

Dynamics and control of wall-bounded shear flows

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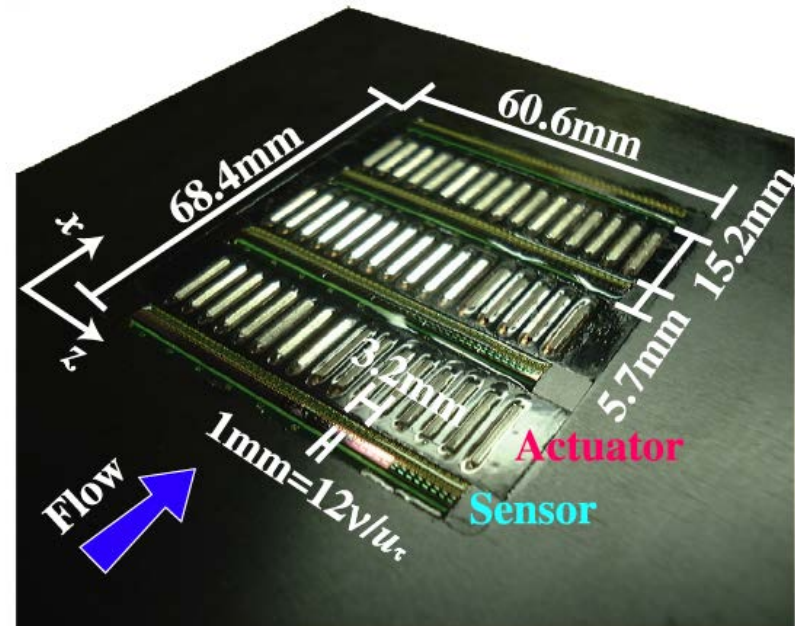
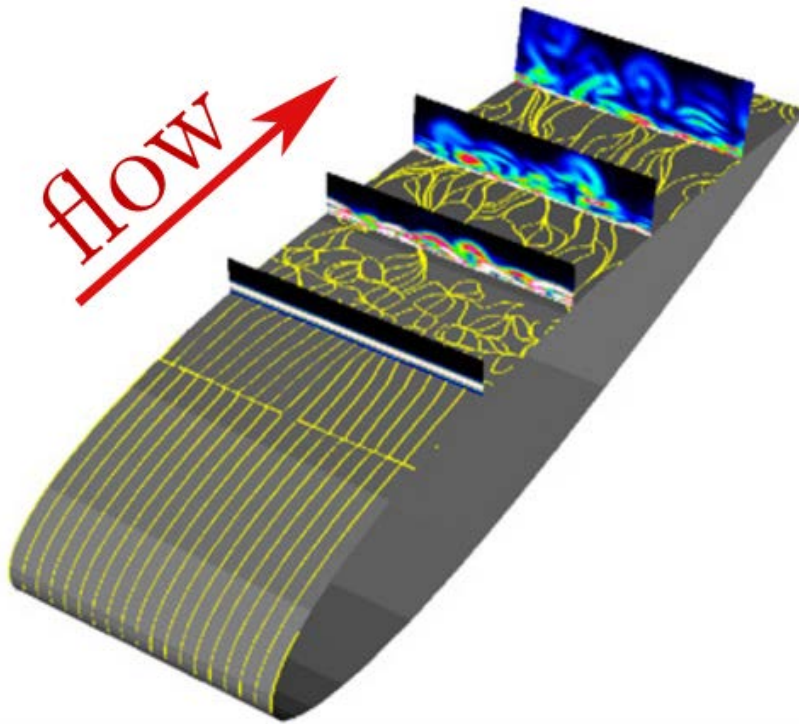
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UNIVERSITY
OF MINNESOTA

Center for Turbulence Research, Stanford University; July 13, 2012

Flow control



- technology:** shear-stress sensors; surface-deformation actuators
- application:** turbulence suppression; skin-friction drag reduction
- challenge:** distributed controller design for complex flow dynamics

Outline

① DYNAMICS AND CONTROL OF WALL-BOUNDED SHEAR FLOWS

- **The early stages of transition**

- ★ initiated by high flow sensitivity

- **Controlling the onset of turbulence**

- ★ simulation-free design for reducing sensitivity

Key issue:
high flow sensitivity

② CASE STUDIES

- **Sensor-free flow control**

- ★ streamwise traveling waves

- **Feedback flow control**

- ★ design of optimal estimators and controllers

③ SUMMARY AND OUTLOOK

Transition to turbulence

- LINEAR HYDRODYNAMIC STABILITY: **unstable normal modes**
 - ★ **successful in:** Benard Convection, Taylor-Couette flow, etc.
 - ★ **fails in:** wall-bounded shear flows (channels, pipes, boundary layers)

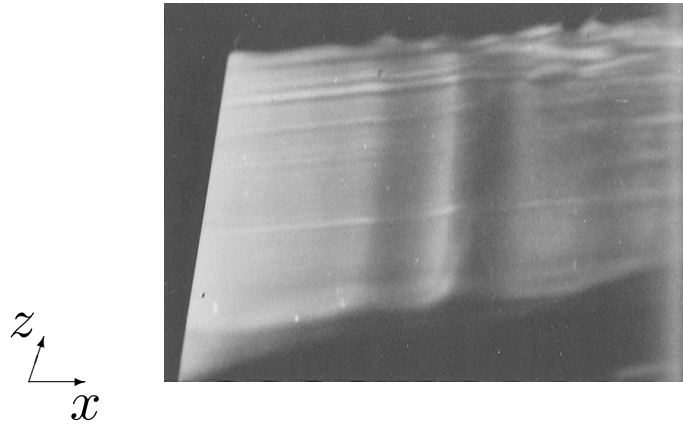
- DIFFICULTY 1
 - Inability to predict: Reynolds number for the onset of turbulence (Re_c)**

 - Experimental onset of turbulence:** $\left\{ \begin{array}{l} \text{much before instability} \\ \text{no sharp value for } Re_c \end{array} \right.$

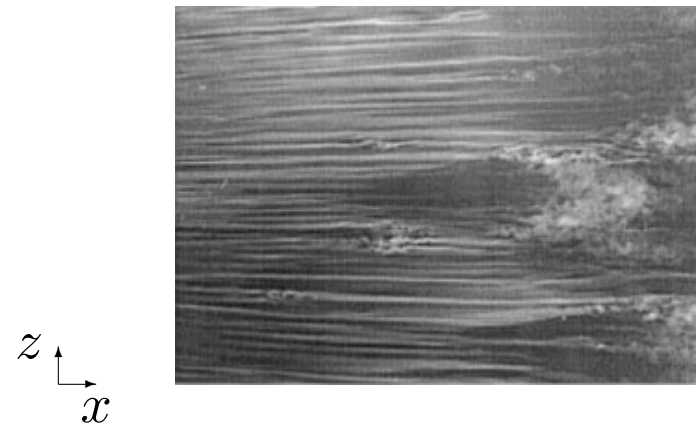
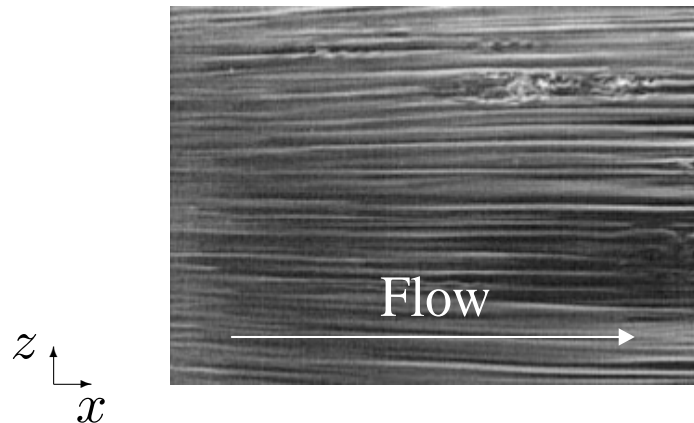
- DIFFICULTY 2
 - Inability to predict: flow structures observed at transition**
(except in carefully controlled experiments)

LINEAR STABILITY:

- ★ For $Re \geq Re_c \Rightarrow$ exp. growing normal modes
 corresponding e-functions
 (TS-waves) } = exp. growing flow structures



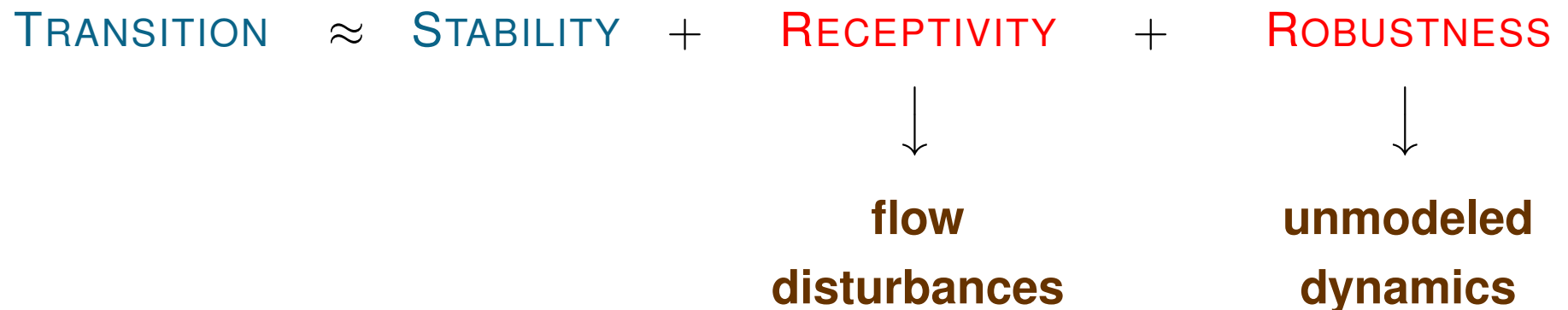
NOISY EXPERIMENTS: **streaky boundary layers and turbulent spots**



Matsubara & Alfredsson, *J. Fluid Mech.* '01

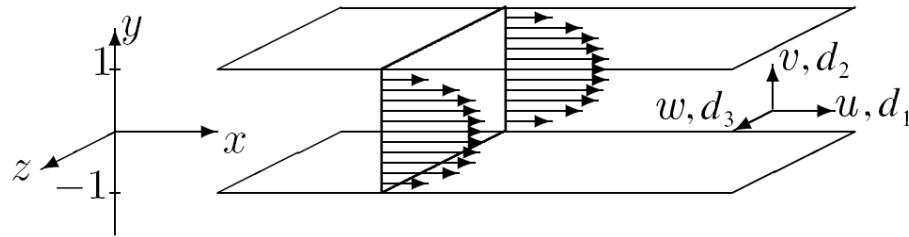
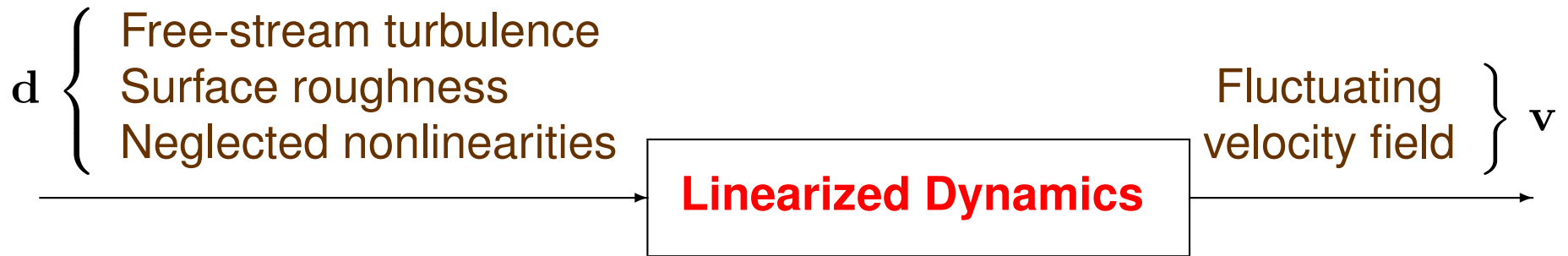
- FAILURE OF LINEAR HYDRODYNAMIC STABILITY
caused by high flow sensitivity
 - ★ large transient responses
 - ★ large noise amplification
 - ★ small stability margins

TO COUNTER THIS SENSITIVITY: **must account for modeling imperfections**



Tools for quantifying sensitivity

- INPUT-OUTPUT ANALYSIS: **spatio-temporal frequency responses**



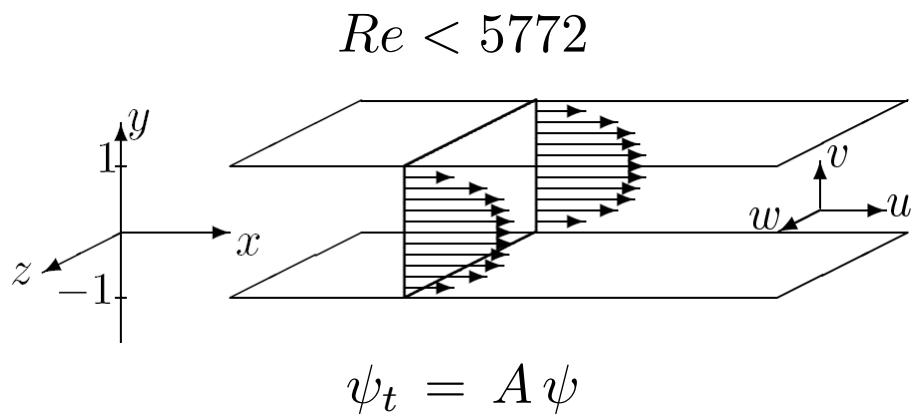
IMPLICATIONS FOR:

