# POD Proper Orthogonal Decomposition

$$\mathbf{U}(\mathbf{X},t) = \sum_{n=1}^{\infty} a_n(t) \Phi^{(n)}(\mathbf{X})$$

POD eigenfunctions are representative of flow organisation

POD coefficients are representative of flow dynamics

## POD has to be applied to inhomogeneous directions

## **POD (fundamentals)**

Eigenfunctions are obtained by solving an optimisation problem:

Find the *directions*  $\Phi$  as *parallel* as possible to the realisations **u** of the flow ie with an inner product (**u**, $\Phi$ ) maximum (average <.>)

The inner product  $(\mathbf{u}, \Phi)$  is the POD projection coefficient  $a_n(t)$  $(\mathbf{U}(\mathbf{X}), \Phi(\mathbf{X})) = \int_{\mathcal{D}} \mathbf{U}(\mathbf{X}) \Phi(\mathbf{X}) d\mathbf{X}$   $a_n(t) = (\mathbf{U}(\mathbf{X}, t), \Phi^{(n)}(\mathbf{X}))$ 



## Problem to be solved:

Eigenvalue Fredholm integral problem (kernel 2 point correlation tensor)

$$\int_{\mathcal{D}} \left\langle \mathbf{U}(\mathbf{X}) \, \mathbf{U}(\mathbf{X}') \right\rangle \, \boldsymbol{\Phi}^{(n)}(\mathbf{X}) \, d\mathbf{X} = \lambda_n \boldsymbol{\Phi}^{(n)}(\mathbf{X}')$$







Direct POD





few spatial nodes long time samples

Hot/cold wire, microphones



dense spatial nodes short time samples

computations, PIV, flow vis.



#### Direct POD

Considering a formal approach, a 'structure'  $\Phi(\underline{X})$  can be defined as the flow realisation with the maximum projection (mean square point of view) on the velocity field  $\underline{u}(\underline{X})$ . Here  $\Phi$  is deterministic (ie steady),  $\underline{u}$  is random. Therefore one searches for  $\Phi$  maximizing  $\overline{|u.\Phi|^2} = \overline{|\alpha|^2}$ with an inner product (or norm) to be defined following the problem in concern. This concept leads to an eigenvalue type problem:

$$\int_{D} R_{ij}(\underline{X}, \underline{X}') \, \Phi_j(\underline{X}') \, d\underline{X}' = \lambda \, \Phi_i(\underline{X}) \tag{2}$$

where  $R_{ij}$  is the two point correlation tensor. Following the 'classical' POD, the inner product is defined as:

$$(\underline{U},\underline{\Phi}) = \int_{D} \underline{U}(\underline{X}) \underline{\Phi}^{*}(\underline{X}) \, d\underline{X}$$
(3)

For a non-inhomogeneous, periodic or stationnary direction, a harmonic decomposition (Fourier transform) has to be used and the more generic form of the POD problem becomes:

$$\int_{D} \Psi_{ij}(\underline{X}, \underline{X}'; \underline{k}) \Phi_{j}^{(n)}(\underline{X}; \underline{k}) \, d\underline{X}' = \lambda^{(n)}(\underline{k}) \cdot \Phi_{i}^{(n)}(\underline{X}; \underline{k}),$$

#### Snapshot POD

The *Snapshot* POD [Sirovich, 1987] can be illustrated by the *rhs* of the preceding figure. In this case, a spatial average is performed and the kernel of the POD problem is now a time-correlation:

$$C(t,t') = \frac{1}{T} \int_{D} u_i(\underline{X},t) u_i(\underline{X},t') d\underline{X}$$

$$= \frac{1}{T} \sum_{n=1}^{N_{POD}} a^{(n)}(t) a^{(n)}(t').$$
(10)

The eigenvalue problem to solve is then:

$$\int_{T} C(t,t') a^{(n)}(t') dt' = \lambda^{(n)} a^{(n)}(t), \tag{11}$$

the 'spatial' eigenfunctions are afterward obtained by projection

$$\Phi^{(n)}(\underline{X}) = \frac{1}{T} \frac{1}{\lambda^{(n)}} \int_{T} u_i(\underline{X}, t) a^{(n)}(t) dt \qquad (12)$$



#### **Direct POD**

• Moin & Moser (J.F.M 1989) DNS of a Channel Flow



FIGURE 10. Two-dimensional zero-phase characteristic eddy in the near-wall domain  $(y^+ \leq 40)$ , (a) contours of u and (b) velocity vectors projected into the (y, z)-plane. Contour increment in (a) is 1. Negative contours are dashed.



#### Snapshot POD

## • Sirovich & Kirby (J. of Opt. Soc. 1987)





Fig. 1. Average face based on an ensemble of 115 faces. In this, as in the other plates, we have refrained from filtering out the high frequencies produced by the digitization. A pleasanter picture can be had by the usual trick of squinting or otherwise blurring the picture.





