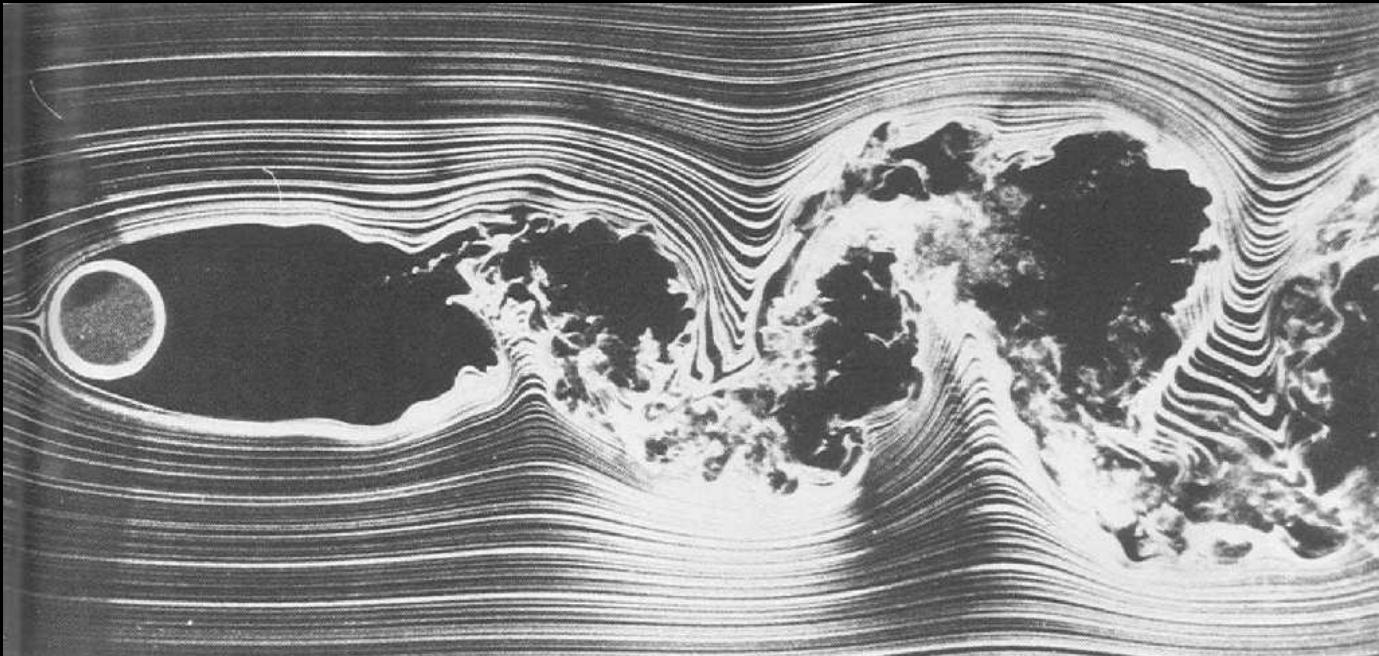


Low-dimensional modelling — POD Galērkin method



Bernd R. Noack
Berlin Institute of Technology

My lectures

1 (Mo) Motivation of Galerkin method, 2 examples

2 (Tu) Empirical Galerkin method based on POD

Purpose of this lecture

- Describe the standard POD Galerkin method
- Illustrate 'add-ons' for physical insights
and control design

3 (Tu) POD-based Galerkin models of natural flow

4 (Th) POD-based Galerkin models of transient
and actuated flow

5 (Th) Towards an attractor control

Overview

1. Introduction

2. Proper Orthogonal Decomposition $\mathbf{u} = \mathbf{u}_0 + \sum_{i=1}^N a_i \mathbf{u}_i$

— Galerkin approximation for flow data

3. Derivation of a dynamical system $\dot{a}_i = f_i(a_1, \dots, a_N)$

— Galerkin projection on the Navier-Stokes equations

4. Modal energy flow analysis

— 'Add-on' for physical insight

5. Summary and outlook

The art of Galerkin modeling

consists of making a good choice for its constitutive elements!

1. Basic mode u_0 :

Candidates:

- steady solution
- averaged solution
- mathematical flow

2. Hilbert space for $u' = u - u_0$:

Candidates (solenoidal subsets):

- $L^2(\Omega)$: $(u, v)_\Omega = \int dx \mathbf{u} \cdot \mathbf{v}$
- $L_\sigma^2(\Omega)$: $(u, v)_\Omega = \int dx \sigma(x) \mathbf{u} \cdot \mathbf{v}$

3. Expansion modes u_i :

modes	BC	NSE	Solution
mathematical	X		
physical	X	X	
empirical	X	X	X

4. Traditional Galerkin projection on NSE:

$$(\mathbf{u}_i, \mathcal{N}(\mathbf{u}^{[0..N]}))_\Omega = 0 \quad \mathcal{N}: \text{Navier-Stokes residual}$$

$$\mathbf{u}^{[0..N]} = \sum_{i=0}^N a_i \mathbf{u}_i, \quad a_0 \equiv 1$$

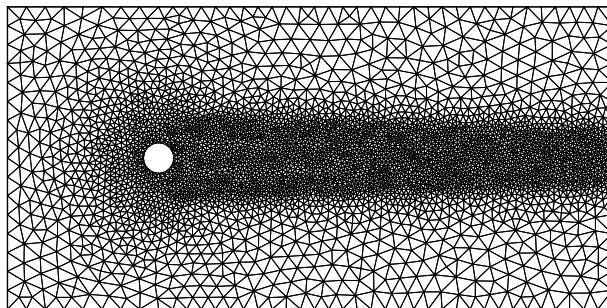
$$\frac{d}{dt} a_i = \nu \sum_{j=0}^N l_{ij} a_j + \sum_{j,k=0}^N q_{ijk} a_j a_k$$

Different Galerkin models

Computational Galerkin model

FEM by Morzyński

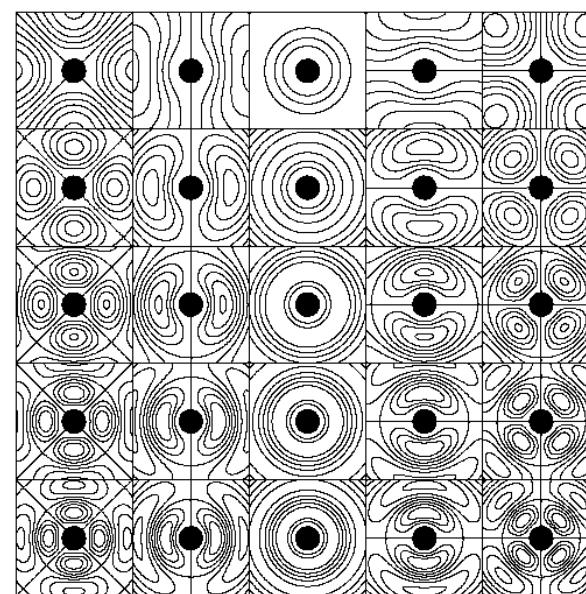
*15838 grid points
31352 triangles*



Mathematical Galerkin model

 Noack & Eckelmann
1994 JFM

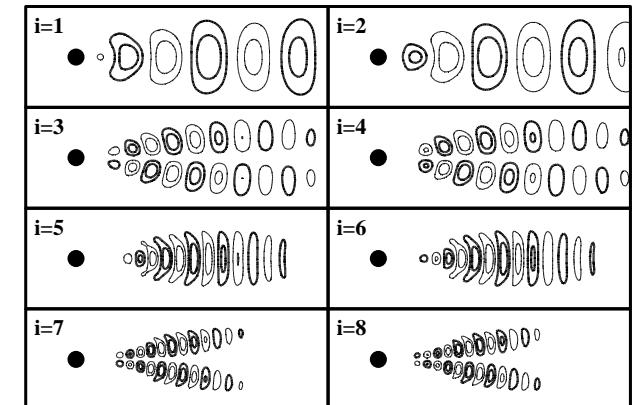
63 modes



Empirical Galerkin model

 Noack & friends
2003 JFM

6 modes



Reduced-, low- and least-order models

Full system

High-fidelity model

reduced-order model (ROM)

low-order model (LODS)