transition: insight into mechanisms

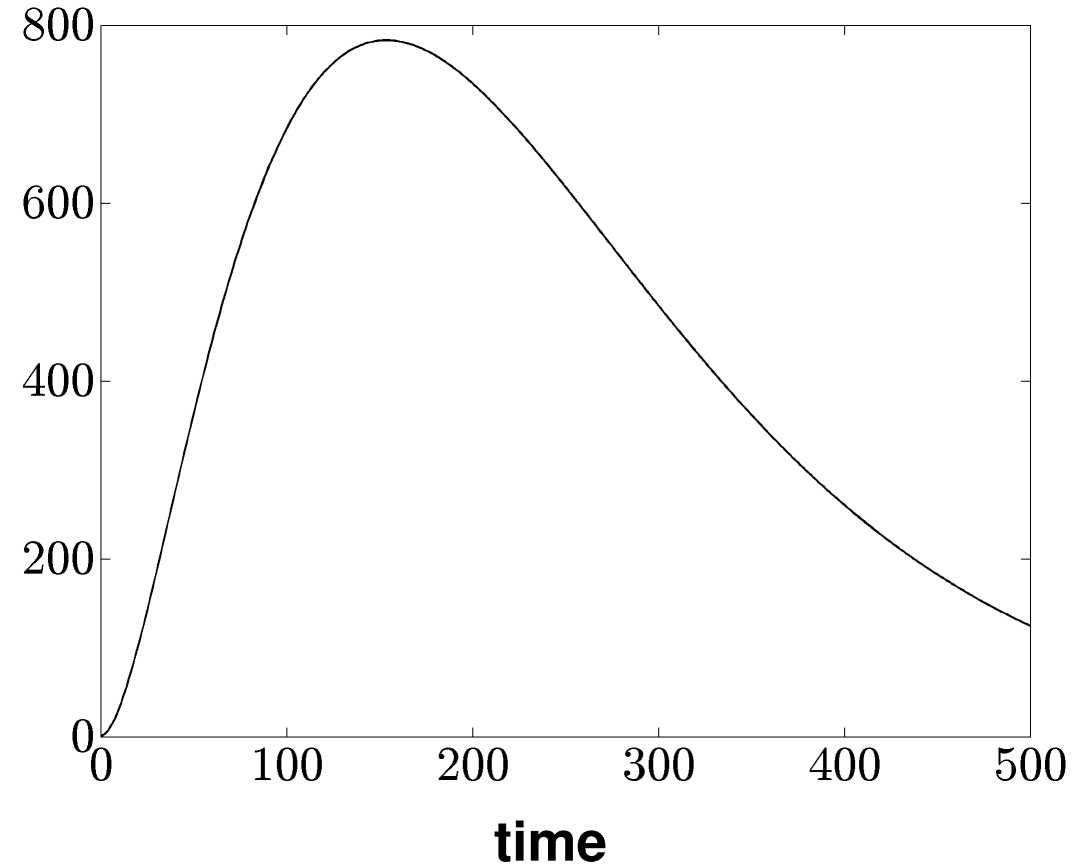
control: control-oriented modeling

Transient growth analysis

- STUDY TRANSIENT BEHAVIOR OF FLUCTUATIONS' ENERGY



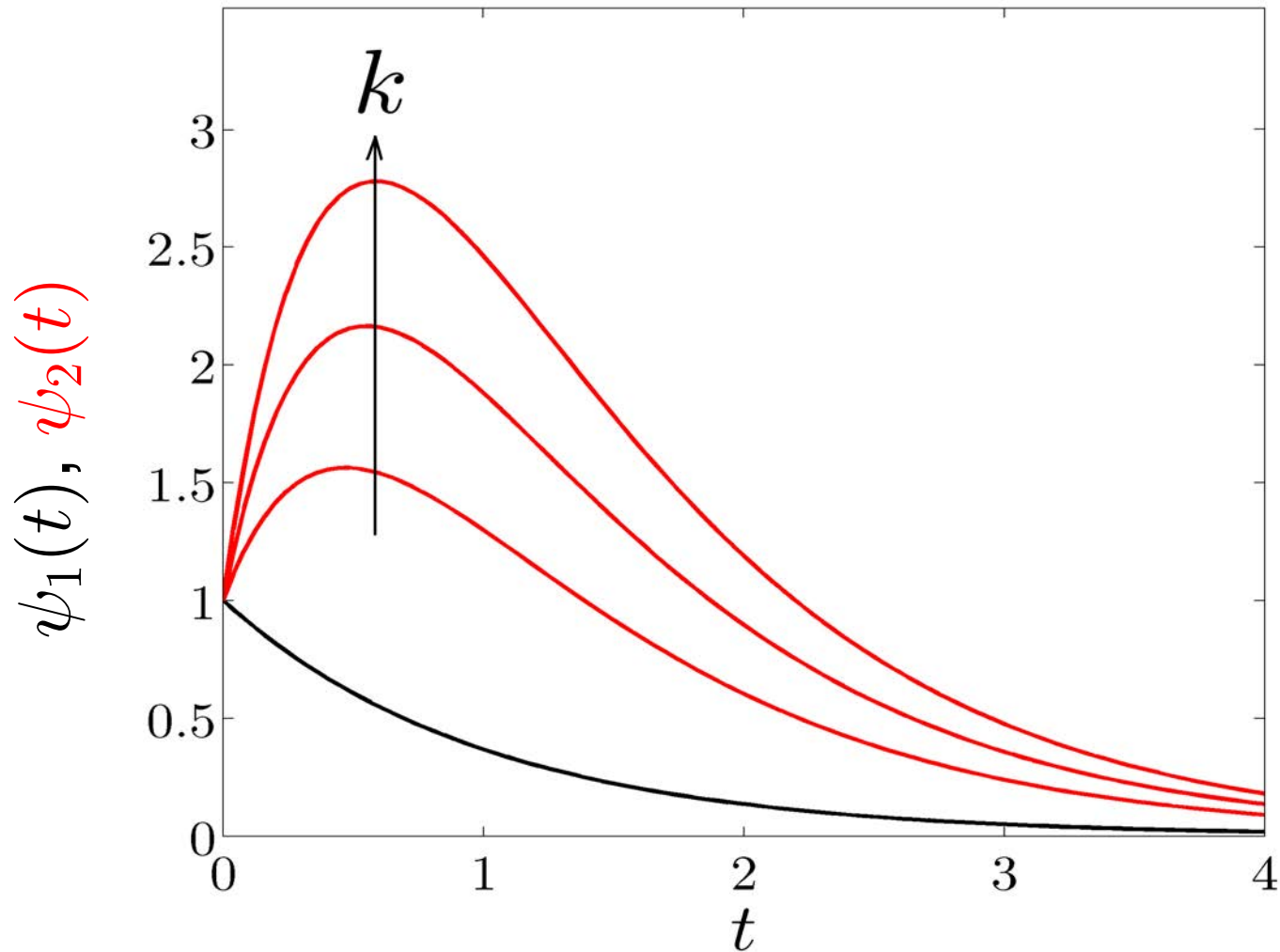
kinetic energy:



👉 **E-values: misleading measure of transient response**

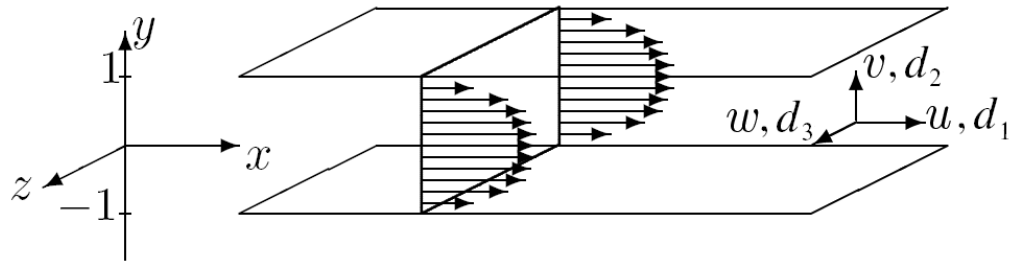
A toy example

$$\begin{bmatrix} \dot{\psi}_1 \\ \dot{\psi}_2 \end{bmatrix} = \begin{bmatrix} -1 & \mathbf{0} \\ \mathbf{k} & -2 \end{bmatrix} \begin{bmatrix} \psi_1 \\ \psi_2 \end{bmatrix}$$



Response to stochastic forcing

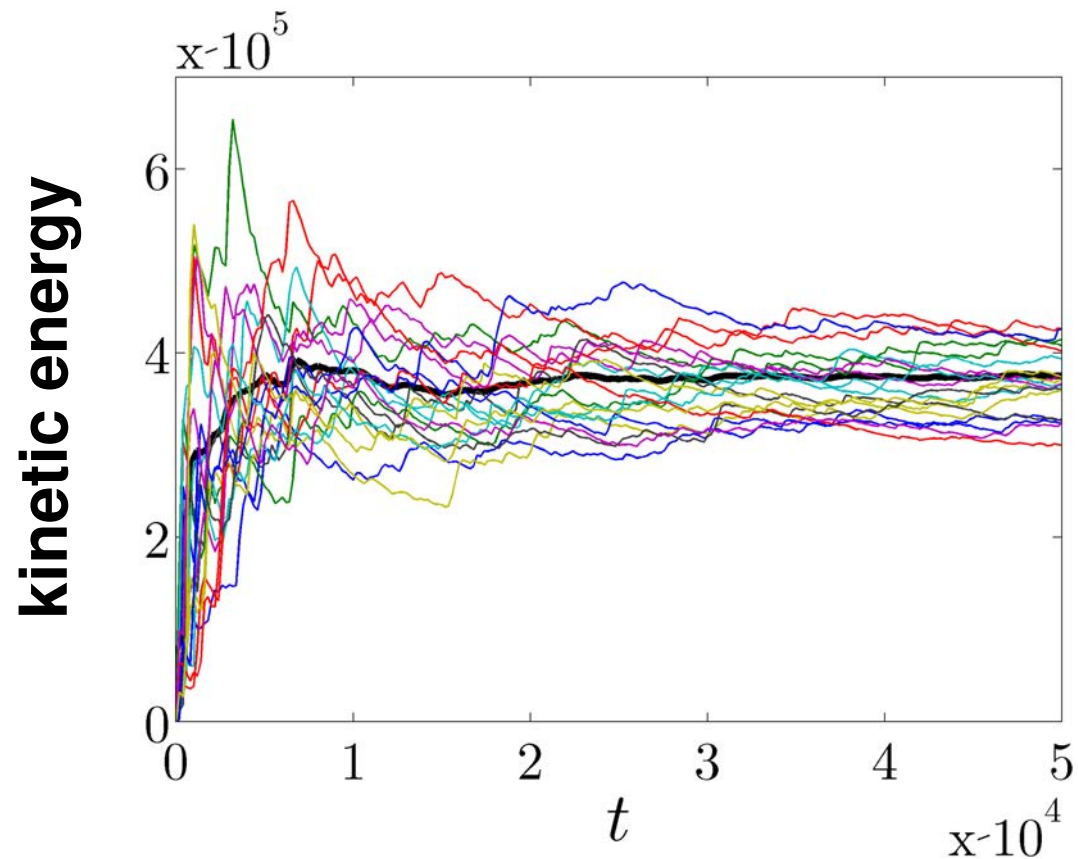
$Re = 2000$



forcing:

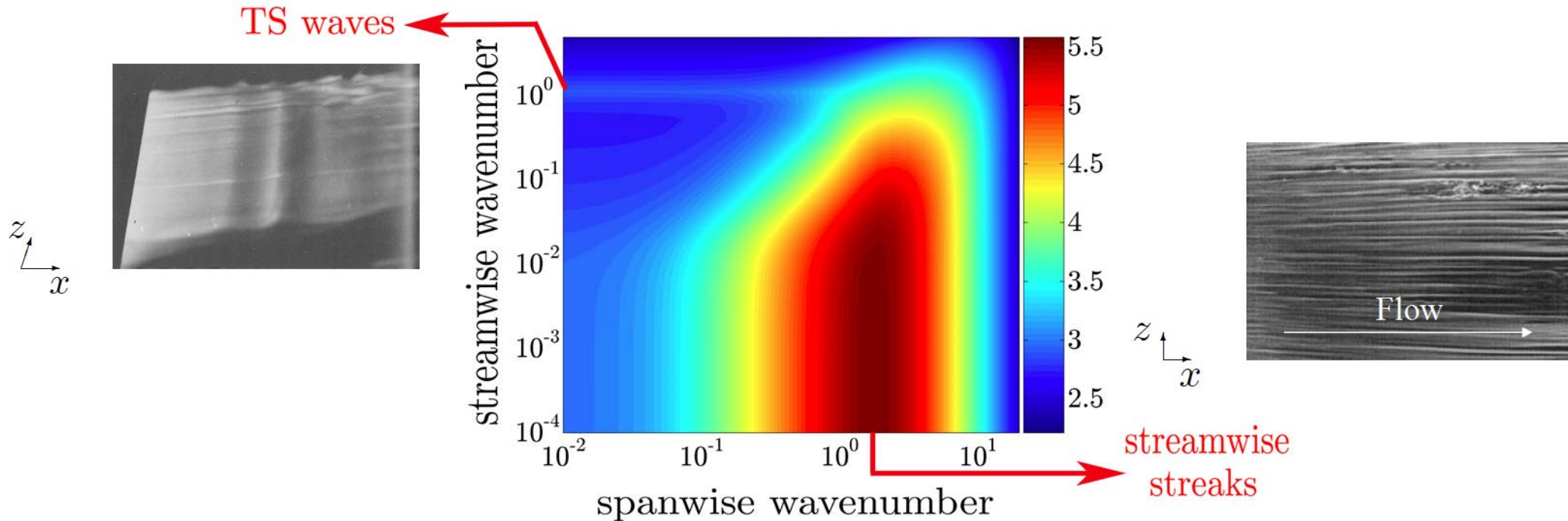
white in t and y
harmonic in x and z

$$\mathbf{d}(x, y, z, t) = \hat{\mathbf{d}}(k_x, y, k_z, t) e^{i(k_x x + k_z z)}$$



Ensemble average energy density

channel flow with $Re = 2000$:



- **Dominance of streamwise elongated structures**
streamwise streaks!

Farrell & Ioannou, Phys. Fluids A '93

Jovanović & Bamieh, J. Fluid Mech. '05

Schmid, Annu. Rev. Fluid Mech. '07

Gayme et al., J. Fluid Mech. '10

ANALYSIS OF LINEAR DYNAMICAL SYSTEMS

State-space representation

state equation: $\dot{\psi}(t) = A \psi(t) + B d(t)$

output equation: $\phi(t) = C \psi(t)$

- **Solution to state equation**

$$\psi(t) = e^{At} \psi(0) + \int_0^t e^{A(t-\tau)} B d(\tau) d\tau$$



**unforced
response**



**forced
response**

Transform techniques

$$\dot{\psi}(t) = A \psi(t) + B d(t) \quad \xrightarrow{\text{Laplace transform}} \quad s \hat{\psi}(s) - \psi(0) = A \hat{\psi}(s) + B \hat{d}(s)$$

$$\psi(t) = e^{At} \psi(0) + \int_0^t e^{A(t-\tau)} B d(\tau) d\tau$$



$$\hat{\psi}(s) = (sI - A)^{-1} \psi(0) + (sI - A)^{-1} B \hat{d}(s)$$

Natural and forced responses

- **Unforced response**

matrix exponential	resolvent
$\psi(t) = e^{At} \psi(0)$	$\hat{\psi}(s) = (sI - A)^{-1} \psi(0)$

- **Forced response**

impulse response	transfer function
$H(t) = C e^{At} B$	$H(s) = C (sI - A)^{-1} B$

- ★ **Response to arbitrary inputs**

$$\phi(t) = \int_0^t H(t - \tau) d(\tau) d\tau \xrightarrow{\text{Laplace transform}} \hat{\phi}(s) = H(s) \hat{d}(s)$$

UNFORCED RESPONSES

Systems with non-normal A

$$\dot{\psi}(t) = A \psi(t)$$

- **Non-normal operator: doesn't commute with its adjoint**

$$A A^* \neq A^* A$$

- ★ **E-value decomposition of A**

$$A v_i = \lambda_i v_i$$

- Let A have a full set of linearly independent e-vectors

$$A = V \Lambda V^{-1}$$

The diagram shows the equation $A = V \Lambda V^{-1}$ where A is an orange square, V is a green square containing the vectors $v_1 \dots v_n$, and Λ is a purple square containing the eigenvalues $\lambda_1 \dots \lambda_n$ on the diagonal. The V matrix is shown on both sides of the equation, representing the change of basis.

★ normal A : unitarily diagonalizable

$$A = V \Lambda V^*$$

- E-value decomposition of A^*

$$A^* w_i = \bar{\lambda}_i w_i$$

choose w_i such that $w_i^* v_j = \delta_{ij}$

$$A^* W = W \bar{\Lambda}$$

- Use V and W^* to diagonalize A

$$A = V \Lambda W^*$$

The diagram shows the decomposition of matrix A into three matrices: V , Λ , and W^* . Matrix V is represented by a green square containing the columns $v_1 \dots v_n$. Matrix Λ is represented by a purple square containing the diagonal elements $\lambda_1 \dots \lambda_n$. Matrix W^* is represented by a blue square containing the rows $w_1^* \dots w_n^*$.

★ solution to $\dot{\psi}(t) = A \psi(t)$

$$\psi(t) = e^{At} \psi(0) = \sum_{i=1}^n e^{\lambda_i t} v_i \langle w_i, \psi(0) \rangle$$

- **Right e-vectors**

- ★ **identify initial conditions with simple responses**

$$\psi(t) = \sum_{i=1}^n e^{\lambda_i t} v_i \langle w_i, \psi(0) \rangle$$

$$\downarrow \psi(0) = v_k$$

$$\psi(t) = e^{\lambda_k t} v_k$$

- E-value decomposition of $A = \begin{bmatrix} -1 & 0 \\ k & -2 \end{bmatrix}$

$$\left\{ v_1 = \frac{1}{\sqrt{1+k^2}} \begin{bmatrix} 1 \\ k \end{bmatrix}, v_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\}$$

$$\left\{ w_1 = \begin{bmatrix} \sqrt{1+k^2} \\ 0 \end{bmatrix}, w_2 = \begin{bmatrix} -k \\ 1 \end{bmatrix} \right\}$$

solution to $\dot{\psi}(t) = A\psi(t)$:

$$\psi(t) = (e^{-t} v_1 w_1^* + e^{-2t} v_2 w_2^*) \psi(0)$$

↓

$$\begin{bmatrix} \psi_1(t) \\ \psi_2(t) \end{bmatrix} = \begin{bmatrix} e^{-t} \psi_1(0) \\ k (e^{-t} - e^{-2t}) \psi_1(0) + e^{-2t} \psi_2(0) \end{bmatrix}$$

- **E-values: misleading measures of transient response**

FORCED RESPONSES

Amplification of disturbances

- **Harmonic forcing**

$$d(t) = \hat{d}(\omega) e^{i\omega t} \xrightarrow{\text{steady-state response}} \phi(t) = \hat{\phi}(\omega) e^{i\omega t}$$

- ★ **Frequency response**

$$\hat{\phi}(\omega) = \underbrace{C (i\omega I - A)^{-1} B}_{H(\omega)} \hat{d}(\omega)$$

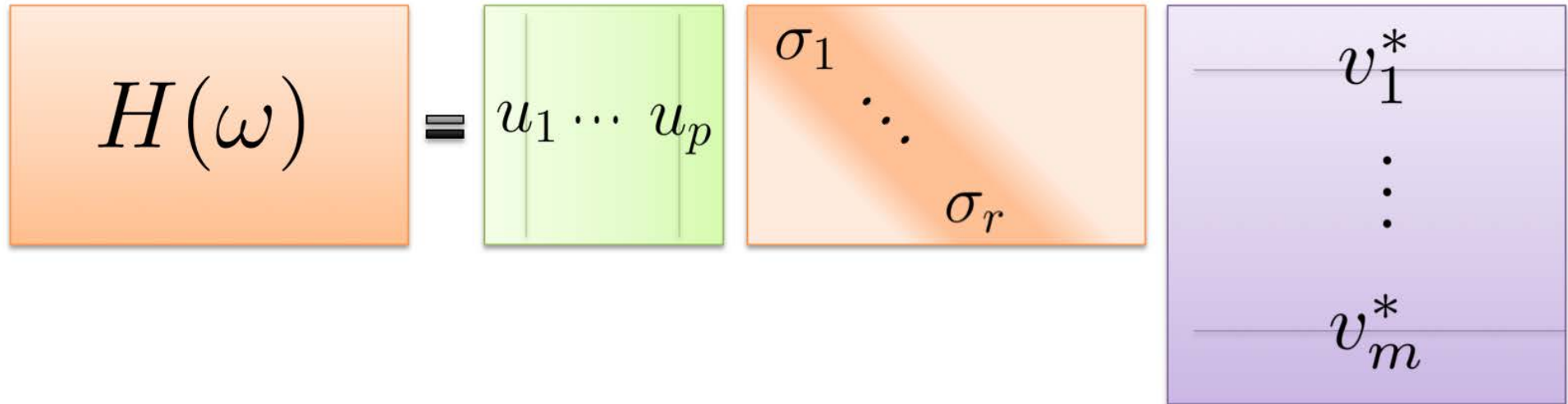
example: 3 inputs, 2 outputs

$$\begin{bmatrix} \hat{\phi}_1(\omega) \\ \hat{\phi}_2(\omega) \end{bmatrix} = \begin{bmatrix} H_{11}(\omega) & H_{12}(\omega) & H_{13}(\omega) \\ H_{21}(\omega) & H_{22}(\omega) & H_{23}(\omega) \end{bmatrix} \begin{bmatrix} \hat{d}_1(\omega) \\ \hat{d}_2(\omega) \\ \hat{d}_3(\omega) \end{bmatrix}$$