Fig. 2. Sample face on top and its caricature below it.



P Fig. 5. Approximation to the exact picture (middle panel of Fig. 3) using 10, 20, 30, and 40 eigenpictures.



# LODS Identification (calibration, assimilation,...)

Development of Low Order Dynamical Systems (LODS) from *reduced* sets arising from experimental/numerical data bases

> Time or non-time resolved information, however representative of the flow dynamics

✓ Total or partial Velocity field

✓ Scalar quantity (concentration, pressure)

## POD based Identification technique





Figure 1: (Left) The original campfire sequence projected into a two-dimensional eigenspace for clarity. It is this 'signature' that we aim to model automatically. The axes show response to the dominant eigenvectors of the campfire images. (Right) One reconstruction of the campfire signature automatically generated using an auto-regressive model.

1000



Figure 2: Three of the resulting frames from the new sequence of the campfire. All frames are synthesised, never having appeared in the original clip.



# **LODS Identification**

Aims: subset of the Dynamical System

• *POD-Galerkin like* equations for a scalar quantity or partial information ( eg : 2D3C slice of a 3D configuration ...)

$$\frac{da_{i}}{dt} = M_{i} + \sum_{j=1}^{N} L_{ij} a_{j} + \sum_{j=1}^{N} \sum_{k=j}^{N} Q_{ijk} a_{j} a_{k}$$

• Identification of the coefficients *M*, *L*, *Q* from non-time resolved samples of the 'as' and of their time derivative. Or from time resolved.

- By using correlations </a> [Verdet 1998, Ricaud 2002]
- By a *least mean square* approach using *Singular Value Decomposition* [Perret et al 2006]



#### http://calins.limsi.fr



http://wallturb.univ-lille1.fr

L+ 300





### $R_{\theta}$ 7800 Ue [m/s] 3 Dual time stereoscopic PIV Temperature [° c] 19 $U_{\tau \, [m/s]}$ 0.121 $\Delta_t \, [\mu s]$ 200 y [wall units] 10 $y^{+}=10$ Mean Flow direction х Wall Х 3 2





Vectorial POD : 
$$POD_{uvw}$$
  
$$\int_{\mathcal{D}} R_{ij}(\mathbf{x}, \mathbf{x}') \ \Phi_j^{(n)}(\mathbf{x}') d\mathbf{x}' = \lambda_n \ \Phi_i^{(n)}(\mathbf{x})$$
Scalar POD :  $POD_u$ 
$$\int_{\mathcal{D}} R_{ii}(\mathbf{x}, \mathbf{x}') \Phi_i(\mathbf{x}') \ d\mathbf{x}' = \lambda \Phi_i(\mathbf{x})$$







 $\rightarrow$  We can expect a decrease of  $\alpha_n$  due to stastical considerations

→Discrepancies from this decay are linked to PIV 'noise measurement'

→We can then define the maximum number of POD modes that can be considered at most to define a ROM from the experiment







- Analysis of POD modes and of their temporal evolution
  - → towards Stochastic model for highest modes ...





















## Correct but phase is missing

## → i.e No advection, ...



## Need to add interactions between modes





## Same plot taking into account scaling law





## Advection

The main feature of the data under analysis is that an advection exists in the streamwise direction x with a mean convective velocity V. Let us consider a model where only this advection is taken into account.

$$\frac{\partial}{\partial t}u_i(x,z) + V \frac{\partial}{\partial x}u_i(x,z) = 0$$

Introducing the POD decomposition, considering a truncation to  $N_{tr}$  modes and if we suppose that the convective velocity is mode independent, this equation writes :

 $|\langle a_n \dot{a}_m \rangle |/\lambda^{(n)}; (b) |(\Phi_{i,x}^{(n)}, \Phi_i^{(m)})|$ 





 $|\langle a_n \dot{a}_m \rangle |/\lambda^{(n)}; (\mathbf{b}) |(\Phi_{i,x}^{(n)}, \Phi_i^{(m)})|$ 





## Same plot taking into account scaling law



FIG. 16 – Comparison of : (a)  $| \langle a_n \dot{a}_m \rangle | / \lambda^{(n)}$ ; (b)  $|(\Phi_{i,x}^{(n)}, \Phi_i^{(m)})|$ . The correlations are plotted in the plane  $(\sqrt{n}, \sqrt{m})$ . (case **Cshort**)



FIG. 13 – Correlation coefficient between A(n,m) and P(n,m) for different truncations.  $C_{AP}$  corresponds to correlation including modes 1 to (m);  $C_{AP}(w = x)$  correspond to correlation where only modes  $\in [m - x : m + x]$  are kept. (case **Cshort**)



$$V^{(n)} = -A(n,m)/P(n,m)$$



# A phase can be added ... to the ROM





Fig. 4 Setup 1. Three stereoscopic PIV system and HWR configuration.