low-dimensional model

least-order model

least-dim. model

$N \approx 999$

Overview

1. Introduction

2. Proper Orthogonal Decomposition

- Galerkin approximation for flow data

3. Derivation of a dynamical system $\dot{a}_i = f_i(a_1, \dots, a_N)$

- Galerkin projection on the Navier-Stokes equations

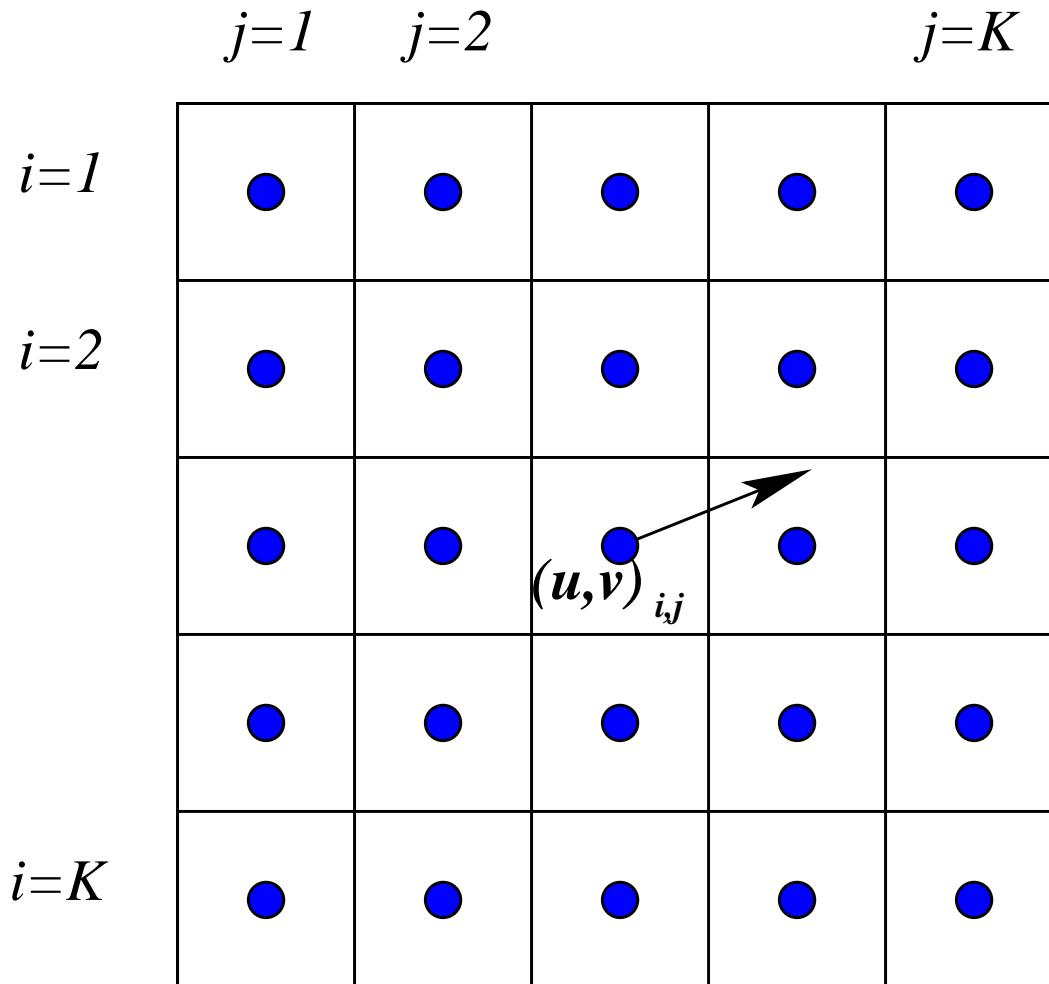
4. Modal energy flow analysis

- 'Add-on' for physical insight

5. Summary and outlook

From flows to phase spaces

Discretized 2D flow



Phase space \mathcal{R}^P

$$u_1 := u_{11}$$

$$u_2 := u_{21}$$

$$u_3 := u_{31}$$

$$u_{K^2} := u_{KK}$$

$$u_{K^2+1} := v_{11}$$

$$\vdots \quad \vdots$$

$$u_P := v_{KK}$$

$$P = 2 \times K^2$$

Autonomous SODE

Phase space \mathcal{R}^P

$$\mathbf{u} := (u_1, u_2, \dots, u_P)^t$$

Dynamics

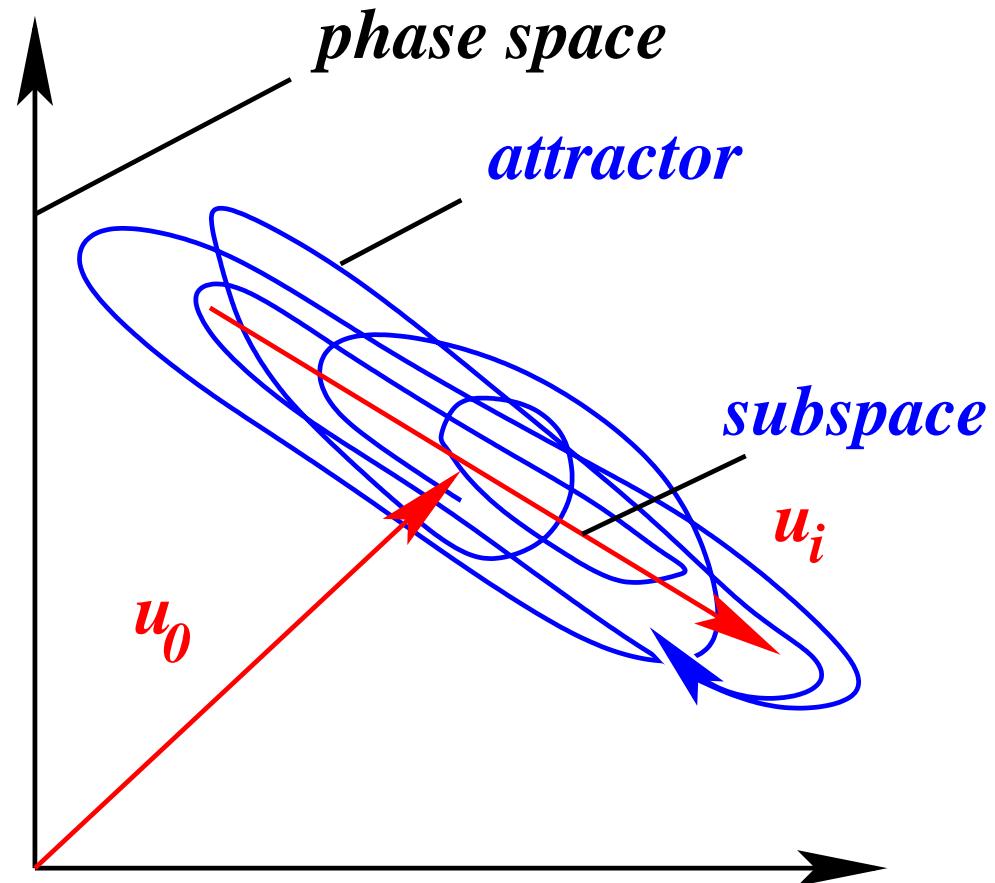
$$\frac{d\mathbf{u}}{dt} = \mathbf{F}(\mathbf{u})$$

Attractor $\mathcal{A} \subset \mathcal{R}^P$

$$\mathbf{u} \rightarrow \mathcal{A} \quad \text{as} \quad t \rightarrow \infty$$

characterized by ergodic measure $p_{\mathcal{A}}(\mathbf{u})$.

Idea of system reduction



Gaussian distribution of attractor

Attractor represented by trajectory $t \in [0, T] \mapsto \mathbf{u} \subset \mathcal{R}^P$

Gaussian probability distribution shall approximate attractor $p_{\mathcal{A}}(\mathbf{u})$

$$p_2(\mathbf{u}) = \frac{\sqrt{|Q|}}{(2\pi)^{P/2}} \exp \left[-\frac{1}{2} (\mathbf{u} - \mathbf{u}_0)^t Q (\mathbf{u} - \mathbf{u}_0) \right]$$

Matching the first statistical moments:

$$\mathbf{u}_0 = \bar{\mathbf{u}} = \int d\mathbf{u} p_2(\mathbf{u}) \mathbf{u} = \frac{1}{T} \int_0^T dt \mathbf{u}$$

Matching the 2nd statistical moments of the fluctuation: $\mathbf{u}' := \mathbf{u} - \mathbf{u}_0$

$$Q = R^{-1}$$

$$R := \overline{\mathbf{u}' \otimes \mathbf{u}'} = \int d\mathbf{u}' p_2(\mathbf{u}_0 + \mathbf{u}') \mathbf{u}' \otimes \mathbf{u}' = \begin{pmatrix} \overline{u'_1 u'_1} & \overline{u'_1 u'_2} & \dots & \overline{u'_1 u'_P} \\ \overline{u'_2 u'_1} & \overline{u'_2 u'_2} & \dots & \overline{u'_2 u'_P} \\ \vdots & \vdots & \ddots & \vdots \\ \overline{u'_P u'_1} & \overline{u'_P u'_2} & \dots & \overline{u'_P u'_P} \end{pmatrix}.$$

POD of attractor

Gaussian probability distribution of attractor $\mathcal{A} \subset \mathbb{R}^P$

$$p_2(\mathbf{u}) = \frac{\sqrt{|Q|}}{(2\pi)^{P/2}} e^{-\frac{1}{2}(\mathbf{u}-\mathbf{u}_0)^t Q (\mathbf{u}-\mathbf{u}_0)}, \quad \mathbf{u}_0 = \bar{\mathbf{u}}, \quad Q^{-1} = R = \overline{\mathbf{u}' \otimes \mathbf{u}'}$$