$H_{ij}(\omega)$ – response from j th input to i th output

Input-output gains

- Determined by **singular values** of $H(\omega)$



left and **right** singular vectors:

$$H(\omega)H^*(\omega) u_i(\omega) = \sigma_i^2(\omega) u_i(\omega)$$

$$H^*(\omega)H(\omega) v_i(\omega) = \sigma_i^2(\omega) v_i(\omega)$$

$\{u_i\}$ orthonormal basis of output space

$\{v_i\}$ orthonormal basis of input space

- **Action of $H(\omega)$ on $\hat{d}(\omega)$**

$$\hat{\phi}(\omega) = H(\omega) \hat{d}(\omega) = \sum_{i=1}^r \sigma_i(\omega) u_i(\omega) \langle v_i(\omega), \hat{d}(\omega) \rangle$$

- **Right singular vectors**

★ **identify input directions with simple responses**

$$\sigma_1(\omega) \geq \sigma_2(\omega) \geq \dots > 0$$

$$\hat{\phi}(\omega) = \sum_{i=1}^r \sigma_i(\omega) u_i(\omega) \langle v_i(\omega), \hat{d}(\omega) \rangle$$

$$\downarrow \hat{d}(\omega) = v_k(\omega)$$

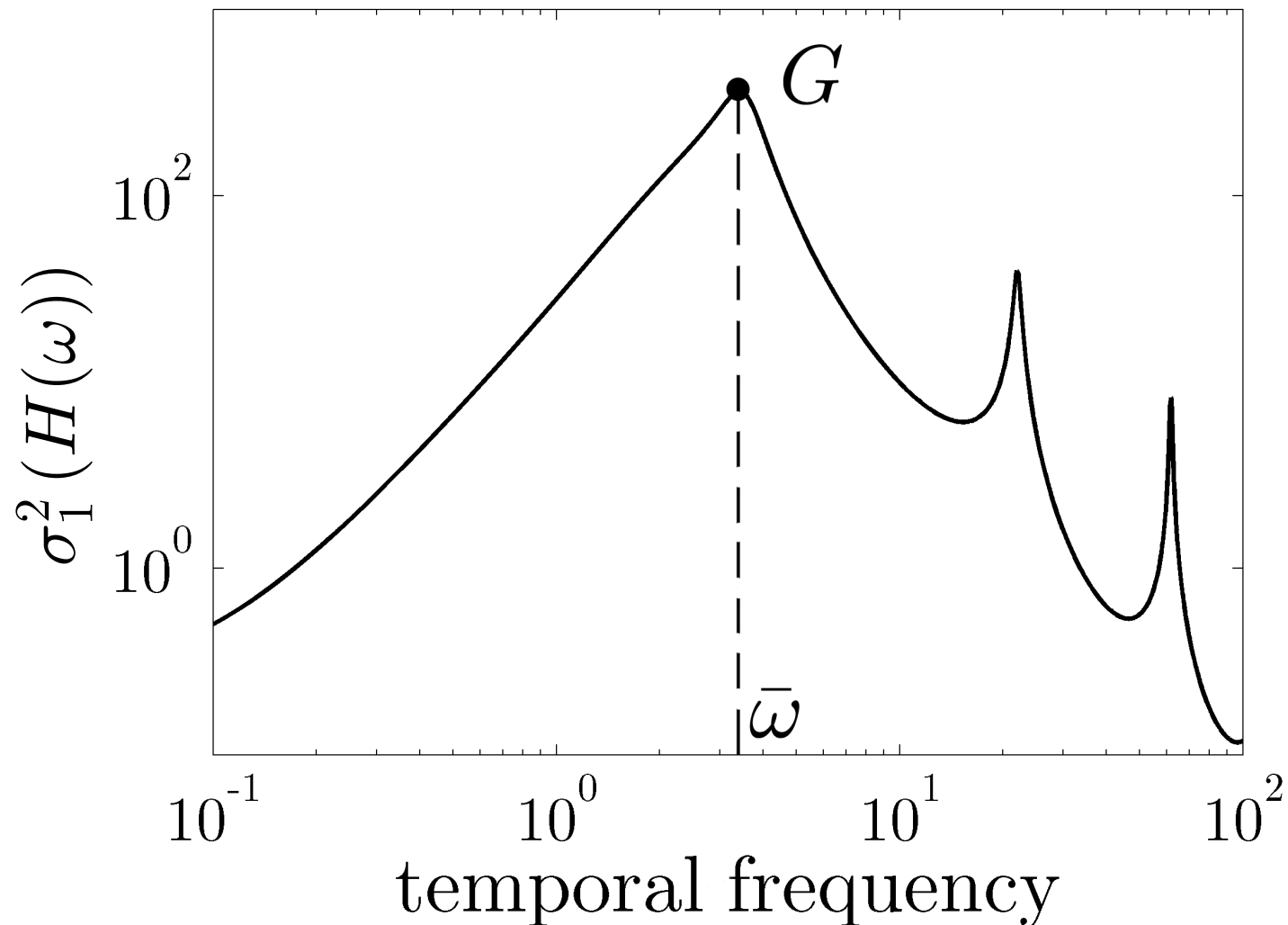
$$\hat{\phi}(\omega) = \sigma_k(\omega) u_k(\omega)$$

$\sigma_1(\omega)$: **the largest amplification at any frequency**

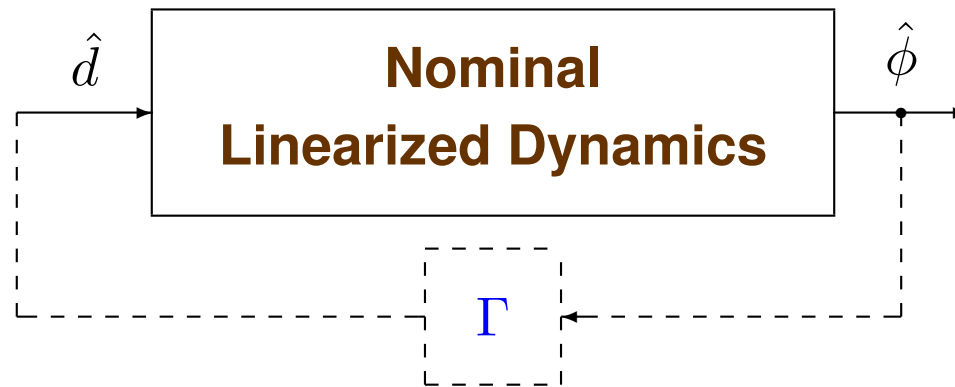
Worst case amplification

- H_∞ norm: an induced L_2 gain (of a system)

$$G = \|H\|_\infty^2 = \max \frac{\text{output energy}}{\text{input energy}} = \max_{\omega} \sigma_1^2(H(\omega))$$



Robustness interpretation



modeling uncertainty

(can be nonlinear or time-varying)

- Closely related to **pseudospectra** of linear operators

$$\dot{\psi}(t) = (A + B \Gamma C) \psi(t)$$

LARGE
worst case amplification



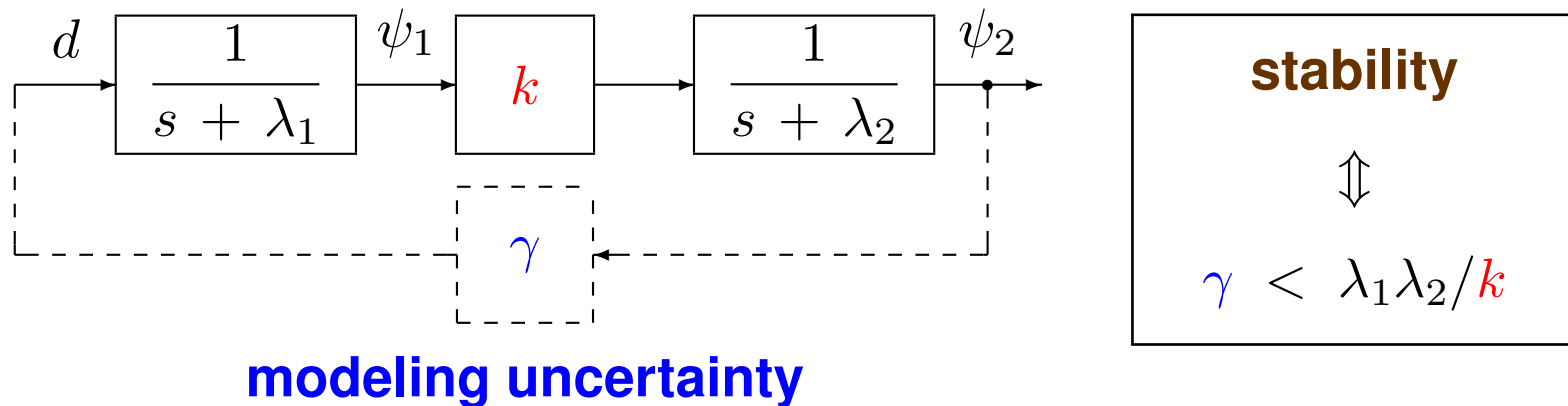
small
stability margins

Back to a toy example

$$\begin{bmatrix} \dot{\psi}_1 \\ \dot{\psi}_2 \end{bmatrix} = \begin{bmatrix} -\lambda_1 & \mathbf{0} \\ k & -\lambda_2 \end{bmatrix} \begin{bmatrix} \psi_1 \\ \psi_2 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} d$$

$$G = \max_{\omega} |H(i\omega)|^2 = \frac{k^2}{(\lambda_1 \lambda_2)^2}$$

ROBUSTNESS



$$\det \left(\begin{bmatrix} s & 0 \\ 0 & s \end{bmatrix} - \begin{bmatrix} -\lambda_1 & \gamma \\ k & -\lambda_2 \end{bmatrix} \right) = s^2 + (\lambda_1 + \lambda_2) s + \underbrace{(\lambda_1 \lambda_2 - \gamma k)}_{> 0}$$

Response to stochastic forcing

- **White-in-time forcing**

$$\mathcal{E} (d(t_1) d^*(t_2)) = I \delta(t_1 - t_2)$$

- ★ **Hilbert-Schmidt norm**

power spectral density:

$$\|H(\omega)\|_{\text{HS}}^2 = \text{trace} (H(\omega) H^*(\omega)) = \sum_{i=1}^r \sigma_i^2(\omega)$$

- ★ **H_2 norm**

variance amplification:

$$\|H\|_2^2 = \frac{1}{2\pi} \int_{-\infty}^{\infty} \|H(\omega)\|_{\text{HS}}^2 d\omega = \int_0^{\infty} \|H(t)\|_{\text{HS}}^2 dt$$

Computation of H_2 and H_∞ norms

$$\dot{\psi}(t) = A \psi(t) + B d(t)$$

$$\phi(t) = C \psi(t)$$

- H_2 norm

- ★ Lyapunov equation

$$\mathcal{E}(d(t_1) d^*(t_2)) = W \delta(t_1 - t_2) \Rightarrow \begin{cases} \|H\|_2^2 = \text{trace}(C P C^*) \\ A P + P A^* = -B W B^* \end{cases}$$

- H_∞ norm

- ★ E-value decomposition of Hamiltonian in conjunction with bisection

$$\|H\|_\infty \geq \gamma \Leftrightarrow \begin{bmatrix} A & \frac{1}{\gamma} B B^* \\ -\frac{1}{\gamma} C^* C & -A^* \end{bmatrix} \text{ has at least one imaginary e-value}$$

BACK TO FLUIDS

Frequency response: channel flow

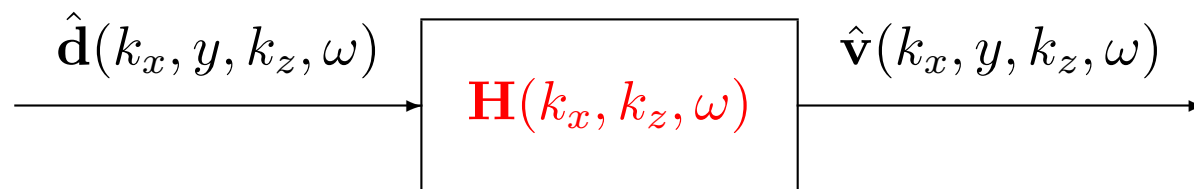
harmonic forcing:

$$\mathbf{d}(x, y, z, t) = \hat{\mathbf{d}}(k_x, y, k_z, \omega) e^{i(k_x x + k_z z + \omega t)}$$

↓ **steady-state response**

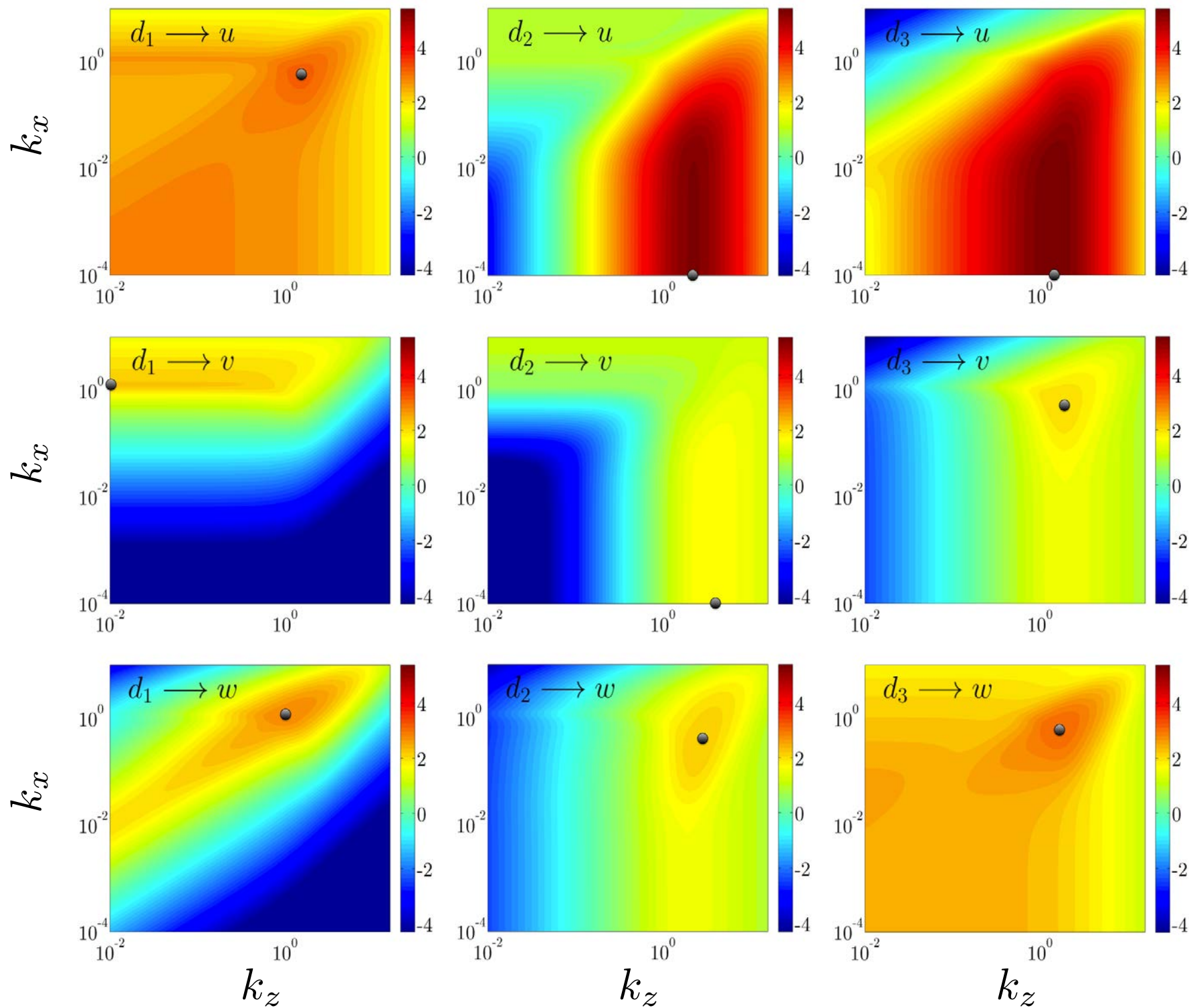
$$\mathbf{v}(x, y, z, t) = \hat{\mathbf{v}}(k_x, y, k_z, \omega) e^{i(k_x x + k_z z + \omega t)}$$

