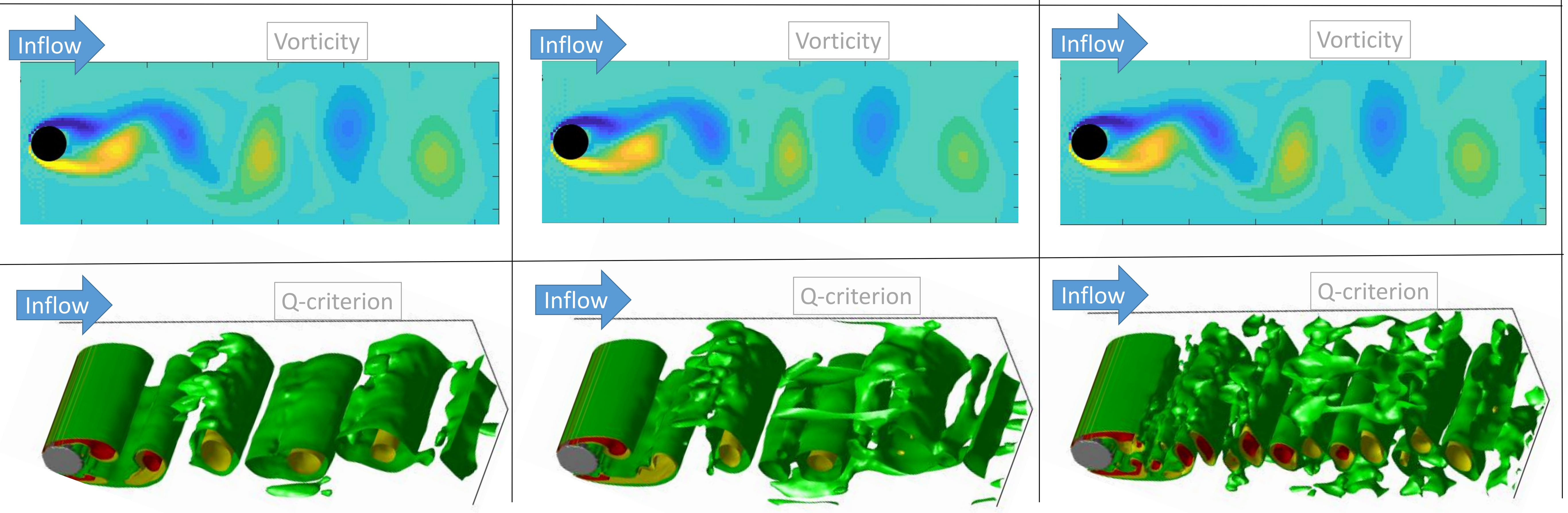
Need for accurate uncertainty / errors quantification : **Novelty is here !**

3. Randomized physics $p(x_{t+1}|x_t)$ → Location uncertainty models (LUM)

Rigorous CFD stochastic closure, with physically-based multiplicative noise

NUMERICAL RESULTS FOR $n = 8$ DEGREES OF FREEDOM (DOF) (ORDER OF THE ROM)

	Reference : PCA-projection of the DNS (Optimal from 8-dof linear decomposition)	**Our method :** POD-Galerkin with Navier-Stokes under location uncertainty (LUM)	**Benchmark :** POD-Galerkin with Navier-Stokes + optimally tuned eddy viscosity & additive noise
Re 100, 2D 10 vortex shedding cycles after the learning period (DNS has 10^4 dof)	Inflow, Vorticity	Inflow, Vorticity	Inflow, Vorticity
Re 300, 3D 14 vortex shedding cycles after the learning period (DNS has 10^7 dof)	Inflow, Q-criterion	Inflow, Q-criterion	Inflow, Q-criterion



Tests description

- Same data assimilation algorithms
- Observation is one spatial resolution points of synthetic 2D PIV measurements, assimilated ten times by vortex shedding cycles.

CPU

- **Generate the simulation dataset :** several hours on a supercomputer (high-resolution CFD).
- **ROM construction :** several hours on a laptop (non-parallelized MATLAB® code).
- **On-line data assimilation:** approximately real time on a laptop (non-parallelized Python™ code).

METHODOLOGY SUMMARY

Off-line : Building ROM
Physics (Navier-Stokes) → DNS code → Data → Stochastic ROM ← Randomized Physics (LU)

On-line : Simulation & data assimilation
Measurements → Data assimilation → Stochastic ROM → Temporal modes b_i → Flow $v = \sum_{i=0}^{n} b_i \phi_i$

CONCLUSION

- Reduced order model (ROM) : for very fast and robust CFD
  Combine data & physics (built off-line) // Closure problem handled by LUM
- Data assimilation : to correct the fast simulation on-line by incomplete/noisy measurements // Model error quantification handled by LUM
- Robust prediction far outside the learning period
  Optimal unsteady flow estimation/prediction in the whole spatial domain

NEXT STEPS

- Real measurements
- Increasing complexity (dof, Reynolds, geometry, …)
- Control loop

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