Principal axes

$$R\mathbf{u}_i = \lambda_i \mathbf{u}_i$$

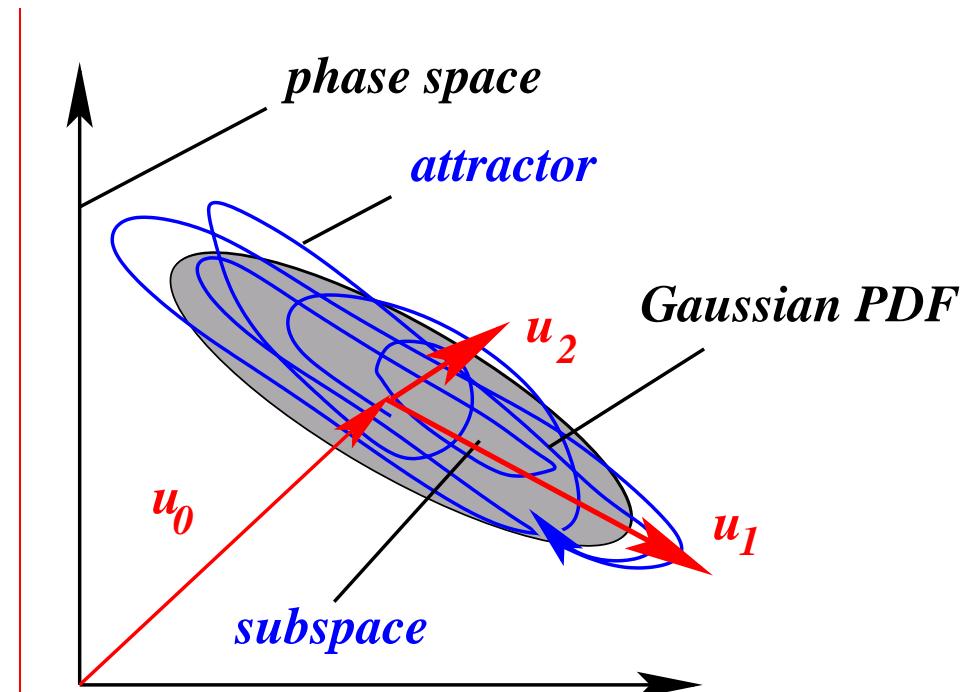
$$\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_P \geq 0.$$

POD decomposition

$$\mathbf{u} = \mathbf{u}_0 + \sum_{i=1}^P a_i \mathbf{u}_i$$

Gaussian distribution

$$p_2(\mathbf{a}) = \frac{e^{-(\sum \frac{a_i^2}{\lambda_i})/2}}{\sqrt{(2\pi)^P \lambda_1 \dots \lambda_P}}$$



\mathbf{u}_i : POD modes,

λ_i : POD eigenvalues

Properties of attractor POD

Trajectory

$$t \in [0, T] \mapsto \mathbf{u} \in \mathcal{R}^P$$

POD expansion $N \leq P$

$$\mathbf{u}^{[N]} = \mathbf{u}_0 + \sum_{i=1}^N a_i \mathbf{u}_i$$

Properties

- POD modes are orthogonal

$$\mathbf{u}_i \cdot \mathbf{u}_j = \delta_{ij}$$

- Fourier coefficients

$$a_i = \mathbf{u}' \cdot \mathbf{u}_i$$

- Statistics of Fourier coefficients

$$\overline{a_i} = 0, \quad \overline{a_i a_j} = \delta_{ij} \lambda_i$$

Properties cont'd

- Correlation matrix

$$R := \overline{\mathbf{u}' \otimes \mathbf{u}'} = \sum_{i=1}^P \lambda_i \mathbf{u}_i \otimes \mathbf{u}_i$$

- Fluctuation energy (trace of $R/2$)

$$K = \frac{1}{2} \overline{\mathbf{u}' \cdot \mathbf{u}'} = \frac{1}{2} \sum_{i=1}^P \lambda_i$$

- **Optimality property:** Let

$$\mathbf{v}^{[N]} = \mathbf{v}_0 + \sum_{i=1}^N b_i \mathbf{v}_i$$

be any other expansion then

$$\overline{\|\mathbf{u} - \mathbf{u}^{[N]}\|^2} \leq \overline{\|\mathbf{u} - \mathbf{v}^{[N]}\|^2}$$

POD analysis — Nomenclature

$$\langle \mathbf{F} \rangle := \frac{1}{M} \sum_{m=1}^M \mathbf{F}^m \quad \dots \dots \dots \text{ensemble average}$$

$$\langle \mathbf{F} \rangle_T := \frac{1}{T} \int_0^T dt \mathbf{F} \quad \dots \dots \dots \text{time average}$$

$$(\mathbf{F})_\Omega := \int_\Omega dV \mathbf{F} \quad \dots \dots \dots \text{volume integral}$$

$$[\mathbf{F}]_{\partial\Omega} := \int_\Omega d\mathbf{A} \cdot \mathbf{F} \quad \dots \dots \dots \text{surface integral}$$

POD in continuum flow limit

Limit $K \rightarrow \infty$ for $\mathcal{R}^P = 2\text{D}$ flow on equidistant $K \times K$ grid

Quantity	\mathcal{R}^P	flow
state space	$\mathbf{u} = (u_1, \dots, u_P)$	$\mathbf{u}(\mathbf{x})$
inner prod.	$\mathbf{u} \cdot \mathbf{v} = \sum u_i v_i \Delta x^2$	$(\mathbf{u}, \mathbf{v})_{\Omega} = \int dV_{\Omega} \mathbf{u} \cdot \mathbf{v}$
correlation	$\mathbf{R} = \overline{\mathbf{u} \cdot \mathbf{u}}$	$\mathbf{R}(\mathbf{x}, \mathbf{y}) = \overline{\mathbf{u}(\mathbf{x}, t) \cdot \mathbf{u}(\mathbf{y}, t)}$
Fredholm equation	$\mathbf{R} \cdot \mathbf{u}_i = \lambda_i \mathbf{u}_i$	$\int d\mathbf{y} \mathbf{R}(\mathbf{x}, \mathbf{y}) \cdot \mathbf{u}_i(\mathbf{y}) = \lambda_i \mathbf{u}_i(\mathbf{x})$
Exp.of \mathbf{R}	$\mathbf{R} = \sum \lambda_i \mathbf{u}_i \mathbf{u}_i$	$\mathbf{R}(\mathbf{x}, \mathbf{y}) = \sum \lambda_i \mathbf{u}_i(\mathbf{x}) \mathbf{u}_i(\mathbf{y})$
Exp. of K	$K = \frac{1}{2} \overline{\mathbf{u} \cdot \mathbf{u}} = \frac{1}{2} \sum \lambda_i$	$K = \frac{1}{2} \overline{(\mathbf{u}, \mathbf{u})_{\Omega}} = \frac{1}{2} \sum \lambda_i$
GA	$\mathbf{u} = \mathbf{u}_0 + \sum a_i(t) \mathbf{u}_i$ $a_i = (\mathbf{u} - \mathbf{u}_0) \cdot \mathbf{u}_i$	$\mathbf{u}(\mathbf{x}, t) = \mathbf{u}_0(\mathbf{x}) + \sum a_i(t) \mathbf{u}_i(\mathbf{x})$ $a_i = (\mathbf{u} - \mathbf{u}_0, \mathbf{u}_i)_{\Omega}$

POD (spatial vs. temporal formulation)

	spatial POD	temporal POD
$f(x, t) =$	$= \sum_{i=1}^N a_i(t) u_i(x)$	$= \sum_{i=1}^N a_i^\star(t) u_i^\star(x)$
eigenmodes	$u_i(x)$	$a_i^\star(t)$
normalisation	$(u_i, u_j)_\Omega = \delta_{ij}$	$\langle a_i^\star a_j^\star \rangle_T = \delta_{ij}$
bi-orthog.	$\langle a_i a_j \rangle_T = \lambda_i \delta_{ij}$	$(u_i^\star, u_j^\star)_\Omega = \lambda_i \delta_{ij}$
coefficients	$a_i = (f, u_i)$	$u_i^\star = \langle f a_i^\star \rangle$
correlation	$R(x, y)$	$R^\star(t, s)$
tensor	$= \langle f(x, t) f(y, t) \rangle_T$	$= (f(x, t), f(x, s))_\Omega$
Fredholm equation	$\int dy R(x, y) u_i(y)$ $= \lambda_i u_i(x)$	$\frac{1}{T} \int ds R(t, s) a_i^\star(s)$ $= \lambda_i a_i^\star(t)$
	Note: $a_i^\star = a_i / \sqrt{\lambda_i}$, $u_i^\star = \sqrt{\lambda_i} u_i$	
application	experimental data $P \ll M$	simulation data $P \gg M$

P : spatial dimension,

M : number of snapshots

POD — mean flow

$$\mathbf{u}_0 = \frac{1}{M} \sum_{m=1}^M \mathbf{u}^m$$

Note that POD is a refined 2-points statistics up to second moments.

$$\langle \mathbf{u}'(\mathbf{x}, t) \otimes \mathbf{u}'(\mathbf{y}, t) \rangle = \sum_{i=1}^{\infty} \lambda_i \mathbf{u}_i(\mathbf{x}) \otimes \mathbf{u}_i(\mathbf{y})$$

Hence, a minimum requirement to the snapshot ensemble is that the single points statistics of the first moments (mean values) and second centered moments (variances, $u_{\text{rms}}(\mathbf{x})$, $v_{\text{rms}}(\mathbf{x})$) are accurate.