- Frequency response: **operator in y**



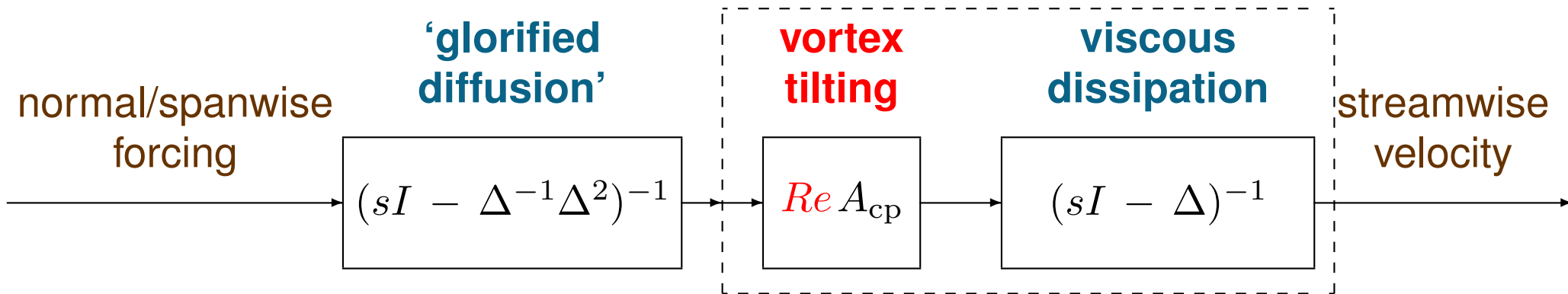
★ **componentwise amplification**

$$\begin{bmatrix} u \\ v \\ w \end{bmatrix} = \begin{bmatrix} H_{u1} & H_{u2} & H_{u3} \\ H_{v1} & H_{v2} & H_{v3} \\ H_{w1} & H_{w2} & H_{w3} \end{bmatrix} \begin{bmatrix} d_1 \\ d_2 \\ d_3 \end{bmatrix}$$



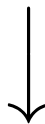
Amplification mechanism in flows with high Re

- HIGHEST AMPLIFICATION: $(d_2, d_3) \rightarrow u$



- LINEARIZED DYNAMICS OF NORMAL VORTICITY η

$$\dot{\eta} = \Delta \eta + Re A_{cp} v$$



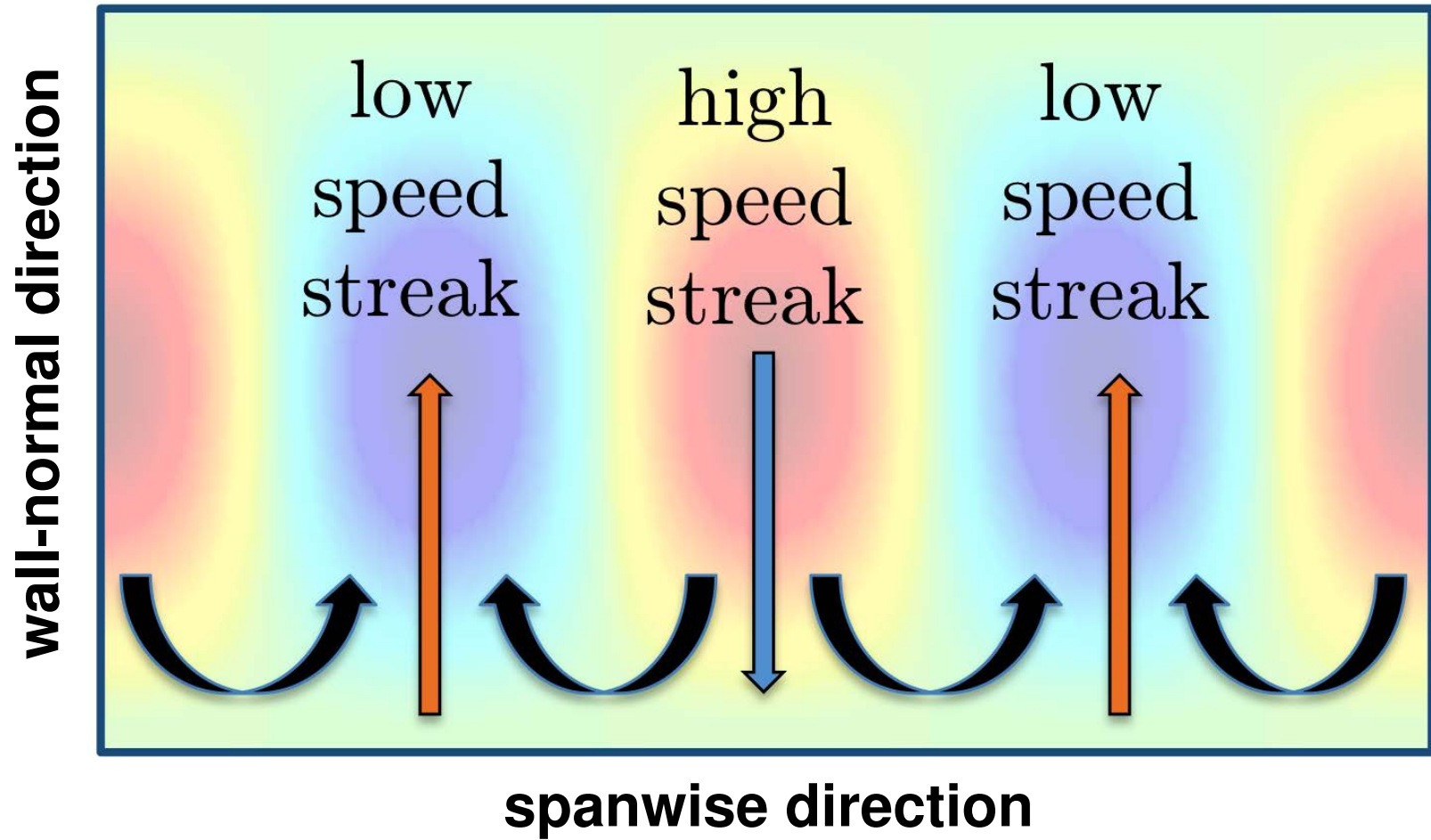
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$$A_{cp} = -(ik_z) U'(y)$$

spanwise variations

background shear

👉 AMPLIFICATION MECHANISM: **vortex tilting** or **lift-up**

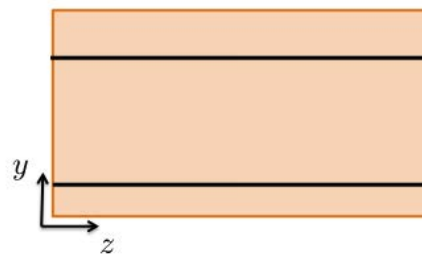
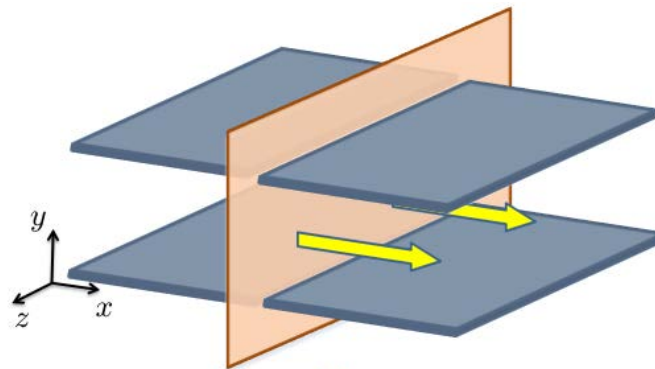
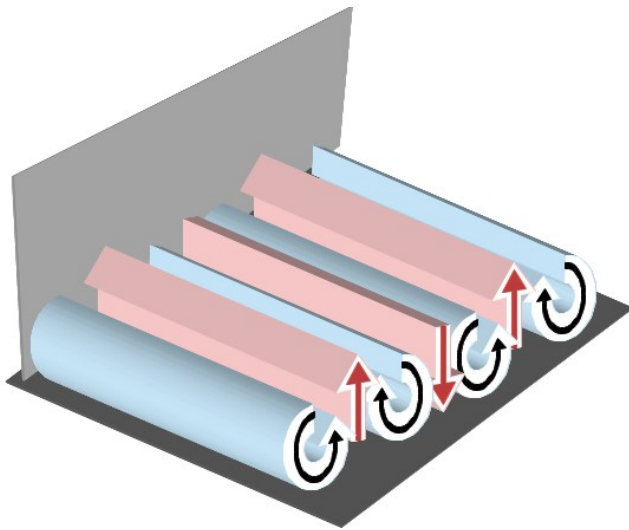


Linear analyses: Input-output vs. Stability

AMPLIFICATION:

$$\mathbf{v} = H \mathbf{d}$$

singular values of H

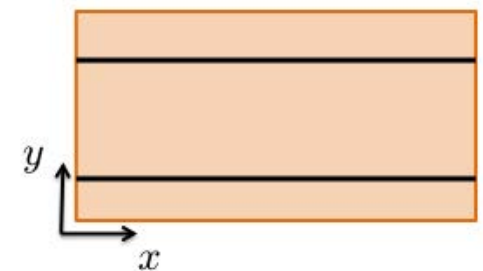
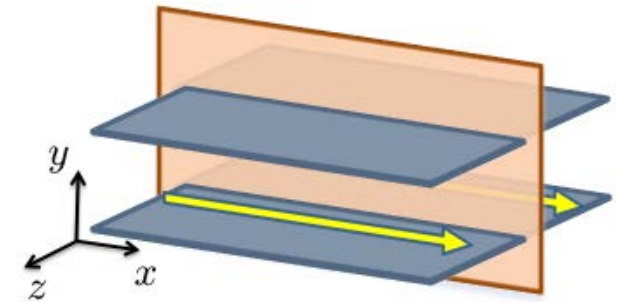


typical structures cross-sectional dynamics

STABILITY:

$$\dot{\boldsymbol{\psi}} = A \boldsymbol{\psi}$$

e-values of A



2D models

FLOW CONTROL

- **Objective**
 - ★ **controlling the onset of turbulence**
- **Transition initiated by**
 - ★ **high flow sensitivity**
- **Control strategy**
 - ★ **reduce flow sensitivity**

Sensor-free flow control

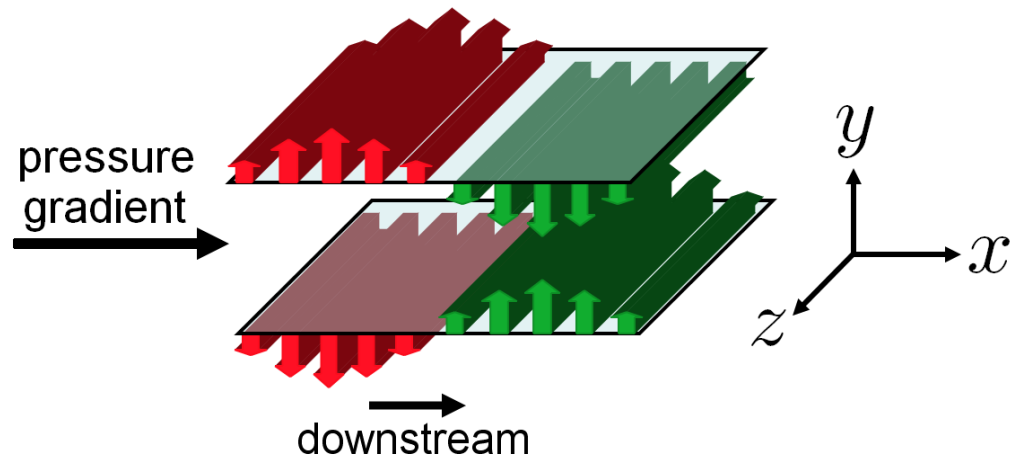
- GEOMETRY MODIFICATIONS
 - ★ riblets
 - ★ surface roughness
 - ★ super-hydrophobic surfaces

- BODY FORCES
 - ★ temporally/spatially oscillatory forces
 - ★ traveling waves

- WALL OSCILLATIONS
 - ★ transverse wall oscillations

common theme: PDEs with spatially or temporally periodic coefficients

Blowing and suction along the walls



$$\text{NORMAL VELOCITY: } V(y = \pm 1) = \mp \alpha \cos(\omega_x(x - ct))$$

- TRAVELING WAVE PARAMETERS:

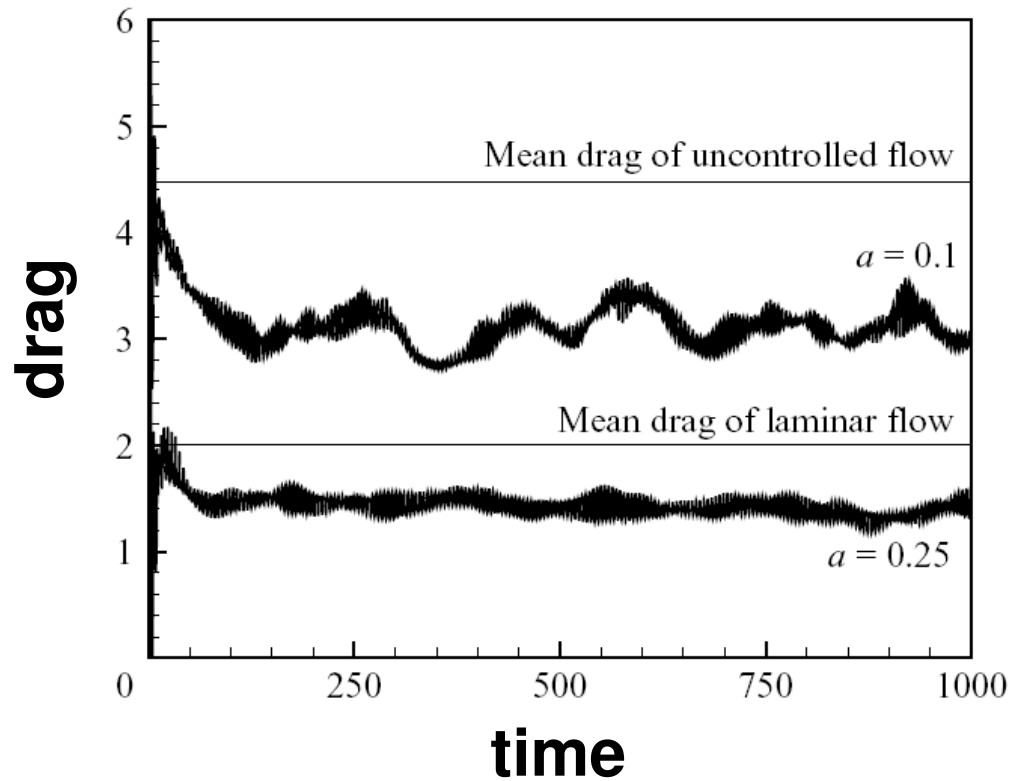
spatial frequency: ω_x

speed: $c \begin{cases} c > 0 & \text{downstream} \\ c < 0 & \text{upstream} \end{cases}$

amplitude: α

- INVESTIGATE THE EFFECTS OF c , ω_x , α ON:

- ★ **base flow**
- ★ **cost of control**
- ★ **onset of turbulence**



CHALLENGE: **selection of wave parameters**

● THIS TALK:

- ★ **cost of control**
- ★ **onset of turbulence**

Effects of blowing and suction?

- DESIRED EFFECTS OF CONTROL:

- ★ **bulk flux** ↗
- ★ **net efficiency** ↗
- ★ **fluctuations' energy** ↘

TRAVELING WAVE

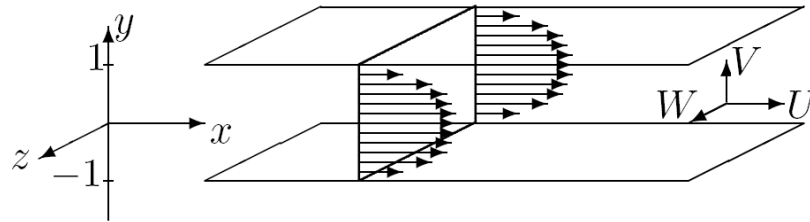
- ★ **induces a bulk flux (pumping)**

PUMPING DIRECTION

- ★ **opposite to a traveling wave direction**



Nominal velocity



$$\begin{aligned}
 V(y = \pm 1) &= \mp \alpha \cos(\omega_x(x - ct)) \\
 &= \mp \alpha \cos(\omega_x \bar{x})
 \end{aligned}
 \Rightarrow \bar{\mathbf{u}} = (U(\bar{x}, y), V(\bar{x}, y), 0)$$

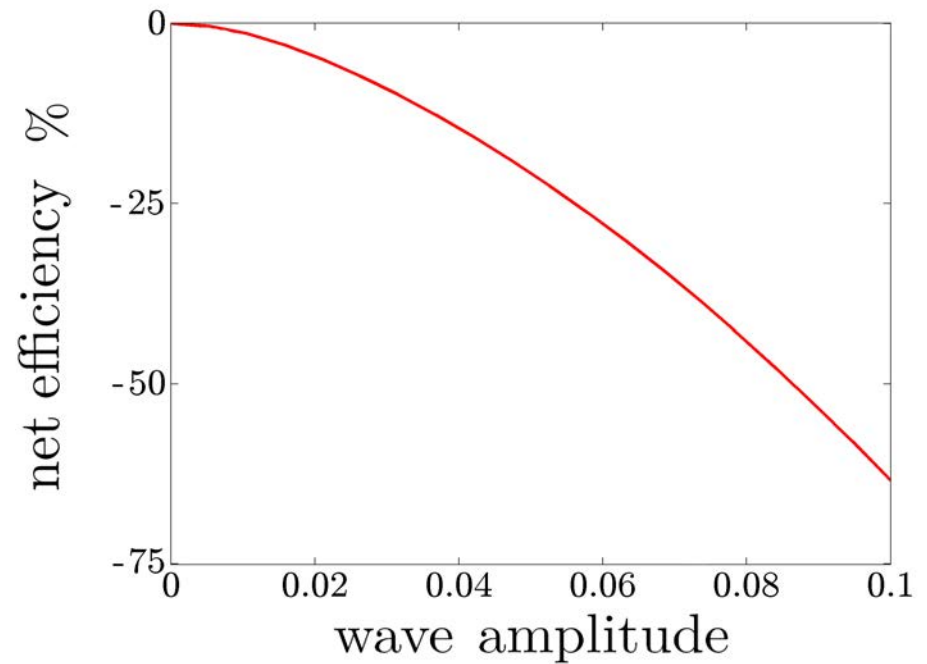
steady in a traveling wave frame
periodic in \bar{x}