#### Table 1 Data Base for the Zero Pressure Gradient turbulent boundary layer

 $U_e$  [m/s]  $Re_{\theta}$  Configuration No of HWR blocks (6 sec.) No of PIV records

9600	600	20,000 HWR + XY & YZ	10
$1100 \times 40$	1100	20,000 HWR + $XZ$	10
6880	1 block of 2.29 s	20,000 HWR + $XZ$	10
0	613	20,000 HWR	10
Total: 60480	Total: 2314		
9600	600	10,000 HWR + XY & YZ	5
$1100 \times 40$	1100	10,000 HWR + XZ	5
2943	1 block of 1.96 s	10,000 HWR + XZ	5
0	620	10,000 HWR	5
Total: 56543	Total: <b>2321</b>		

#### A data base for APG Turbulent Boundary Layer also obtained...



## **Instantaneous Snaphots**







Fig. 3 Mean velocity profiles physical linear and semi-logarithmic representations



Fig. 4 Turbulence intensity profiles









Fig. 3 The 143 hot wires rake built by LEA (left); Zoom on the closest to the wall probes of one individual comb of the rake (center - top) and view of rake connectors (center - bottom); The Chalmers constant temperature anemometers system (right).

- Logarithmic distribution from  $z=\pm 4 \text{ mm} \pm 140 \text{ mm}$ ; Smallest spanwise separation z + = 80
- Logarithmic distribution from y= 0.3 to 307 mm ; First wire y+ = 6



# Hot-wire rake calibration

- Many probes to handle → in situ
- 4 levels of external velocity : [3, 5, 7 and 10 m/s]
- Time consuming procedure:
  - Thermal stabilisation of the wind-tunnel
  - Convergence of statistics → long duration [50 runs of 180 000 samples of 6 s each] → 20 minutes of signal at 30kHz over 143+3 channels....
- Use of *canonical profiles* (measured with a single hot wire )
- Use PIV measurements in cross section upstream, close to the rake to adjust calibration coefficients
- CTA deliver signals that are not linearly related to velocity





blocking effect : model based on complex potential  $f(z') = \phi + i\psi = U_0 \cdot z' + \frac{m}{2\pi} \ln(z') - \frac{m}{2\pi}$ But does not modify fluctuating parts and correlations:





#### We can reach much larger scales by using HWR



**Fig. 8** Space time correlations obtained from the HWR plotted by using Taylor's hypothesis (contour lines) compared to the spatial correlations obtained from the PIV experiment (colored maps). X - Z plane (top) and X - Y plane (bottom).



#### TIME-RESOLVED RECONSTRUCTION OF SUPER-STREAKS IN HIGH REYNOLDS NUMBER TURBULENT BOUNDARY LAYER OVER A FLAT PLATE

S. Roux<sup>1</sup>, F. Kerhervé<sup>2</sup>, J.M. Foucaut<sup>2</sup>, M. Stanislas<sup>2</sup>, J. Delville<sup>3</sup>
1 Laboratoire de Thermocinétique de Nantes UMR 6607, Université de Nantes (France)
2 Laboratoire de Mécanique de Lille, UMR CNRS 8107, EC-Lille, Univ. Lille 1 (France)
3 Institut PPRIME, CNRS UPR 3346, Université de Poitiers, ENSMA, France







Use L-SE to reconstruct very long time histories of the boundary layer  $\rightarrow$  super-streaks

- use H-W instantaneous velocity to estimate the 2D3C velocity
- Multi time formulation:

$$\hat{u}_i(\mathbf{x},t') = \sum_{k=1}^{N_h} a_{i,k}(\mathbf{x}) u^h(\mathbf{x}'_k,t' + \tau(\mathbf{x},\mathbf{x}')) \quad i = 1,2,3$$

- ${\mathcal T}$  is the optimum time delay (when max of correlation)
- Linear system solved by using SVD + penalisation procedure (Tikhonov)
- Here L-SE = interpolator ..
- from 143 HW signals
- → PIV spatial resolution







Figure 7. Conditional estimated field at different time steps. The red contours highlight center of vortical structures identified by the criteria of Graftieaux *et al.* (2001) around the low-speed streak of interest.



Figure 6. Reconstructed streamwise low-speed fluctuations  $u'/U_{\infty} < -0.15$  in a plane parallel to the wall located at  $y^+ = 361$  using the Taylor's hypothesis with free flow velocity.

- Wandering
- Average longitudinal Length about 10 O

→ cf Huthckins Marusic 2007



# Thank you