POD — correlation matrix

$$C^{mn} = \frac{1}{M} (\mathbf{u}^m - \mathbf{u}_0, \mathbf{u}^n - \mathbf{u}_0)_{\Omega}$$

Note that the mean value is subtracted. Otherwise:

- The first POD mode is approximately the mean flow.
- The fluctuation has to be orthogonal to the mean flow.
- Convergence of the POD with $N \rightarrow \infty$ is not guaranteed.
- λ_i cannot be interpreted as variances.
- The POD Galerkin approximation $\mathbf{u} = \sum a_i \mathbf{u}_i$ does not fulfill the boundary conditions for arbitrary a_i .
- The POD Galerkin model is non physical, allows for varying oncoming velocities, etc.
- The beauty of POD modelling is lost.

POD — Eigenproblem

Fredholm equation (discretized in time domain):

$$\mathbf{C} \cdot \mathbf{e}_i = \lambda_i \mathbf{e}_i.$$

Here, $\mathbf{C} := (C^{mn}) \in \mathcal{R}^{M \times M}$, $\mathbf{e}_i := (e_1^i, e_2^i, \dots, e_M^i)$.

- \mathbf{C} is symmetric $\Rightarrow \lambda_i \in \mathcal{R}$ and

$$\mathbf{e}_i \cdot \mathbf{e}_j = \delta_{ij}$$

- \mathbf{C} is positiv semi-definite $\Rightarrow \forall i: \lambda_i \geq 0$

POD — eigenmodes

$$\mathbf{u}_i := \frac{1}{\sqrt{M \lambda_i}} \sum_{m=1}^M e_m^i (\mathbf{u}^m - \mathbf{u}_0)$$

Validation:

- Check $(\mathbf{u}_i, \mathbf{u}_j)_\Omega = \delta_{ij}$
- Check $\mathcal{K} = \frac{1}{2} \langle \|\mathbf{u}'\|_\Omega^2 \rangle = \frac{1}{2} \text{trace } C = \frac{1}{2} \sum_{m=1}^M \lambda_m$

POD — Fourier coefficients

$$a_i(t_m) = a_i^m := \sqrt{\lambda_i M} e_m^i$$

Validation:

- Check $a_i^m = (\mathbf{u}^m - \mathbf{u}_0, \mathbf{u}_i)_\Omega$
- Check $\langle a_i \rangle = \frac{1}{M} \sum_{m=1}^M a_i^m = 0$
- Check $\langle a_i a_j \rangle = \frac{1}{M} \sum_{m=1}^M a_i^m a_j^m = \lambda_i \delta_{ij}$

Overview

1. Introduction

2. Proper Orthogonal Decomposition $\mathbf{u} = \mathbf{u}_0 + \sum_{i=1}^N a_i \mathbf{u}_i$

— Galerkin approximation for flow data

3. Derivation of a dynamical system $\dot{a}_i = f_i(a_1, \dots, a_N)$

— Galerkin projection on the Navier-Stokes equations

4. Modal energy flow analysis

— 'Add-on' for physical insight

5. Summary and outlook

Galerkin projection on subspace

Evolution equation (EE) in \mathcal{R}^P

$$\frac{d\mathbf{u}}{dt} = \mathbf{F}(\mathbf{u})$$

Galerkin approximation (GA):

ONS, e.g. POD $N \leq P$

$$\mathbf{u}^{[0..N]} = \mathbf{u}_0 + \sum_{i=1}^N a_i \mathbf{u}_i$$

Goal=Galerkin system (GS)

$$\frac{da_i}{dt} = f_i(\mathbf{a}), \quad i = 1, \dots, N$$

Galerkin projection (GP)

- Generally no exact derivation of GS possible.
- N equations need to be derived from the EE.

Traditional Galerkin projection (GP) of the time derivative:

$$\begin{aligned}\mathbf{u}_i \cdot \frac{d\mathbf{u}^{[0..N]}}{dt} &= \mathbf{u}_i \cdot \left[\sum_{j=1}^N \frac{da_j}{dt} \mathbf{u}_j \right] \\ &= \sum_{j=1}^N \frac{da_j}{dt} \mathbf{u}_i \cdot \mathbf{u}_j \\ &= \frac{da_i}{dt}\end{aligned}$$

exploiting $\mathbf{u}_i \cdot \mathbf{u}_j = \delta_{ij}$.

GP of the flow (r.h.s.)

$$\begin{aligned}f_i(\mathbf{a}) &:= \mathbf{u}_i \cdot \mathbf{F}(\mathbf{u}^{[0..N]}) \\ &= \mathbf{u}_i \cdot \mathbf{F} \left(\mathbf{u}_0 + \sum_{j=1}^N a_j \mathbf{u}_j \right)\end{aligned}$$

■ GS is determined!

Weak form of Navier-Stokes equation

Navier-Stokes equation

$$R[\mathbf{u}] := \partial_t \mathbf{u} + \nabla \cdot (\mathbf{u} \otimes \mathbf{u}) - \nu \Delta \mathbf{u} + \nabla p = 0$$

Weak form of the Navier-Stokes equation. $\forall \mathbf{v}(\mathbf{x})$

$$(\mathbf{v}, R[\mathbf{u}]) := I(\mathbf{v}, \partial_t \mathbf{u}) + C(\mathbf{v}, \mathbf{u}, \mathbf{u}) - \nu D(\mathbf{v}, \mathbf{u}) + [\mathbf{v}, p]_{\partial\Omega} = 0$$

with bilinear and trilinear operators

$$I(\mathbf{u}, \mathbf{v}) := (\mathbf{u}, \mathbf{v})_{\Omega},$$

$$D(\mathbf{u}, \mathbf{v}) := (\mathbf{u}, \Delta \mathbf{v})_{\Omega},$$

$$C(\mathbf{u}, \mathbf{v}, \mathbf{w}) := (\mathbf{u}, \nabla \cdot (\mathbf{v} \otimes \mathbf{w}))_{\Omega}$$

$$[\mathbf{u}, f]_{\partial\Omega} := \oint_{\partial\Omega} d\mathbf{A} \cdot \mathbf{u} f$$

POD analysis — Nomenclature

$$\langle \mathbf{F} \rangle := \frac{1}{M} \sum_{m=1}^M \mathbf{F}^m \quad \dots \dots \dots \text{ensemble average}$$

$$\langle \mathbf{F} \rangle_T := \frac{1}{T} \int_0^T dt \mathbf{F} \quad \dots \dots \dots \text{time average}$$

$$(\mathbf{F})_\Omega := \int_\Omega dV \mathbf{F} \quad \dots \dots \dots \text{volume integral}$$

$$[\mathbf{F}]_{\partial\Omega} := \int_\Omega d\mathbf{A} \cdot \mathbf{F} \quad \dots \dots \dots \text{surface integral}$$

$$I(\mathbf{u}, \mathbf{v}) = (\mathbf{u}, \mathbf{v})_\Omega = (\mathbf{u} \cdot \mathbf{v})_\Omega \quad \dots \dots \dots \text{inner product}$$

$$D(\mathbf{u}, \mathbf{v}) = (\mathbf{u} \cdot \Delta \mathbf{v})_\Omega \quad \dots \dots \dots \text{for viscous term}$$

$$C(\mathbf{u}, \mathbf{v}, \mathbf{w}) = (\mathbf{u}, \nabla \cdot [\mathbf{v} \otimes \mathbf{w}])_\Omega \quad \dots \dots \dots \text{for convection term}$$

Galerkin projection — local acceleration

Galerkin projection (GP) generates N equations for N unknown $a_i(t)$

$$\left(\mathbf{u}_i, R \left[\sum_{j=0}^N a_j(t) \mathbf{u}_j(\mathbf{x}) \right] \right)_{\Omega} = 0, \quad i = 1, \dots, N$$