- SMALL AMPLITUDE BLOWING/SUCTION
weakly-nonlinear analysis

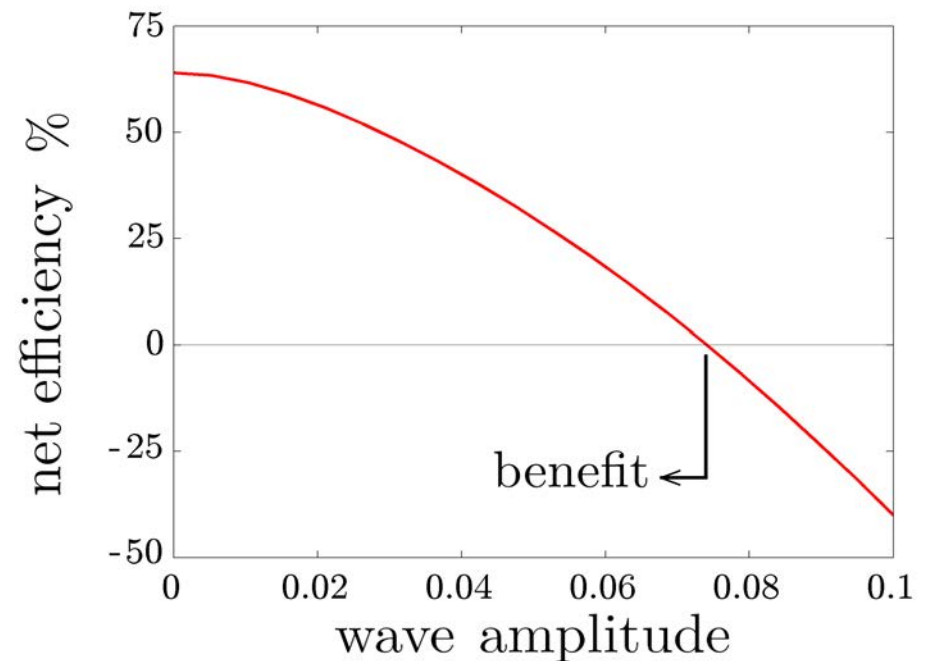
$$\begin{aligned}
 U(\bar{x}, y) &= \underbrace{U_0(y)}_{\text{parabola}} + \alpha^2 \underbrace{U_{2,0}(y)}_{\text{mean drift}} + \alpha \underbrace{(U_{1,-1}(y) e^{-i\omega_x \bar{x}} + U_{1,1}(y) e^{i\omega_x \bar{x}})}_{\text{oscillatory: no mean drift}} \\
 &\quad + \alpha^2 (U_{2,-2}(y) e^{-2i\omega_x \bar{x}} + U_{2,2}(y) e^{2i\omega_x \bar{x}}) \\
 &\quad + O(\alpha^3)
 \end{aligned}$$

Best-case scenario for net efficiency

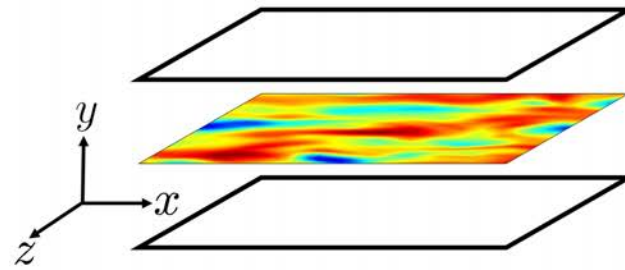
ASSUME: {
 no control: laminar
 with control: laminar



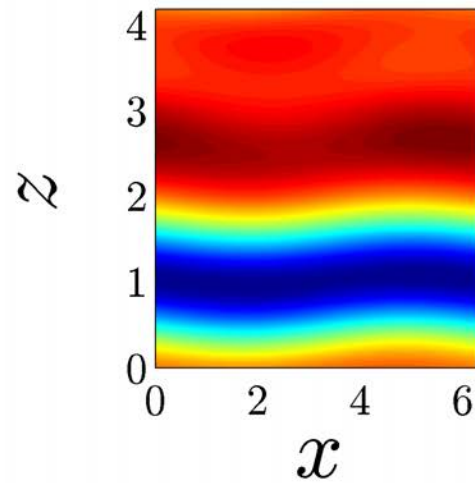
ASSUME: {
 no control: turbulent
 with control: laminar



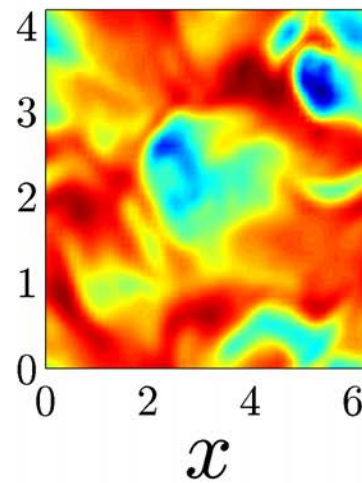
Velocity fluctuations: DNS preview



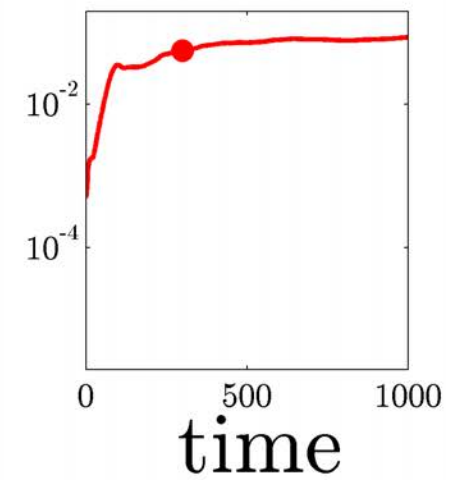
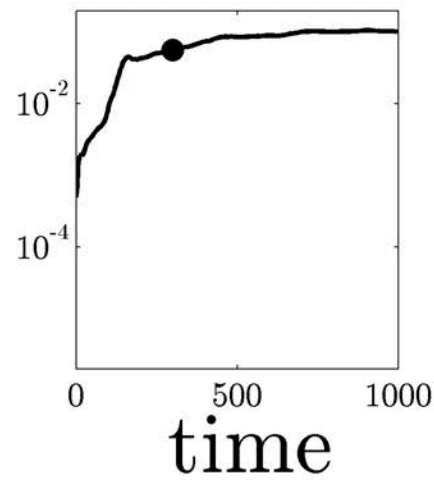
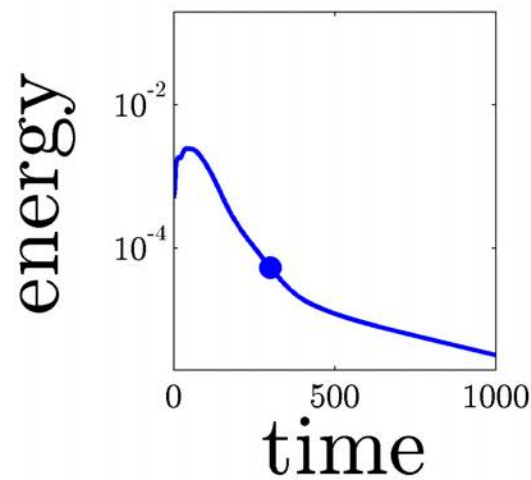
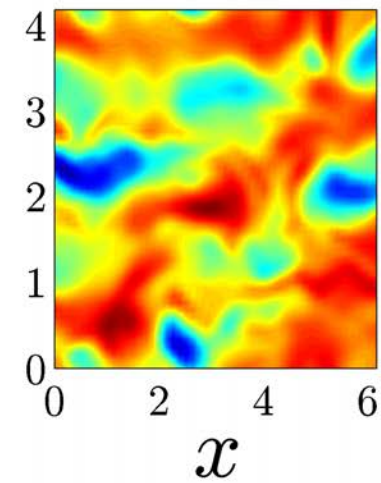
downstream



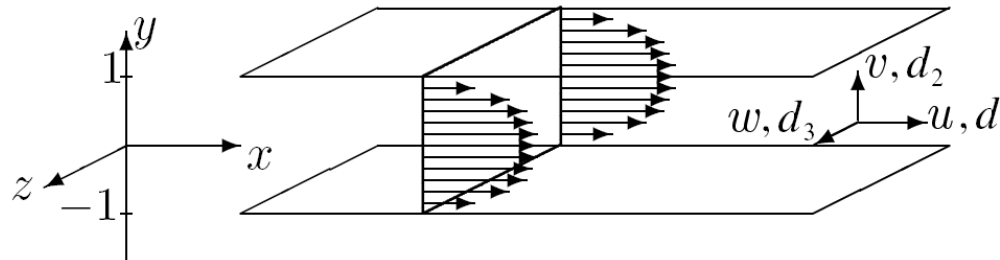
no control



upstream



Ensemble average energy density: controlled flow



EVOLUTION MODEL: **linearization around** $(U(\bar{x}, y), V(\bar{x}, y), 0)$

★ **periodic coefficients in** $\bar{x} = x - ct$

$$\left. \begin{aligned} \psi_t &= A\psi + B\mathbf{d} \\ \mathbf{v} &= C\psi \end{aligned} \right\} \begin{array}{ll} \mathbf{d} = \mathbf{d}(\bar{x}, y, z, t) & \rightsquigarrow \text{stochastic body forcing} \\ \mathbf{v} = (u, v, w) & \rightsquigarrow \text{velocity fluctuations} \\ \psi = (v, \eta) & \rightsquigarrow \text{normal velocity/vorticity} \end{array}$$

- Simulation-free approach to determining **energy density**

Moarref & Jovanović, J. Fluid Mech. '10

effect of small wave amplitude:

$$\begin{array}{ccc}
 \text{energy density} & = & \text{energy density} + \underbrace{\alpha^2}_{\text{small}} E_2(\theta, k_z; Re; \omega_x, c) + O(\alpha^4) \\
 \downarrow & & \downarrow \\
 \text{with control} & & \text{w/o control}
 \end{array}$$

$(\theta, k_z) \rightsquigarrow$ spatial wavenumbers

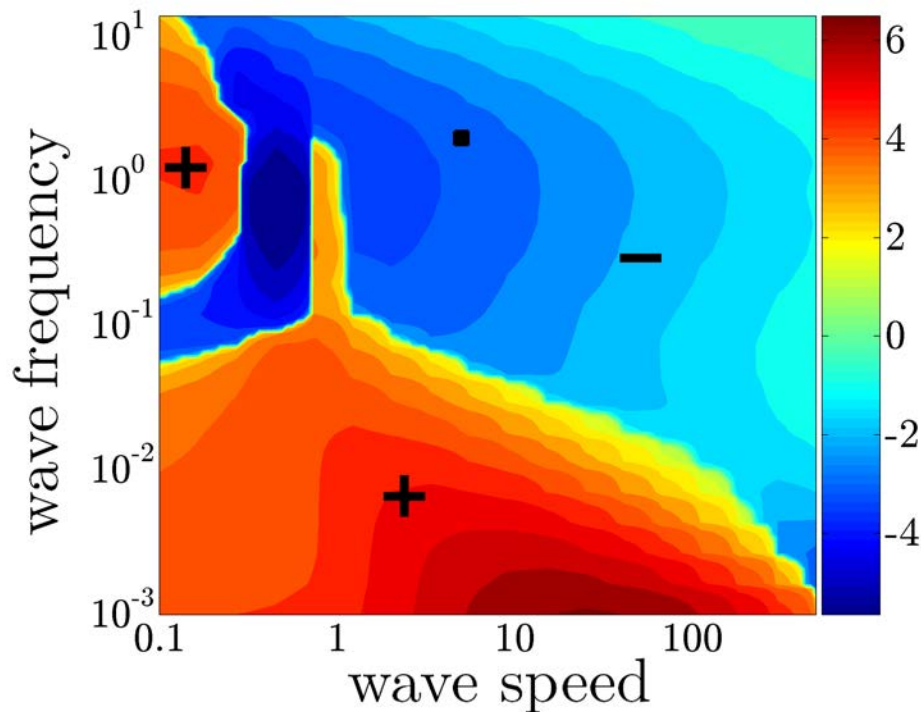
Energy amplification: controlled flow with $Re = 2000$

explicit formula:

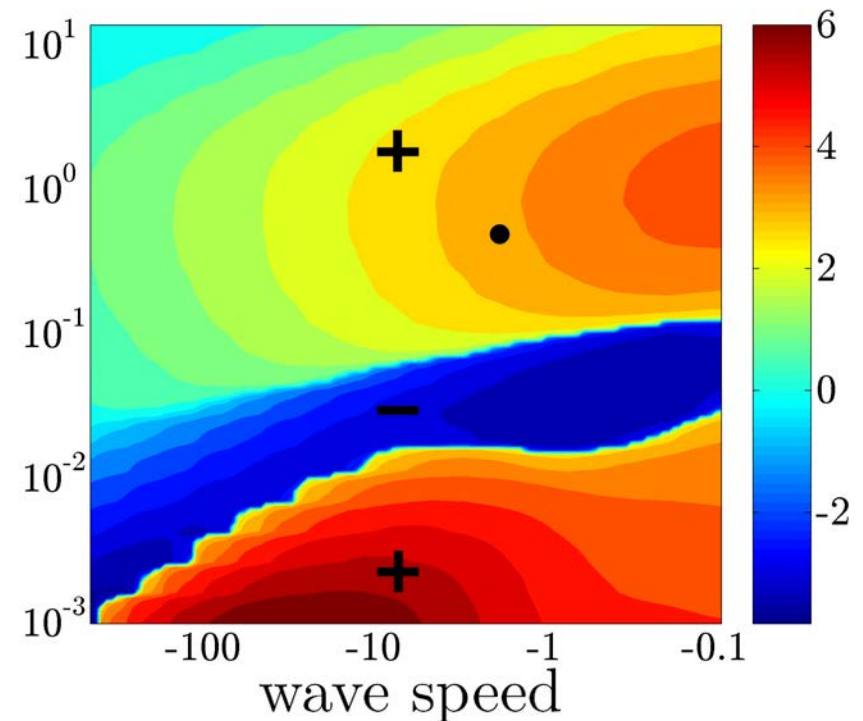
$$\frac{\text{energy density with control}}{\text{energy density w/o control}} \approx 1 + \alpha^2 g_2(\theta, k_z; \omega_x, c)$$

- ($\theta = 0$, $k_z = 1.78$): **most energy w/o control**

g_2 , downstream:



g_2 , upstream:



Recap

facts revealed by perturbation analysis:

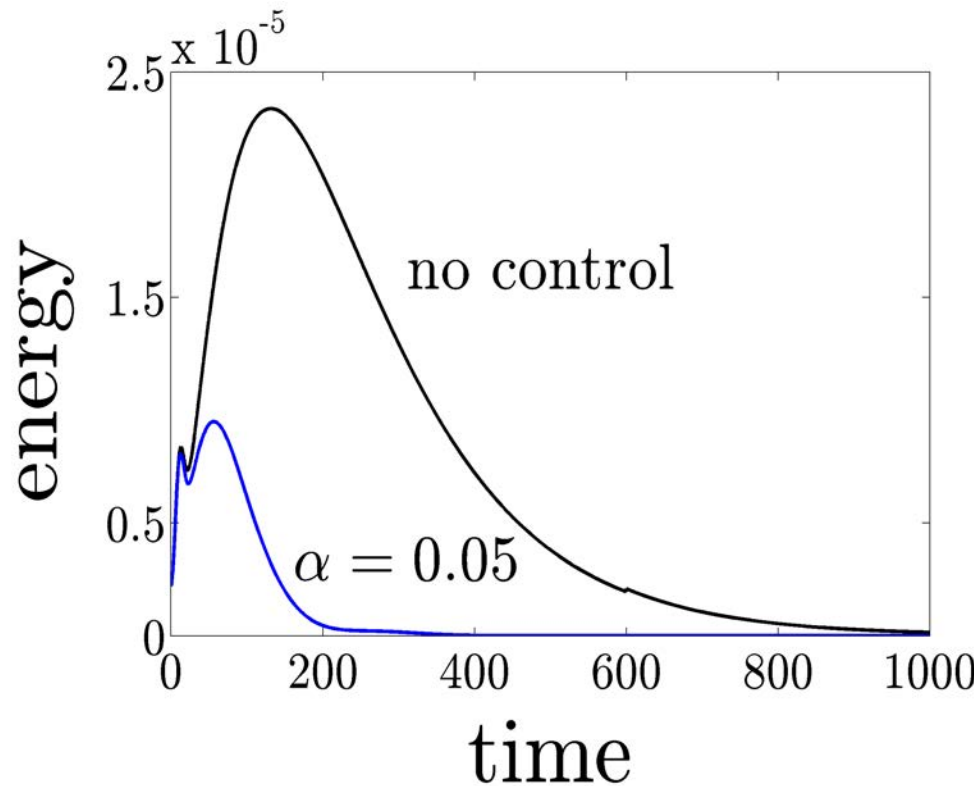
Blowing/Suction Type	Nominal flow analysis	Energy amplification analysis
Downstream	reduce bulk flux	reduce amplification ✓
Upstream	increase bulk flux ✓	promote amplification

Moarref & Jovanović, J. Fluid Mech. '10

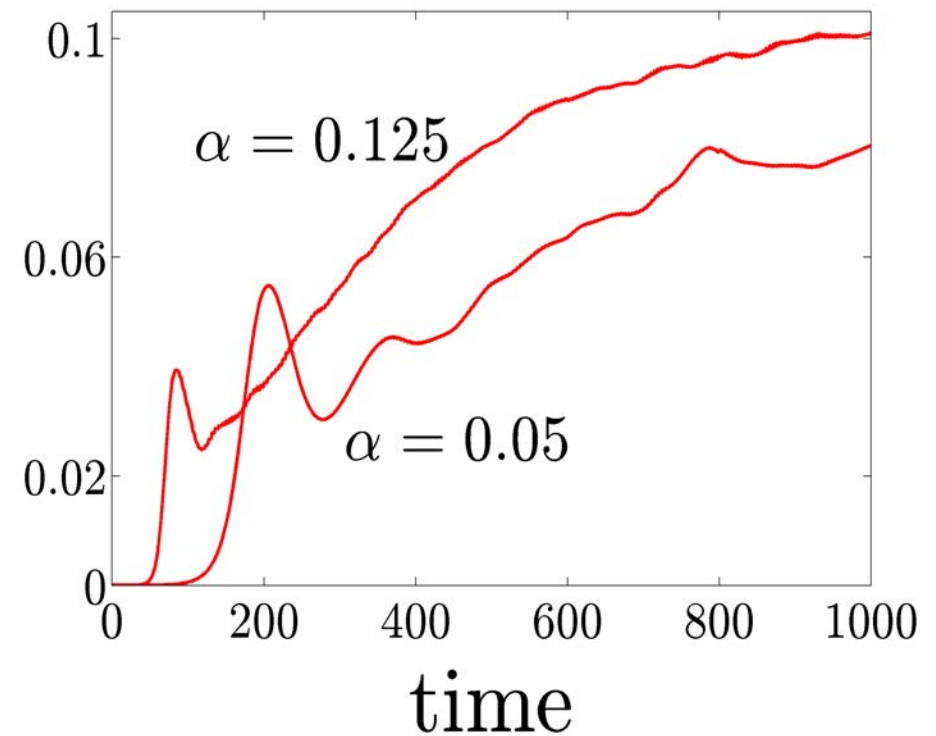
DNS results: avoidance/promotion of turbulence

small initial energy
(flow with no control stays laminar)

DOWNSTREAM: NO TURBULENCE

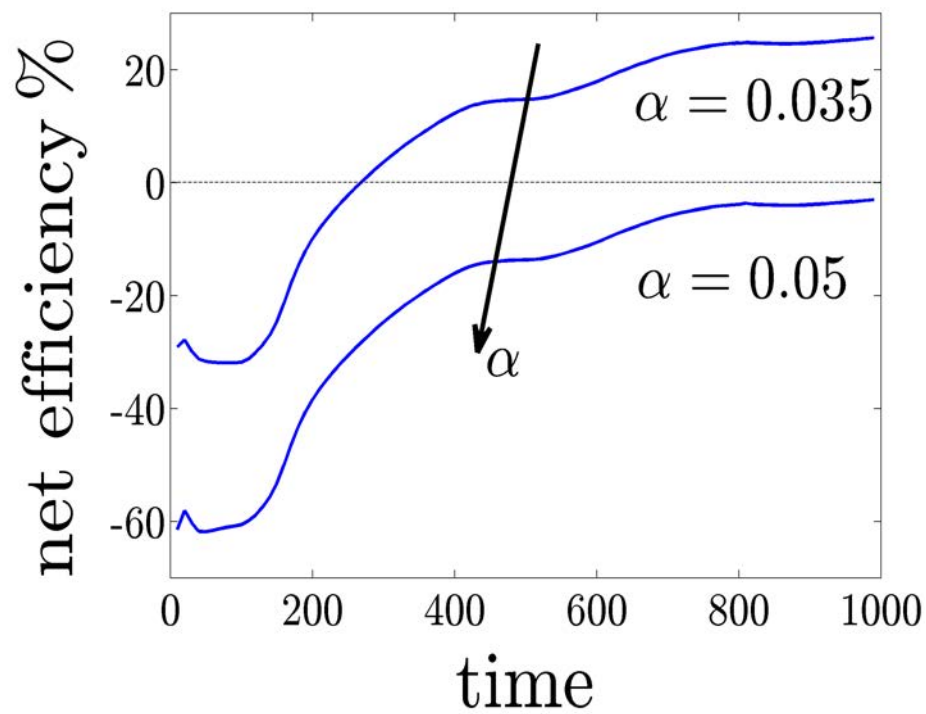
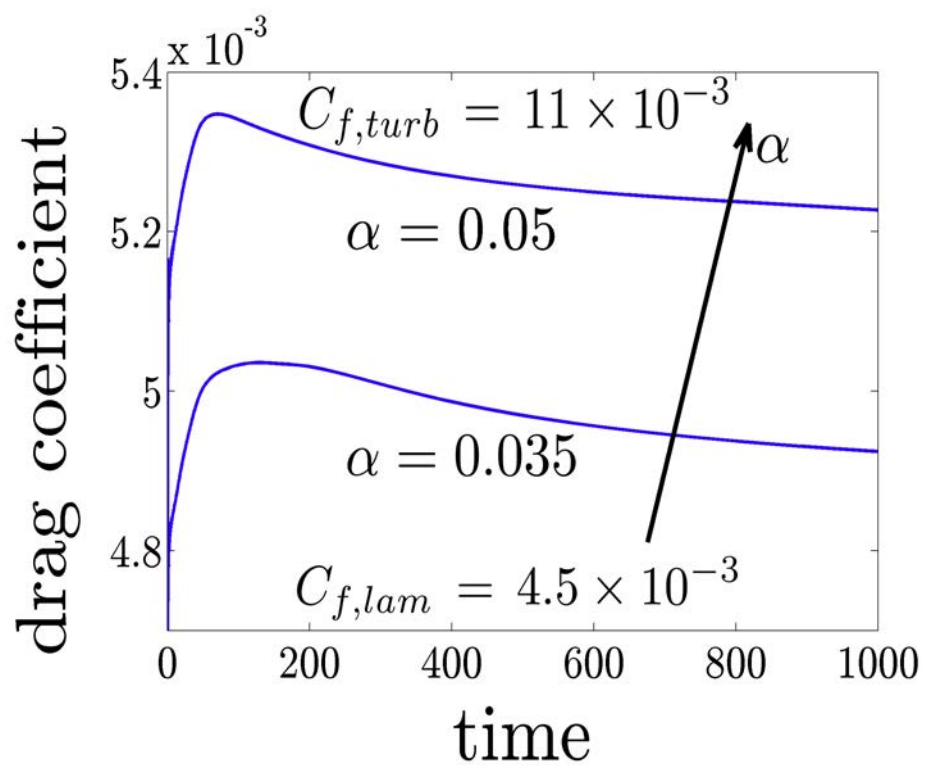
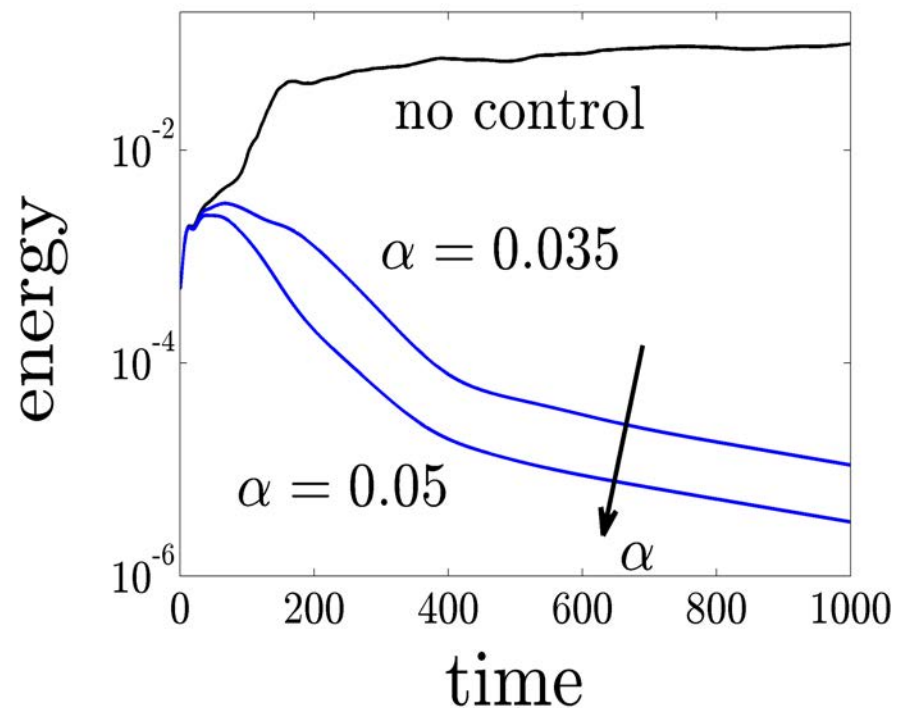


UPSTREAM: PROMOTES TURBULENCE

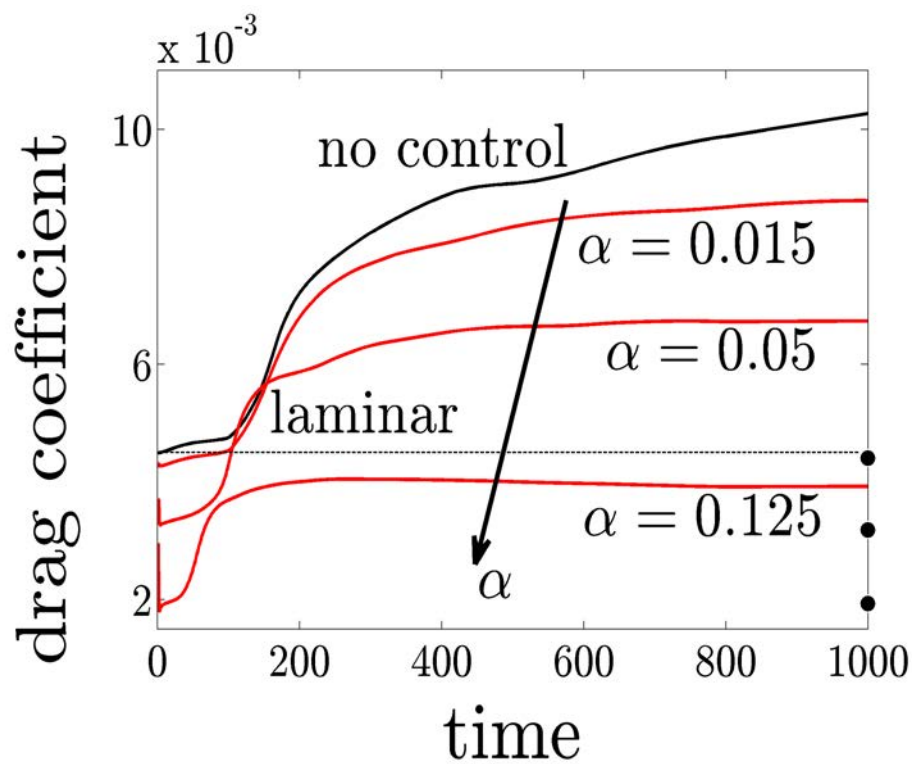


DOWNSTREAM
moderate initial energy

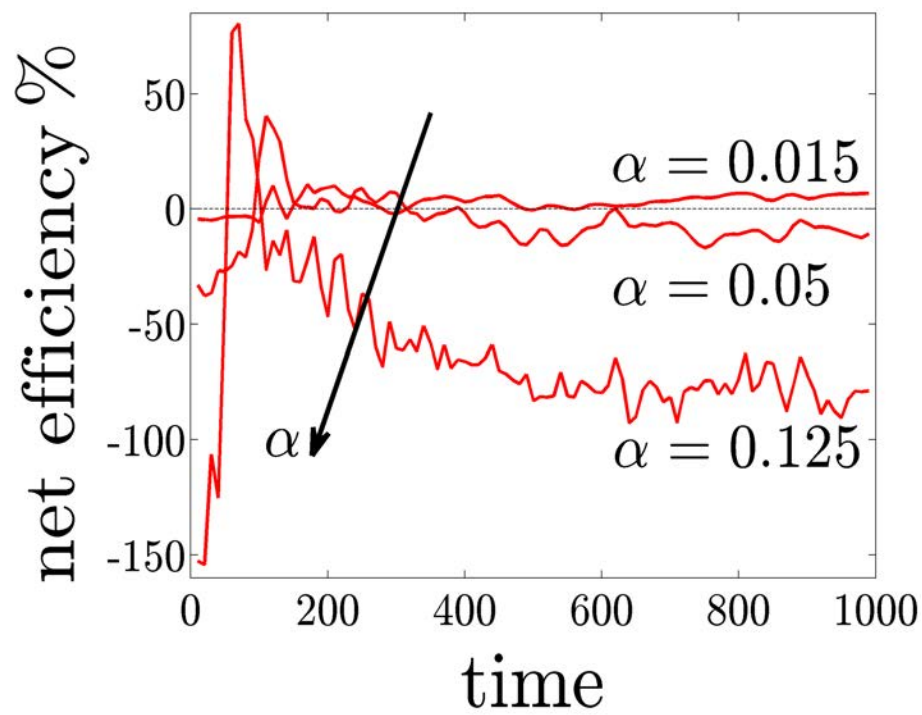
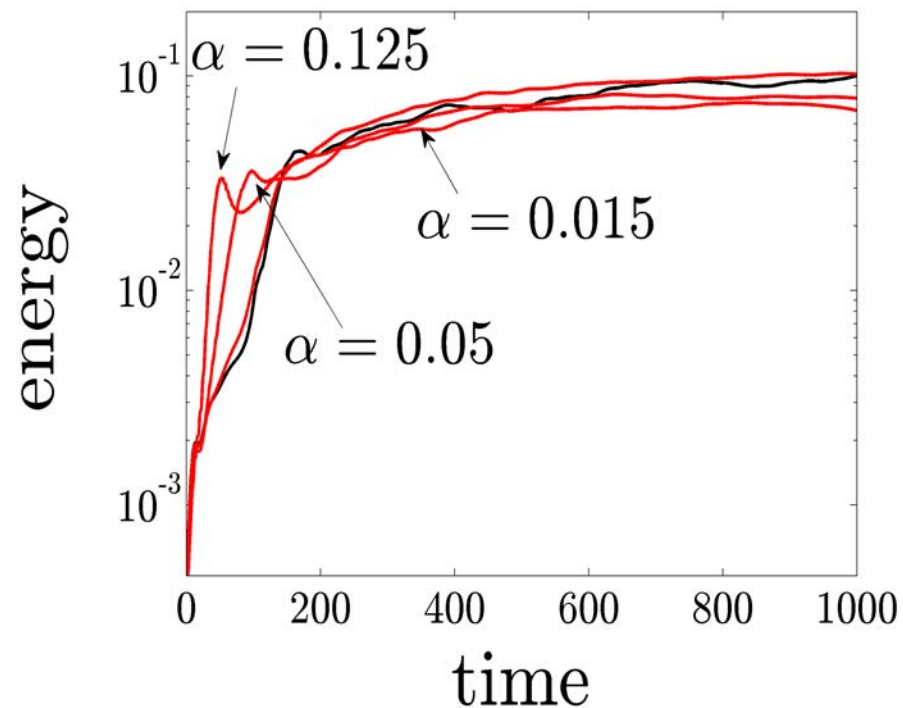
NO TURBULENCE:



UPSTREAM
moderate initial energy



TURBULENCE:



OPTIMAL CONTROL AND ESTIMATION

Linear Quadratic Regulator (LQR)

- Minimize quadratic objective subject to linear dynamic constraint

$$\text{minimize } J(\psi, u) = \frac{1}{2} \int_0^T (\langle \psi(\tau), Q \psi(\tau) \rangle + \langle u(\tau), R u(\tau) \rangle) d\tau + \frac{1}{2} \langle \psi(T), Q_T \psi(T) \rangle$$

$$\text{subject to } A \psi(t) + B u(t) - \dot{\psi}(t) = 0$$

$$\psi(0) = \psi_0, \quad t \in [0, T]$$

- ★ optimization variable is a function

$$u: [0, T] \longrightarrow \mathbb{H}_u$$

- ★ state and control weights

$$\begin{cases} Q, Q_T & \text{self-adjoint, non-negative} \\ R & \text{self-adjoint, positive} \end{cases}$$

- ★ infinite number of constraints

- **Introduce Lagrangian**

$$\mathcal{L}(\psi, u, \lambda) = J(\psi, u) + \int_0^T \langle \lambda(\tau), A\psi(\tau) + Bu(\tau) - \dot{\psi}(\tau) \rangle d\tau$$

- ★ **form variations wrt ψ, u, λ**

$$\mathcal{L}(\psi, u + \tilde{u}, \lambda) - \mathcal{L}(\psi, u, \lambda) = \int_0^T \langle Ru(\tau) + B^*\lambda(\tau), \tilde{u}(\tau) \rangle d\tau = 0$$