GP of time derivative $\left(\mathbf{u}_i, \partial_t \sum_{j=0}^N a_j(t) \mathbf{u}_j(\mathbf{x}) \right)_{\Omega}$

$$= \left(\mathbf{u}_i, \sum_{j=0}^N \frac{da_j}{dt}(t) \mathbf{u}_j(\mathbf{x}) \right)_{\Omega} = \left(\mathbf{u}_i, \sum_{j=0}^N \frac{da_j}{dt}(t) \mathbf{u}_j(\mathbf{x}) \right)_{\Omega}$$

$$= \sum_{j=1}^N \left(\mathbf{u}_i, \frac{da_j}{dt} \mathbf{u}_j(\mathbf{x}) \right)_{\Omega} = \sum_{j=1}^N \frac{da_j}{dt} (\mathbf{u}_i, \mathbf{u}_j)_{\Omega}$$

$$= \sum_{j=1}^N \frac{da_j}{dt} \delta_{ij} = \frac{da_i}{dt}$$

Galerkin projection — viscous term

$$\text{GP of viscous term } \nu \left(\mathbf{u}_i, \Delta \sum_{j=0}^N a_j(t) \mathbf{u}_j(\mathbf{x}) \right)_{\Omega}$$

$$\begin{aligned} &= \nu \color{red}{D} \left(\mathbf{u}_i, \sum_{j=0}^N a_j \mathbf{u}_j \right) \\ &= \nu \sum_{j=0}^N D \left(\mathbf{u}_i, a_j \mathbf{u}_j \right) \\ &= \nu \sum_{j=0}^N \color{red}{a_j} \underbrace{D \left(\mathbf{u}_i, \mathbf{u}_j \right)_{\Omega}}_{=:l_{ij}} \\ &= \nu \sum_{j=0}^N \color{red}{l_{ij}} a_j \end{aligned}$$

Galerkin projection — convection term

$$\begin{aligned} \text{GP of convection term} &= -\mathbf{C} \left(\mathbf{u}_i, \sum_{j=0}^N a_j \mathbf{u}_j, \sum_{k=0}^N a_k \mathbf{u}_k \right)_{\Omega} \\ &= - \sum_{j=0}^N \sum_{k=0}^N C(\mathbf{u}_i, a_j \mathbf{u}_j, a_k \mathbf{u}_k) \\ &= - \sum_{j=0}^N \sum_{k=0}^N a_j a_k \underbrace{C(\mathbf{u}_i, \mathbf{u}_j, \mathbf{u}_k)}_{=: q_{ijk}^c} \\ &= \sum_{j,k=0}^N q_{ijk}^c a_j a_k \end{aligned}$$

Galerkin projection — pressure term

Pressure-Poisson equation

$$\Delta p = -\nabla \cdot \nabla \cdot \mathbf{u} \otimes \mathbf{u}$$

Pressure expansion *(Noack et al. 2005 JFM)*

$$p^{[0..N]}(\mathbf{x}, t) = \sum_{j=0}^N \sum_{k=0}^N p_{jk}(\mathbf{x}) a_j(t) a_k(t)$$

$$\text{GP of pressure term } -(\mathbf{u}_i, \nabla p)_\Omega = -[\mathbf{u}_i, p^{[0..N]}]_{\partial\Omega}$$

$$= - \left[\mathbf{u}_i, \sum_{j=0}^N \sum_{k=0}^N p_{jk} a_j a_k \right]_{\partial\Omega}$$

$$= - \sum_{j=0}^N \sum_{k=0}^N a_j a_k \underbrace{[\mathbf{u}_i, p_{jk}]_{\partial\Omega}}_{=: -q_{ijk}^p} = \sum_{j,k=0}^N q_{ijk}^p a_j a_k$$

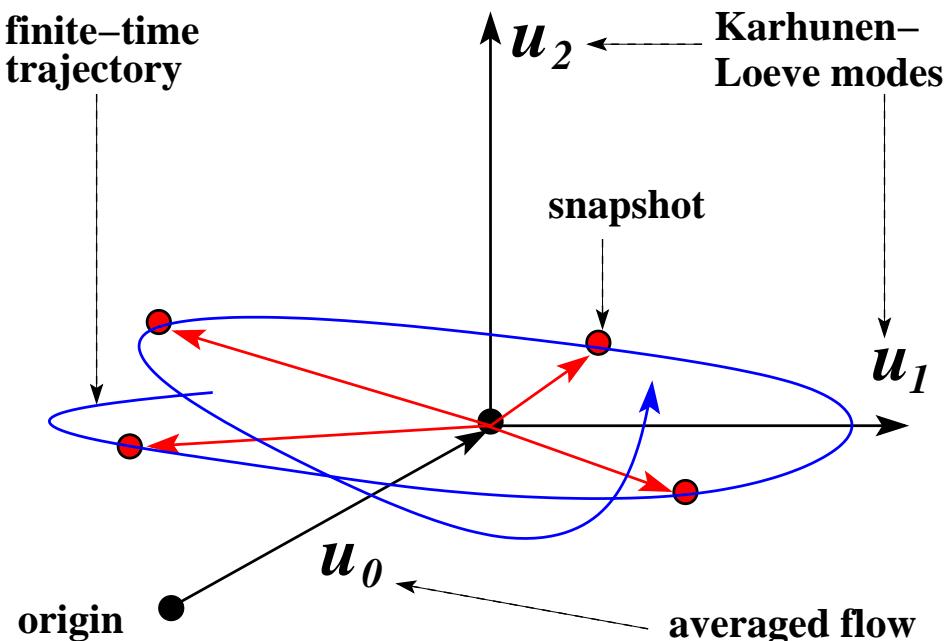
Galerkin method — summary

Galerkin method

$$\begin{array}{ccccccc}
 \mathbf{u} & \rightarrow & \partial_t \mathbf{u} & = & \nu \Delta \mathbf{u} & - \nabla(\mathbf{u} \mathbf{u}) & - \nabla p \\
 \downarrow & & \downarrow & & \downarrow & & \downarrow \\
 \mathbf{u} = \sum_{i=0}^N a_i \mathbf{u}_i & \rightarrow & \frac{da_i}{dt} & = & \nu \sum_{j=0}^N l_{ij} a_j & + \sum_{j,k=0}^N (q_{ijk} + q_{ijk}^\pi) a_j a_k &
 \end{array}$$

Galerkin approximation

(Karhunen-Loëve decomposition, principal axes)



Galerkin projection

$$\begin{aligned}
 (\mathbf{u}, \mathbf{v})_\Omega &:= \int dV \mathbf{u} \cdot \mathbf{v} \\
 (\mathbf{u}_i, \partial_t \mathbf{u})_\Omega &= \int dV \mathbf{u}_i \cdot \partial_t \left(\sum_{j=0}^N a_j \mathbf{u}_j \right) \\
 &= \sum_{j=1}^N \frac{da_j}{dt} \int dV \mathbf{u}_i \cdot \mathbf{u}_j \\
 &= \frac{d}{dt} a_i
 \end{aligned}$$

Overview

1. Introduction

2. Proper Orthogonal Decomposition $\mathbf{u} = \mathbf{u}_0 + \sum_{i=1}^N a_i \mathbf{u}_i$

— Galerkin approximation for flow data

3. Derivation of a dynamical system $\dot{a}_i = f_i(a_1, \dots, a_N)$

— Galerkin projection on the Navier-Stokes equations

4. Modal energy flow analysis

— 'Add-on' for physical insight

5. Summary and outlook

Global energy flow analysis

—  Noack, Papas & Monkewitz (2005) JFM —

In a nutshell:

Reynolds decomposition	$\mathbf{u} = \mathbf{u}_0 + \mathbf{u}', \quad \mathbf{u}_0 = \bar{\mathbf{u}}$
Navier-Stokes equation (NSE)	$\mathcal{R}[\mathbf{u}] = 0$
Reynolds equation (RE)	$\mathcal{R}[\mathbf{u}_0 + \mathbf{u}'] = 0$
weak formulation of NSE	$\forall \mathbf{v}: (\mathbf{v}, \mathcal{R}[\mathbf{u}])_{\Omega} = 0$
Balance eq. of turbulent kinetic energy (TKE):	$(\mathbf{u}', \mathcal{R}[\mathbf{u}_0 + \mathbf{u}'])_{\Omega} = 0$

In some detail:

NSE	NSE II	RE	NSE II-RE	TKE	
$\partial_t \mathbf{u} =$	$\partial_t \mathbf{u}' =$	$0 =$	$\partial_t \mathbf{u}' =$	$\frac{d}{dt} \int dV \frac{1}{2} \ \mathbf{u}'\ ^2 =$	$dK/dt =$
$-\nabla \cdot \mathbf{u} \mathbf{u}$	$-\nabla \cdot \mathbf{u}_0 \mathbf{u}_0$ $-\nabla \cdot \mathbf{u}' \mathbf{u}_0$ $-\nabla \cdot \mathbf{u}_0 \mathbf{u}'$ $-\nabla \cdot \mathbf{u}' \mathbf{u}'$	$-\nabla \cdot \mathbf{u}_0 \mathbf{u}_0$	$-\nabla \cdot \mathbf{u}' \mathbf{u}_0$ $-\nabla \cdot \mathbf{u}_0 \mathbf{u}'$ $-\nabla \cdot \mathbf{u}' \mathbf{u}'$ $+\nabla \cdot \overline{\mathbf{u}' \mathbf{u}'}$	$-\int dV \overline{\mathbf{u}' \mathbf{u}'} : \nabla \mathbf{u}_0$ $-\oint dA \cdot \mathbf{u}_0 \frac{1}{2} \ \mathbf{u}'\ ^2$ $-\int dV \overline{\mathbf{u}' \cdot \nabla \cdot \mathbf{u}' \mathbf{u}'}$	$+P$ $+C$ $+T$
$+\nu \Delta \mathbf{u}$	$+\nu \Delta \mathbf{u}_0$ $+\nu \Delta \mathbf{u}'$	$+\nu \Delta \mathbf{u}_0$	$+\nu \Delta \mathbf{u}'$	$+\nu \int dV \overline{\mathbf{u}' \cdot \Delta \mathbf{u}'}$	$+D$
$-\nabla p$	$-\nabla p_0$ $-\nabla p'$	$-\nabla p_0$	$-\nabla p'$	$-\oint dA \cdot \overline{\mathbf{u}' p'}$	$+F$

Global energy flow analysis

—  Noack, Papas & Monkewitz (2005) JFM —

energy flow
at boundary

pressure power

mean flow

production

dissipation

temperature

energy flow
at boundary

convection

Modal fluid dynamics

—  Noack, Papas & Monkewitz (2005) JFM —

In a nutshell:

Galerkin approximation . . .

$$\mathbf{u} = \mathbf{u}_0 + \mathbf{u}', \quad \mathbf{u}_0 := \bar{\mathbf{u}}, \quad \mathbf{u}' := \sum_{i=1}^N a_i \mathbf{u}_i$$

Navier-Stokes Eq.

$$\mathcal{R}(\mathbf{u}) = 0$$

Galerkin system

$$(\mathbf{u}_i, \mathcal{R}(\mathbf{u}^{[N]}))_\Omega = 0$$

Modal energy flow balance

$$\left(a_i \mathbf{u}_i, \mathcal{R}(\mathbf{u}^{[N]}) \right)_\Omega = 0$$

Global energy flow balance

$$(\mathbf{u}', \mathcal{R}(\mathbf{u}^{[N]}))_\Omega = 0$$

$$\bar{F} = \frac{1}{T} \int_0^T dt F$$

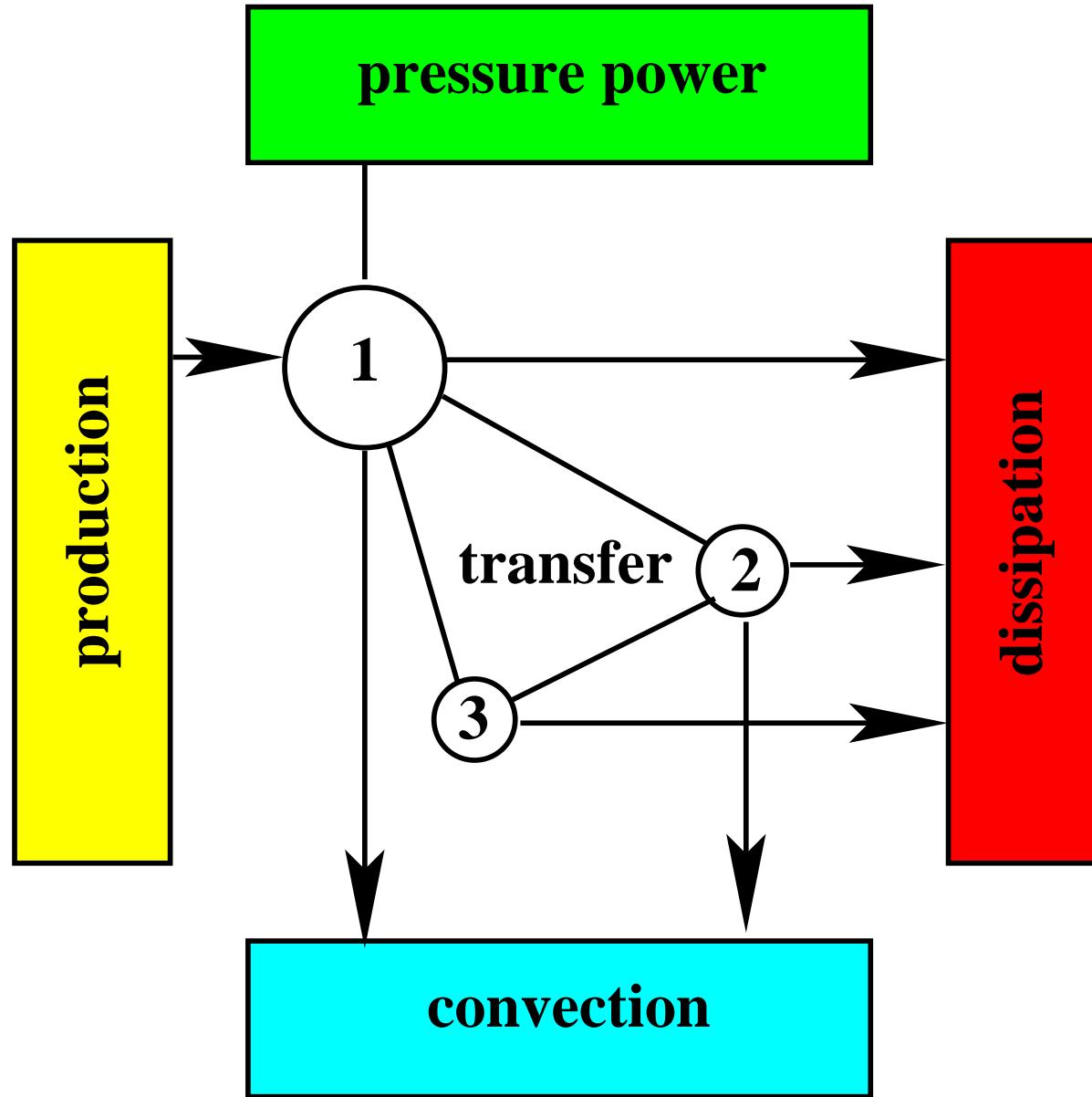
$$(\mathbf{u}, \mathbf{v})_\Omega := \int_{\Omega} dV \mathbf{u} \cdot \mathbf{v}$$

Im some detail:

NSE	NSE II	GS	modal E	
$\partial_t \mathbf{u} =$	$\partial_t \mathbf{u}' =$	$da_i/dt =$	$\frac{d}{dt} \bar{a}_i^2 / 2 =$	$d K_i / dt =$
$-\nabla \cdot \mathbf{u} \mathbf{u}$	$-\nabla \cdot \mathbf{u}_0 \mathbf{u}_0$ $-\nabla \cdot \mathbf{u}' \mathbf{u}_0$ $-\nabla \cdot \mathbf{u}_0 \mathbf{u}'$ $-\nabla \cdot \mathbf{u}' \mathbf{u}'$	$+q_{i00}$ $+ \sum_{j=1}^N q_{ij0} a_j$ $+ \sum_{j=1}^N q_{i0j} a_j$ $+ \sum_{j,k=1}^N q_{ijk} a_j a_k$	$+2q_{ii0} \frac{K_i}{K_i}$ $+2q_{i0i} \frac{K_i}{K_i}$ $+ \sum_{j,k=1}^N q_{ijk} \bar{a}_i a_j a_k$	$+P_i$ $+C_i$ $+T_i$
$+\nu \Delta \mathbf{u}$	$+\nu \Delta \mathbf{u}_0$ $+\nu \Delta \mathbf{u}'$	$+\nu l_{i0}$ $+\nu \sum_{j=1}^N l_{ij} a_j$	$+2\nu l_{ii} K_i$	$+D_i$
$-\nabla p$	$-\nabla p$	$+ \sum_{j,k=1}^N q_{ijk}^\pi a_j a_k$	$+ \sum_{j,k=1}^N q_{ijk}^\pi \bar{a}_i a_j a_k$	$+F_i$

Modal energy flow analysis

—  Noack, Papas & Monkewitz (2005) JFM —



$$\begin{array}{rcl} P & = & \sum P_i \\ + & & + \\ D & = & \sum D_i \\ + & & + \\ C & = & \sum C_i \\ + & & + \\ T & = & \sum T_i \\ + & & + \\ F & = & \sum F_i \\ = & & = \\ 0 & = & 0 \end{array}$$