↓

$$u(t) = -R^{-1}B^*\lambda(t), \quad t \in [0, T]$$

necessary conditions for optimality:

$$\text{wrt } \lambda \Rightarrow \dot{\psi}(t) = A\psi(t) + Bu(t), \quad \psi(0) = \psi_0$$

$$\text{wrt } \psi \Rightarrow \dot{\lambda}(t) = -Q\psi(t) - A^*\lambda(t), \quad \lambda(T) = Q_T\psi(T)$$

$$\text{wrt } u \Rightarrow u(t) = -R^{-1}B^*\lambda(t), \quad t \in [0, T]$$

Solution to finite horizon LQR

two-point boundary value problem:

$$\begin{bmatrix} \dot{\psi}(t) \\ \dot{\lambda}(t) \end{bmatrix} = \begin{bmatrix} A & -B R^{-1} B^* \\ -Q & -A^* \end{bmatrix} \begin{bmatrix} \psi(t) \\ \lambda(t) \end{bmatrix}$$

$$\begin{bmatrix} \psi_0 \\ 0 \end{bmatrix} = \begin{bmatrix} I & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \psi(0) \\ \lambda(0) \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ Q_T & -I \end{bmatrix} \begin{bmatrix} \psi(T) \\ \lambda(T) \end{bmatrix}$$

$$u(t) = -R^{-1} B^* \lambda(t)$$

- **Differential Riccati Equation**

can show: $\lambda(t) = X(t) \psi(t)$

$$\begin{aligned} -\dot{X}(t) &= A^* X(t) + X(t) A + Q - X(t) B R^{-1} B^* X(t) \\ X(T) &= Q_T \end{aligned}$$

★ **optimal controller: determined by state-feedback**

$$u(t) = -K(t) \psi(t)$$

$$K(t) = R^{-1} B^* X(t)$$

Infinite horizon LQR

$$\text{minimize } J = \frac{1}{2} \int_0^{\infty} (\langle \psi(\tau), Q \psi(\tau) \rangle + \langle u(\tau), R u(\tau) \rangle) d\tau$$

$$\text{subject to } \dot{\psi}(t) = A \psi(t) + B u(t)$$

- **Optimal controller:**
$$\begin{cases} u(t) = -K \psi(t) \\ K = R^{-1} B^* X \end{cases}$$

★ $X = X^*$ – **non-negative solution to Algebraic Riccati Equation (ARE)**

$$A^* X + X A + Q - X B R^{-1} B^* X = 0$$

$$\left. \begin{array}{l} (A, B) \text{ stabilizable} \\ (A, Q) \text{ detectable} \end{array} \right\} \Rightarrow \text{stability of } \dot{\psi}(t) = (A - B K) \psi(t)$$

Scalar example

$$\dot{\psi} = a\psi + u$$

$$J = \frac{1}{2} \int_0^{\infty} (q\psi^2(\tau) + ru^2(\tau)) d\tau$$

- **Optimal controller**

$$k_{lqr} = a + \sqrt{a^2 + \frac{q}{r}} \Rightarrow \psi(t) = \exp\left(-\sqrt{a^2 + \frac{q}{r}} t\right) \psi(0)$$

tradeoff:

	large q/r	small q/r
convergence rate	fast ✓	slow
control effort	large	low ✓

State-feedback H_2 controller

$$\text{minimize } \lim_{t \rightarrow \infty} \mathcal{E} \left(\langle \psi(t), Q \psi(t) \rangle + \langle u(t), R u(t) \rangle \right)$$

$$\text{subject to } \dot{\psi}(t) = A \psi(t) + B_d d(t) + B_u u(t)$$

$$\mathcal{E} (d(t_1) d^*(t_2)) = W_d \delta(t_1 - t_2)$$

- **Minimum variance controller**

state-feedback controller:

$$u(t) = -K \psi(t)$$

$$K = R^{-1} B_u^* X$$

$$0 = A^* X + X A + Q - X B_u R^{-1} B_u^* X$$

State estimation

state equation: $\dot{\psi}(t) = A\psi(t) + B_d d(t) + B_u u(t)$

measured output: $\varphi(t) = C\psi(t) + n(t)$

$d(t)$ – process disturbance; $n(t)$ – measurement noise

- **Estimator (observer)**

- ★ **copy of the system** + **linear injection term**

$$\dot{\hat{\psi}}(t) = A\hat{\psi}(t) + 0 \cdot d(t) + B_u u(t) + L(\varphi(t) - \hat{\varphi}(t))$$

$$\hat{\varphi}(t) = C\hat{\psi}(t) + 0 \cdot n(t)$$

- ★ **estimation error:** $\tilde{\psi}(t) = \psi(t) - \hat{\psi}(t)$

$$\dot{\tilde{\psi}}(t) = (A - LC)\tilde{\psi}(t) + \begin{bmatrix} B_d & -L \end{bmatrix} \begin{bmatrix} d(t) \\ n(t) \end{bmatrix}$$

$$\tilde{\varphi}(t) = C\tilde{\psi}(t) + n(t)$$

(A, C) : detectable \Rightarrow can design L to provide stability of the error dynamics

Kalman filter

$$\dot{\psi}(t) = A\psi(t) + B_d d(t) + B_u u(t)$$

$$\varphi(t) = C\psi(t) + n(t)$$

$$\mathcal{E}(d(t_1)d^*(t_2)) = W_d \delta(t_1 - t_2); \quad \mathcal{E}(n(t_1)n^*(t_2)) = W_n \delta(t_1 - t_2)$$

- **Kalman filter: optimal estimator**

- ★ **minimizes steady-state variance of** $\tilde{\psi}(t) = \psi(t) - \hat{\psi}(t)$

Kalman gain:

$$L = Y C^* W_n^{-1}$$

$$0 = AY + YA^* + B_d W_d B_d^* - Y C^* W_n^{-1} C Y$$

Output-feedback H_2 controller

$$\text{minimize } \lim_{t \rightarrow \infty} \mathcal{E} \left(\langle \psi(t), Q \psi(t) \rangle + \langle u(t), R u(t) \rangle \right)$$

$$\text{subject to } \dot{\psi}(t) = A \psi(t) + B_d d(t) + B_u u(t)$$

$$\varphi(t) = C \psi(t) + n(t)$$

$$\mathcal{E} (d(t_1) d^*(t_2)) = W_d \delta(t_1 - t_2); \quad \mathcal{E} (n(t_1) n^*(t_2)) = W_n \delta(t_1 - t_2)$$

- **Minimum variance controller**

observer-based controller:

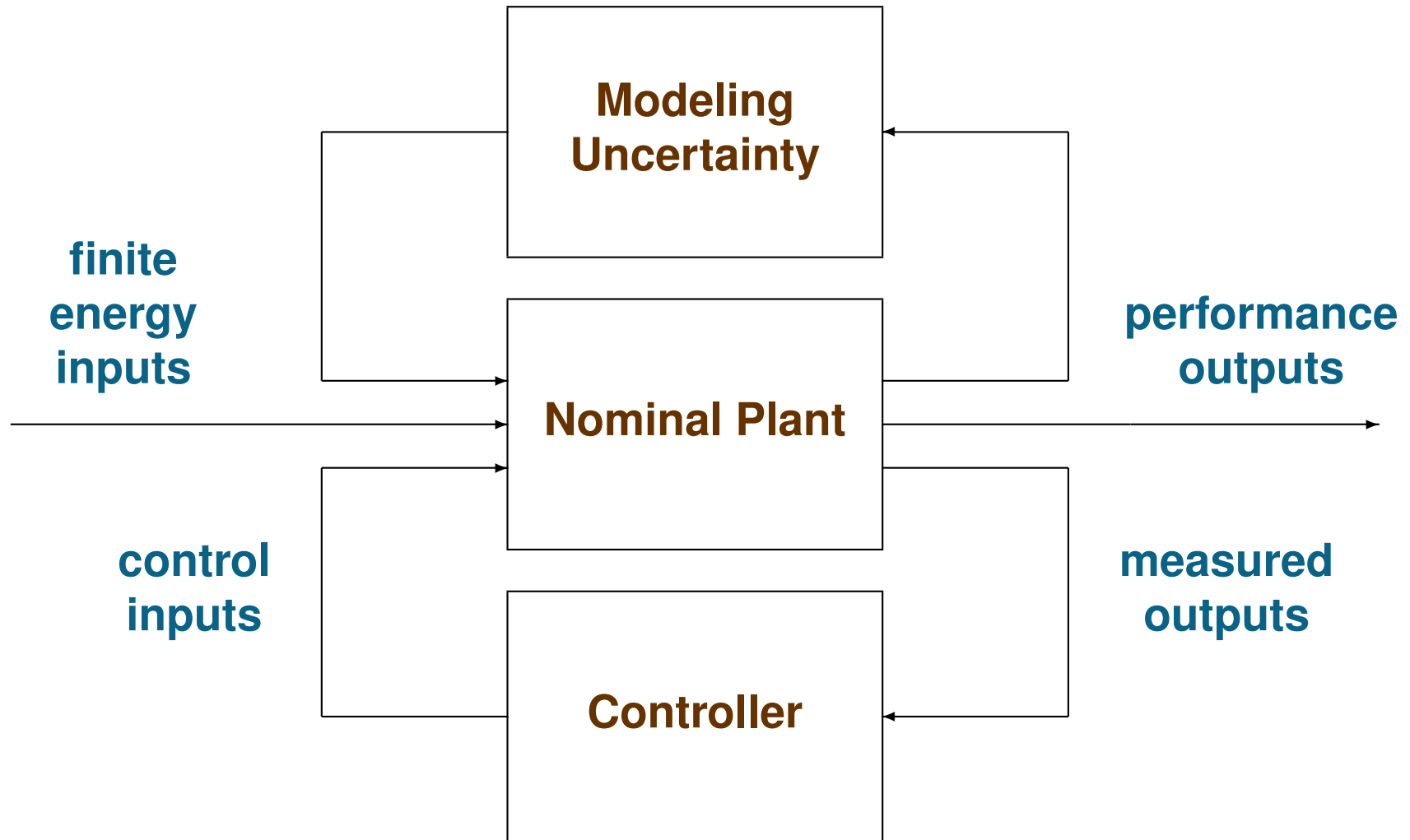
$$\dot{\hat{\psi}}(t) = (A - L C) \hat{\psi}(t) + B_u u(t) + L \varphi(t)$$

$$u(t) = -K \hat{\psi}(t)$$

★ **feedback and observer gains:** $\begin{cases} K & \text{LQR gain} \\ L & \text{Kalman gain} \end{cases}$

H_∞ controller

- BLENDS CLASSICAL WITH OPTIMAL CONTROL



Boundary actuation

- Example: heat equation

$$\phi_t(y, t) = \phi_{yy}(y, t) + d(y, t)$$

$$\phi(-1, t) = u(t)$$

$$\phi(+1, t) = 0$$

- Problem: control doesn't enter additively into the equation
- Coordinate transformation

$$\psi(y, t) = \phi(y, t) - f(y) u(t)$$

★ Choose $f(y)$ to obtain $\psi(\pm 1, t) = 0$

★ Many possible choices

Conditions for selection of f :

$$\{f(-1) = 1, f(1) = 0\} \xrightarrow{\text{simple option}} f(y) = \frac{1 - y}{2}$$

- In new coordinates:

$$\phi_t(y, t) = \phi_{yy}(y, t) + d(y, t)$$

$$\phi(-1, t) = u(t)$$

$$\phi(+1, t) = 0$$

$$\downarrow \phi(y, t) = \psi(y, t) + f(y) u(t)$$

$$\psi_t(y, t) + f(y) \dot{u}(t) = \psi_{yy}(y, t) + f''(y) u(t) + d(y, t)$$

$$\psi(\pm 1, t) = 0$$

- New input: $v(t) = \dot{u}(t)$

$$\frac{d}{dt} \begin{bmatrix} \psi(t) \\ u(t) \end{bmatrix} = \begin{bmatrix} A_0 & f'' \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \psi(t) \\ u(t) \end{bmatrix} + \begin{bmatrix} I \\ 0 \end{bmatrix} d(t) + \begin{bmatrix} -f \\ I \end{bmatrix} v(t)$$

$$\phi(t) = \begin{bmatrix} I & f \end{bmatrix} \begin{bmatrix} \psi(t) \\ u(t) \end{bmatrix}$$

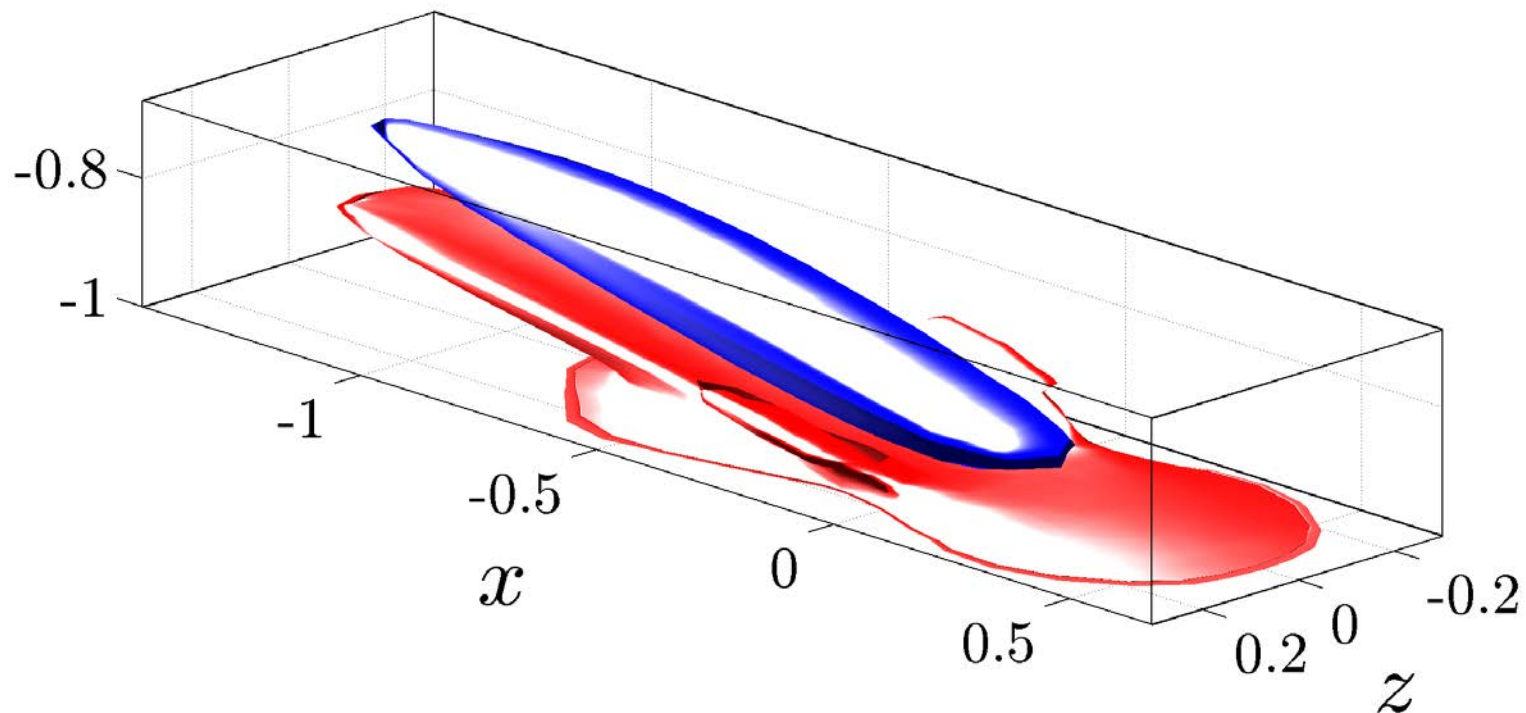
$$A_0 = \frac{d^2}{dy^2} \text{ with Dirichlet BCs}$$

Blowing and suction along the walls

$$v(x, \pm 1, z, t) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-1}^1 K_v^{\pm}(x - \xi, y, z - \zeta) v(\xi, y, \zeta, t) dy d\xi d\zeta + \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-1}^1 K_{\eta}^{\pm}(x - \xi, y, z - \zeta) \eta(\xi, y, \zeta, t) dy d\xi d\zeta$$