Modal energy flow balance

$$\frac{dK_i}{dt} = P_i + D_i + C_i + T_i + F_i = 0$$

$$\frac{dK_i}{dt} = \frac{1}{2} \frac{d}{dt} a_i^2 = \left\langle \left(\mathbf{u}^{[i]}, \partial_t \mathbf{u}^{[0..N]} \right)_{\Omega} \right\rangle = 0$$

$$D_i = \nu l_{ii} \lambda_i = +\nu \left\langle D \left(\mathbf{u}^{[i]}, \mathbf{u}^{[0..N]} \right) \right\rangle$$

$$P_i = q_{ii0}^c \lambda_i = - \left\langle C \left(\mathbf{u}^{[i]}, \mathbf{u}^{[0]}, \mathbf{u}^{[0..N]} \right) \right\rangle$$

$$C_i = q_{i0i}^c \lambda_j = - \left\langle C \left(\mathbf{u}^{[i]}, \mathbf{u}^{[0..N]}, \mathbf{u}^{[0]} \right) \right\rangle$$

$$T_i = \sum_{j=1}^N \sum_{k=1}^N q_{ijk}^c \langle a_i a_j a_k \rangle = - \left\langle C \left(\mathbf{u}^{[i]}, \mathbf{u}^{[1..N]}, \mathbf{u}^{[1..N]} \right) \right\rangle$$

$$F_i = \sum_{j=0}^N \sum_{k=0}^N q_{ijk}^p \langle a_i a_j a_k \rangle = - \left\langle \left[\mathbf{u}^{[i]}, p^{[0..N]} \right]_{\partial\Omega} \right\rangle$$

Modal energy flow balance

Galerkin projection (GP) onto $\mathbf{u}^{[i]} = a_i \mathbf{u}_i$ generates N equations for N modal energy flow budgets

$$\left(\mathbf{u}^{[i]}, R \left[\sum_{j=0}^N a_j(t) \mathbf{u}_j(\mathbf{x}) \right] \right)_{\Omega} = 0, \quad i = 1, \dots, N$$

\Rightarrow

$$\begin{aligned} & \left(\mathbf{u}^{[i]}, \partial_t \mathbf{u}^{[0..N]} \right)_{\Omega} + C \left(\mathbf{u}^{[i]}, \mathbf{u}^{[0..N]}, \mathbf{u}^{[0..N]} \right) \\ & - \nu D \left(\mathbf{u}^{[i]}, \mathbf{u}^{[0..N]} \right) + \left[\mathbf{u}^{[i]}, p^{[0..N]} \right]_{\partial\Omega} = 0 \end{aligned}$$

Here, the modal energy flow is monitored instantaneously.

POD dynamical system — modal balance equations

Galerkin system

$$\frac{da_i}{dt} = \nu \sum_{j=0}^N l_{ij} a_j + \sum_{j=0}^N \sum_{k=0}^N q_{ijk} a_j a_k \quad (1)$$

Galerkin-Reynolds equation = $\langle (1) \rangle$

using $\langle a_i \rangle = 0$ and $\langle a_i a_j \rangle = \lambda_i \delta_{ij}$

$$0 = \nu l_{i0} + \sum_{j=0}^N q_{ijj} \lambda_j \quad (2)$$

Modal energy flow equation = $\langle a_i \times (1) \rangle$

$$0 = \nu l_{ii} \lambda_i + \sum_{j=0}^N \sum_{k=0}^N q_{ijk} \langle a_i a_j a_k \rangle \quad (3)$$

Overview

1. Introduction
2. Proper Orthogonal Decomposition $\mathbf{u} = \mathbf{u}_0 + \sum_{i=1}^N a_i \mathbf{u}_i$
 - Galerkin approximation for flow data
3. Derivation of a dynamical system $\dot{a}_i = f_i(a_1, \dots, a_N)$
 - Galerkin projection on the Navier-Stokes equations
4. Modal energy flow analysis
 - 'Add-on' for physical insight
5. Summary and outlook

POD Galerkin method — Summary 1

(-1) Given M snapshots $\{\mathbf{u}^m = \mathbf{u}(\mathbf{x}, t_m)\}_{m=1}^M$

(0) Write subroutines for

$I(\mathbf{u}, \mathbf{v}) := (\mathbf{u}, \mathbf{v})_{\Omega},$	$D(\mathbf{u}, \mathbf{v}) := (\mathbf{u}, \Delta \mathbf{v})_{\Omega},$
$C(\mathbf{u}, \mathbf{v}, \mathbf{w}) := (\mathbf{u}, \nabla \cdot (\mathbf{v} \otimes \mathbf{w}))_{\Omega}$	$[\mathbf{u}, f]_{\partial\Omega} := \oint_{\partial\Omega} d\mathbf{A} \cdot \mathbf{u} f$

(1) Compute mean flow $\mathbf{u}_0 = \frac{1}{M} \sum_{m=1}^M \mathbf{u}^m$

(2) Compute correlation matrix $\mathbf{C}^{mn} = I(\mathbf{u}^m - \mathbf{u}_0, \mathbf{u}^n - \mathbf{u}_0)$

(3) Perform spectral analysis $\mathbf{C} \mathbf{e}_i = \lambda_i \mathbf{e}_i, \mathbf{e}_i \cdot \mathbf{e}_j = \delta_{ij}$

(4) Compute POD modes $\mathbf{u}_i = \frac{1}{\sqrt{\lambda_i M}} \sum_{m=1}^M e_m^i (\mathbf{u}^m - \mathbf{u}_0)$

(5) Compute Fourier coefficients $a_i^m := \sqrt{\lambda_i M} e_m^i$

POD Galerkin method — Summary 2

(6) Perform Galerkin projection

$$\dot{a}_i = \nu \sum_{j=0}^N l_{ij} a_j + \sum_{j,k=0}^N q_{ijk}^c a_i a_j$$

where $l_{ij} := D(\mathbf{u}_i, \mathbf{u}_j)$ and $q_{ijk}^c := C(\mathbf{u}_i, \mathbf{u}_j, \mathbf{u}_k)$.

(7) Compute modal energy flow analysis

$$dK_i/dt = 0 = P_i + D_i + C_i + T_i + F_i,$$

where $K_i = \overline{a_i^2}/2$, $P_i = q_{ii0} \lambda_i$, $C_i = q_{i0i} \lambda_i$, $D_i = \nu l_{ii} \lambda_i$,
 $T_i = q_{ijk}^c \overline{a_i a_j a_k}$, $F_i \approx 0$ (often).

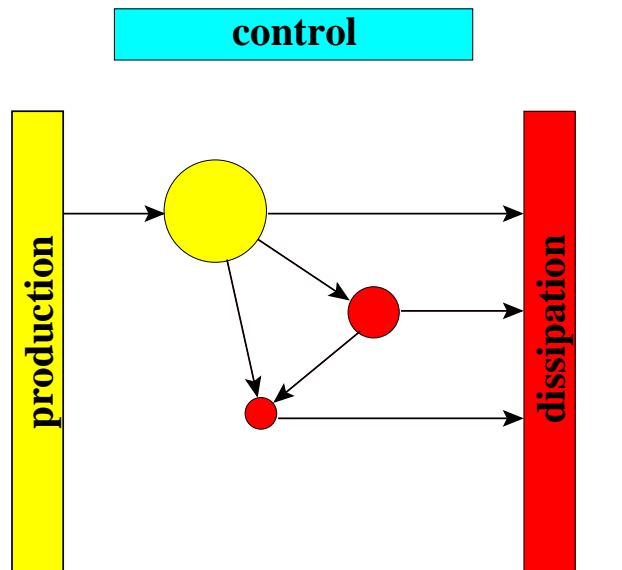
POD model for flow control

- **Galerkin approximation** $\mathbf{u} = \sum_{i=1}^N a_i \mathbf{u}_i$, $\mathbf{a} = (a_1, a_2, \dots, a_N)$ data compression
 $O(1)$ Million grid points $\Rightarrow O(10)$ Fourier coefficients
- **Modal energy flow analysis** $\frac{dE_i}{dt} = P_i + D_i + C_i + T_i + F_i$ understanding of mode sociology
- Quasi-spectral understanding of data
- **Galerkin system** $\frac{da}{dt} = \mathbf{f}(\mathbf{a})$ efficient time integration
Computation time drastically reduced
- **Dynamics exploration** $\frac{da}{dt} = \mathbf{f}(\mathbf{a})$ data base extrapolation
- **Observer design:** $S(t) = \sum a_i(t) \mathbf{u}_i(\mathbf{x}) \cdot \mathbf{e}_x \Rightarrow \hat{\mathbf{a}}(t) \Rightarrow \mathbf{u}(\mathbf{x}, t)$
 $\frac{d\hat{\mathbf{a}}}{dt} = \mathbf{f}(\hat{\mathbf{a}}) + L(S - \hat{S})$ completion of experimental data
- **Control design:** $\frac{da}{dt} = \mathbf{f}(\mathbf{a}, G)$ MIMO control law $G=G(S)$
Linearization rarely works!
Only a simple tune-able control law *structure*
is generally applicable to experiment.
- **Real world check:** Only simple (low-dimensional) control strategies
will survive real-world online-capability and robustness