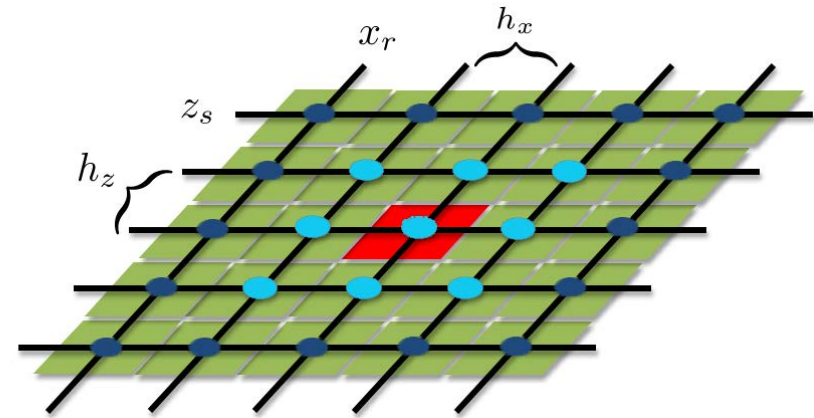
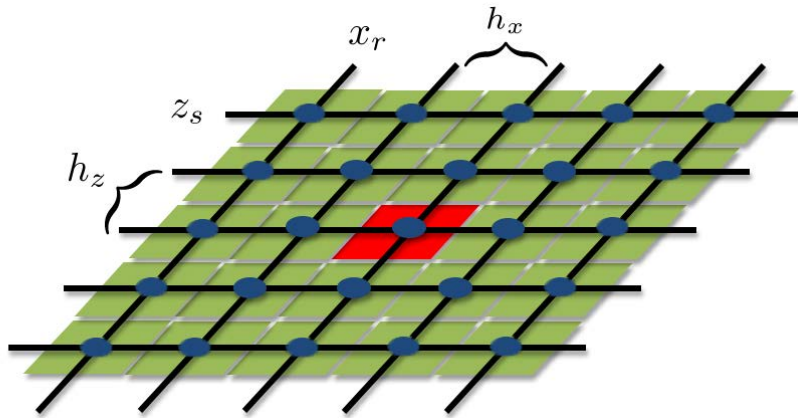
- **Optimal controller: exponentially decaying convolution kernels**

$$K_v^{-}(0 - \xi, y, 0 - \zeta):$$

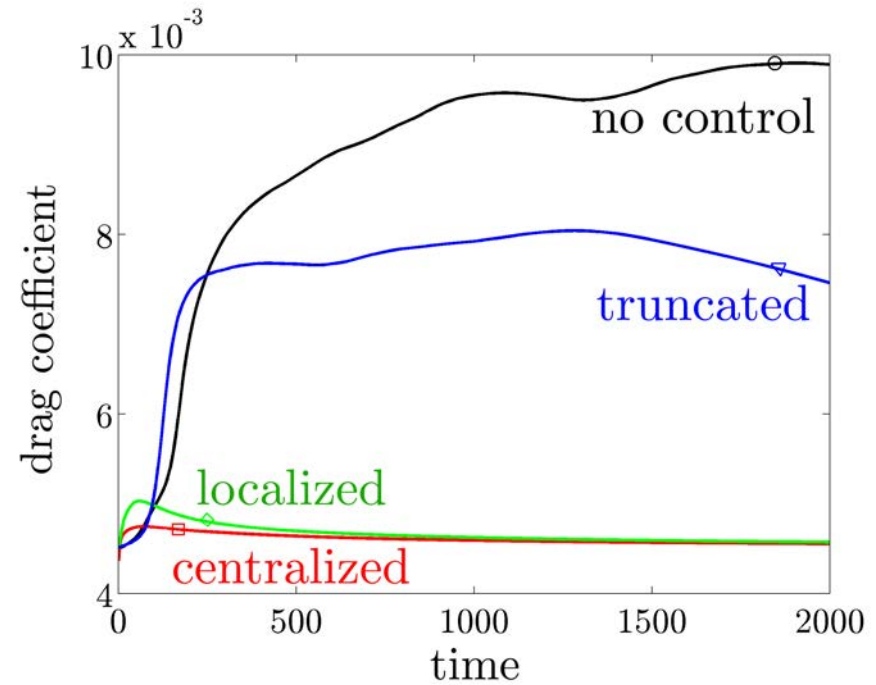
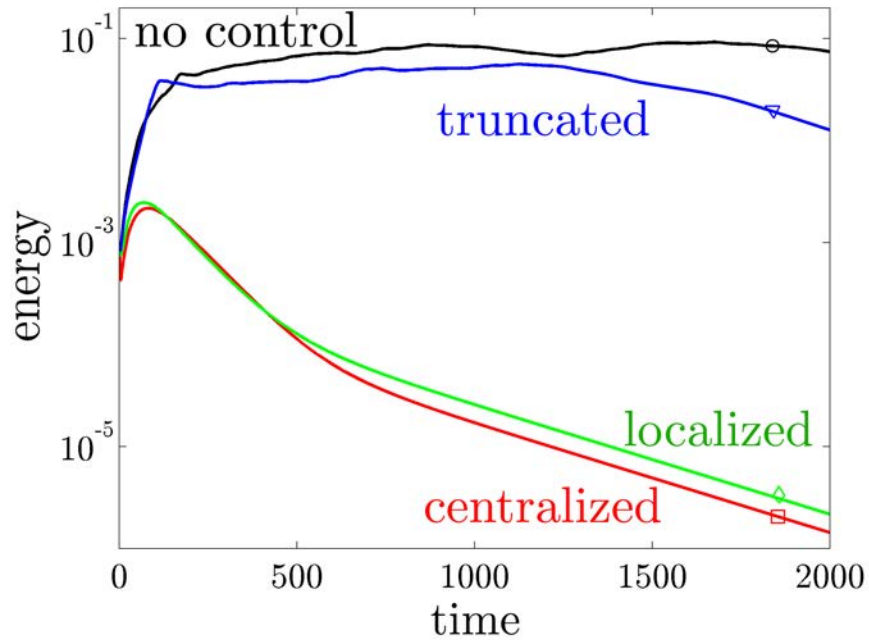


Optimal localized control

- Blowing and suction along the discrete lattice



★ DNS verification



Sparsity-promoting optimal control

- Strike balance between **quadratic performance** and **sparsity** of K

$$\begin{array}{ccc} \text{minimize} & J(K) & + & \gamma \text{card}(K) \\ & \downarrow & & \downarrow \\ & \text{variance} & & \text{sparsity-promoting} \\ & \text{amplification} & & \text{penalty function} \end{array}$$

- $\text{card}(K)$ – number of non-zero elements of K

$$K = \begin{bmatrix} 5.1 & -2.3 & 0 & 1.5 \\ 0 & 3.2 & 1.6 & 0 \\ 0 & -4.3 & 1.8 & 5.2 \end{bmatrix} \Rightarrow \text{card}(K) = 8$$

- $\gamma > 0$ – quadratic performance vs. sparsity tradeoff

SUMMARY AND OUTLOOK

Summary: transition

- INPUT-OUTPUT ANALYSIS

- ★ quantifies flow sensitivity

- ★ reveals distinct mechanisms for subcritical transition

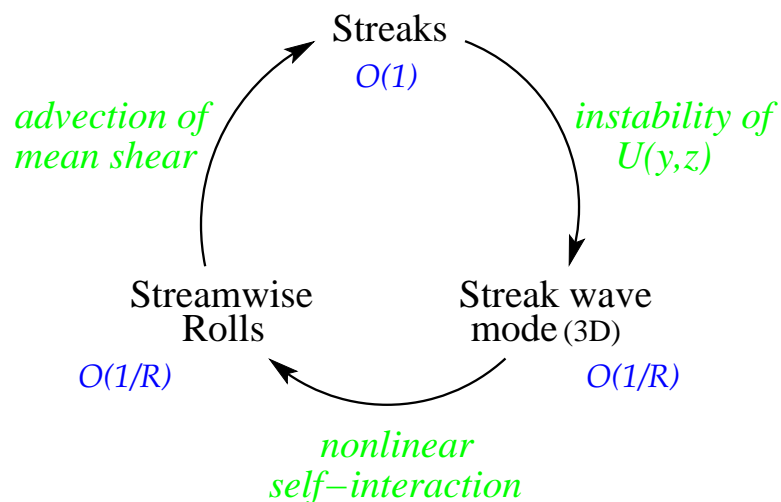
streamwise streaks, oblique waves, TS-waves

- ★ exemplifies the importance of streamwise elongated flow structures

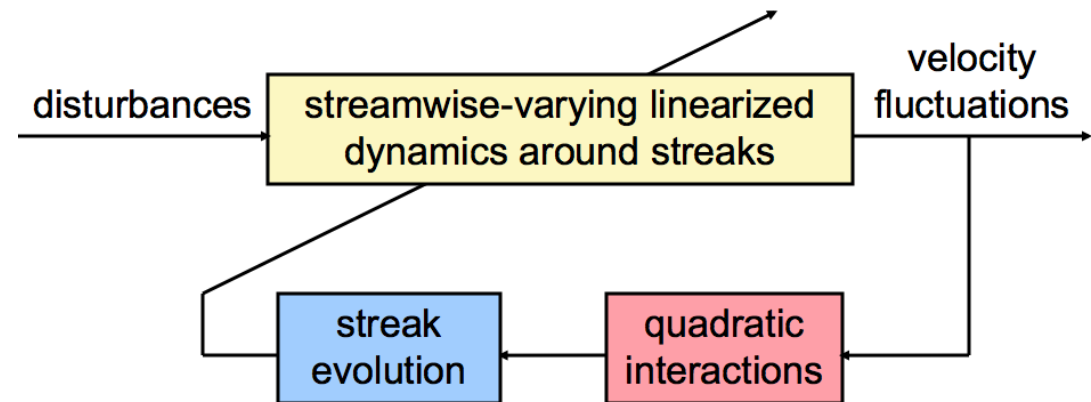
Jovanović & Bamieh, J. Fluid Mech. '05

- LATER STAGES OF TRANSITION

- ★ **challenge: relative roles of flow sensitivity and nonlinearity**



Waleffe, Phys. Fluids '97



Farrell & Ioannou, CTR Summer Program '12

Summary: sensor-free flow control

- CONTROLLING THE ONSET OF TURBULENCE

facts revealed by perturbation analysis:

Blowing/Suction Type	Nominal flow analysis	Energy amplification analysis
Downstream	reduce bulk flux	reduce amplification ✓
Upstream	increase bulk flux ✓	promote amplification

- POWERFUL SIMULATION-FREE APPROACH TO PREDICTING FULL-SCALE RESULTS
 - ★ DNS verification

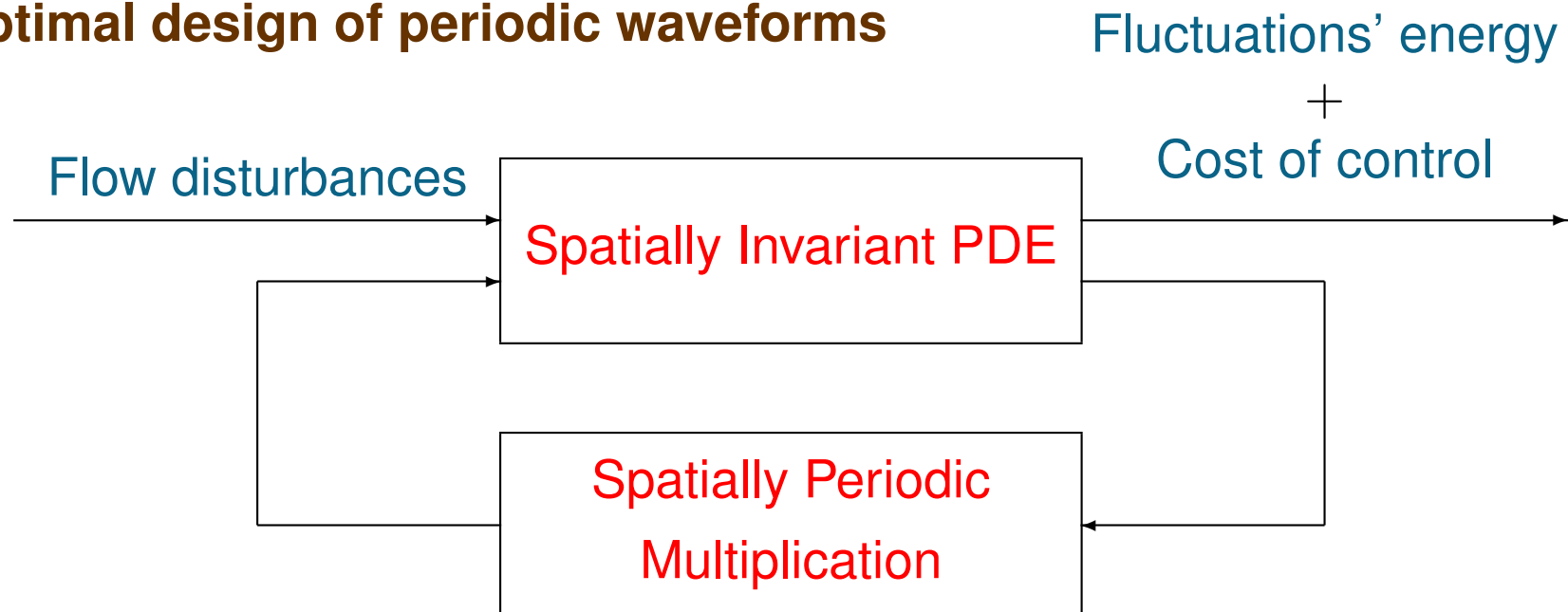
Moarref & Jovanović, J. Fluid Mech. '10

Lieu, Moarref, Jovanović, J. Fluid Mech. '10

Outlook: model-based sensor-free flow control

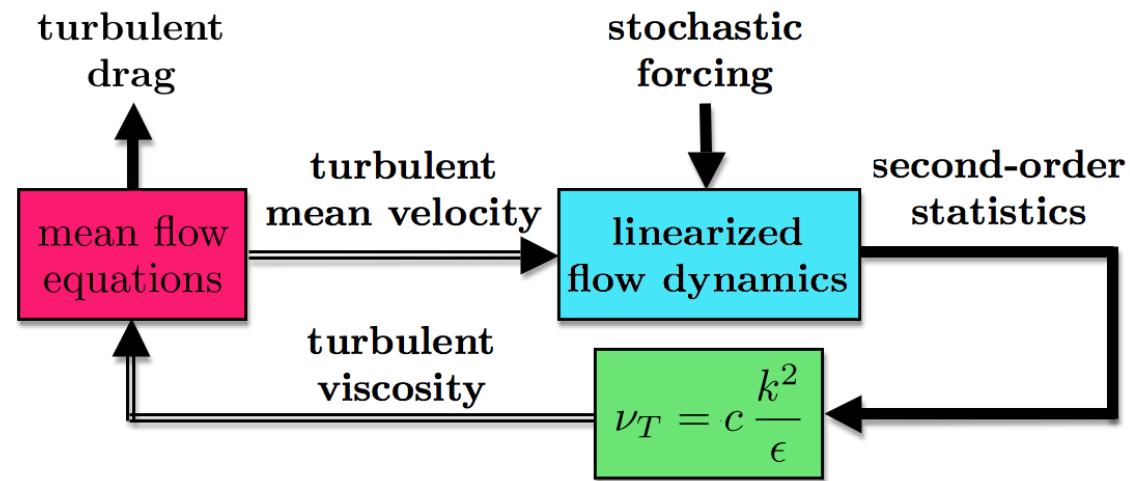
GEOMETRY MODIFICATIONS	WALL OSCILLATIONS	BODY FORCES
riblets super-hydrophobic surfaces	transverse oscillations	oscillatory forces traveling waves

- USE DEVELOPED THEORY TO DESIGN GEOMETRIES AND WAVEFORMS FOR
 - ★ control of transition/skin-friction drag reduction
- CHALLENGES
 - ★ **control-oriented modeling of turbulent flows**
 - ★ **optimal design of periodic waveforms**

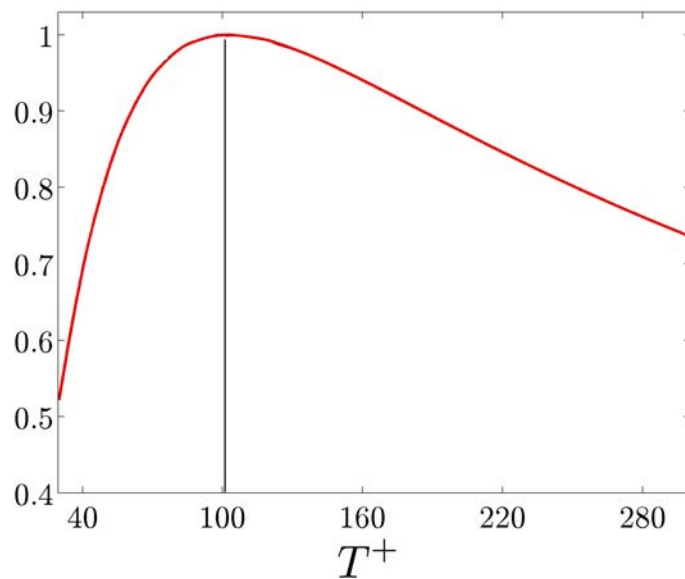


- CONTROL OF TURBULENT FLOWS

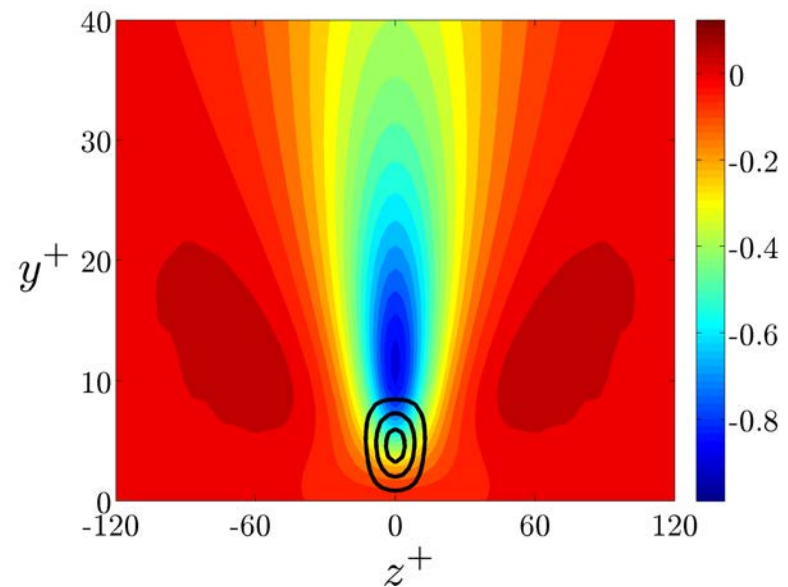
control-oriented modeling



model-based control design



flow structures

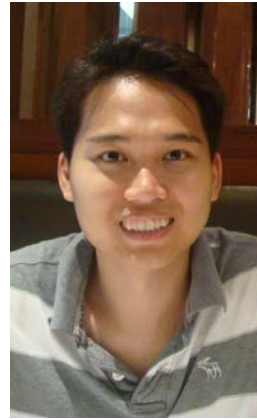


Acknowledgments

TEAM:



Rashad Moarref
(Caltech)



Binh Lieu
(U of M)



Armin Zare
(U of M)

SUPPORT:

NSF CAREER Award CMMI-06-44793

NSF Award CMMI-09-27720

U of M IREE Early Career Award

CTR Summer Programs '06, '10, '12

COMPUTING RESOURCES:

Minnesota Supercomputing Institute

SPECIAL THANKS:

Prof. Moin