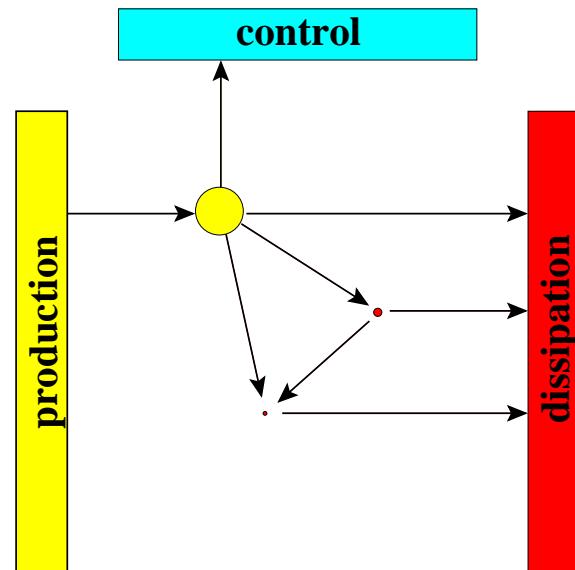
Feedback flow control strategies based on modal energy flow analysis

— single active mode —

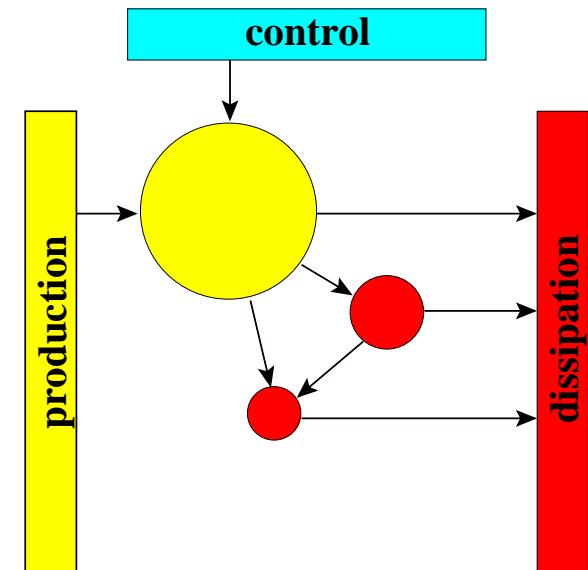
a) natural flow



b) suppression



c) enhancement

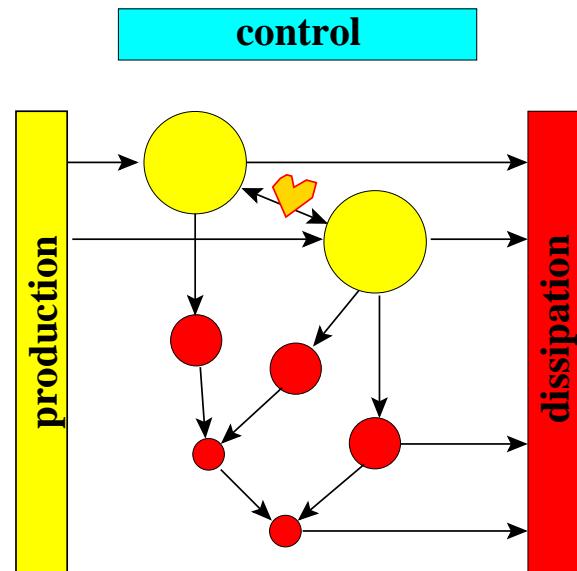


Example: von Kármán vortex shedding

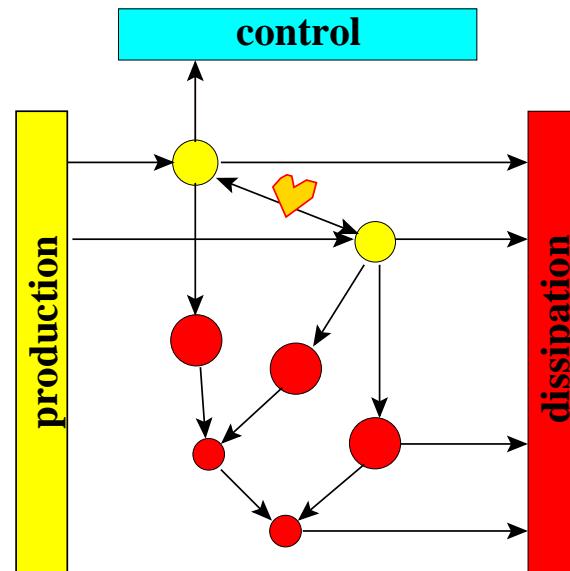
Feedback flow control strategies based on modal energy flow analysis

— 2 synergizing active modes —

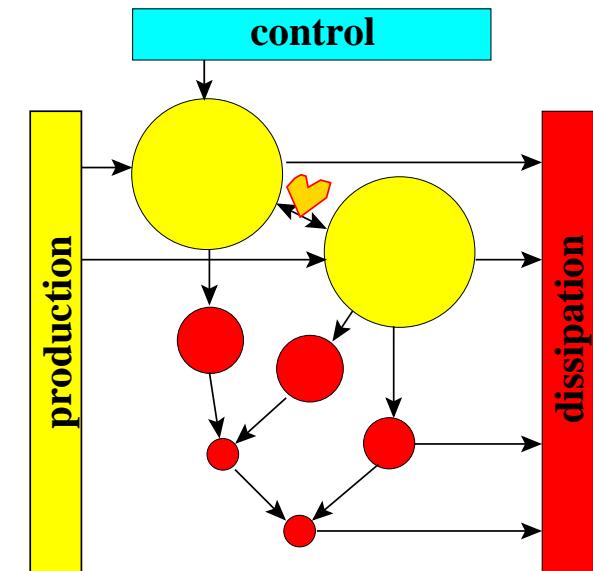
a) natural flow



b) suppression



c) enhancement

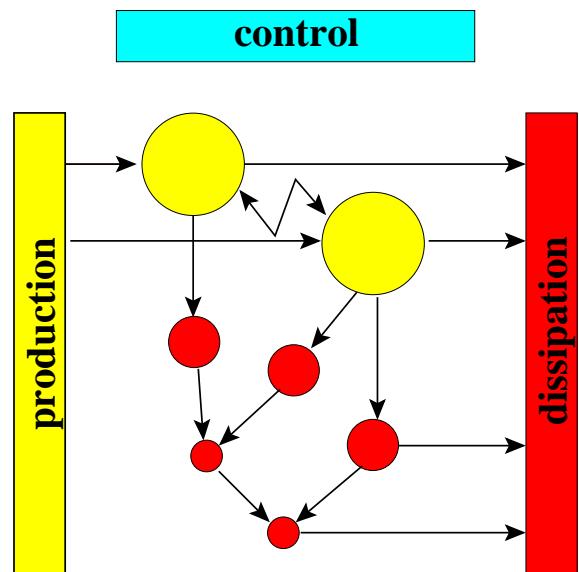


Example: vortex pairing (mode 1) of Kelvin-Helmholtz instability (mode 2)

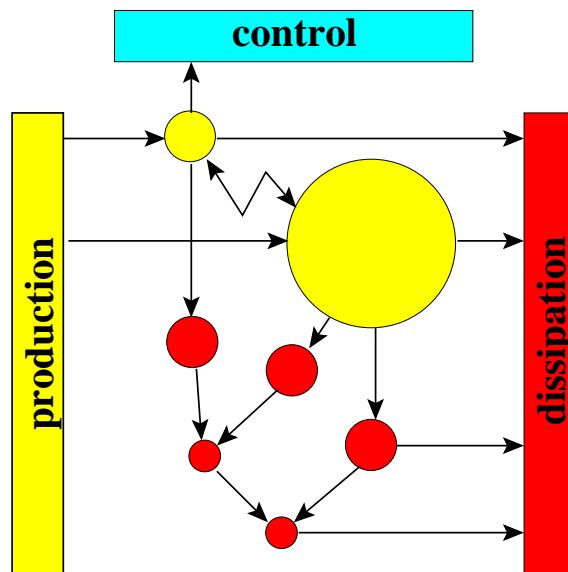
Feedback flow control strategies based on modal energy flow analysis

— 2 competing active modes —

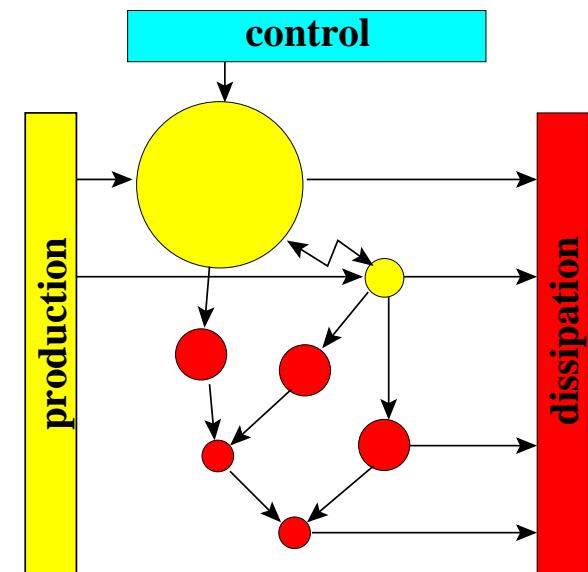
a) natural flow



b) suppression



c) enhancement



Example: Shear-layer vortices (mode 1) excited by cylinder rotation suppress vortex shedding (mode 2)

[Bergmann & Cordier 2005 PF]