

Control of shear flows subject to stochastic excitations

Jérôme Hœpffner *KTH, Sweden*



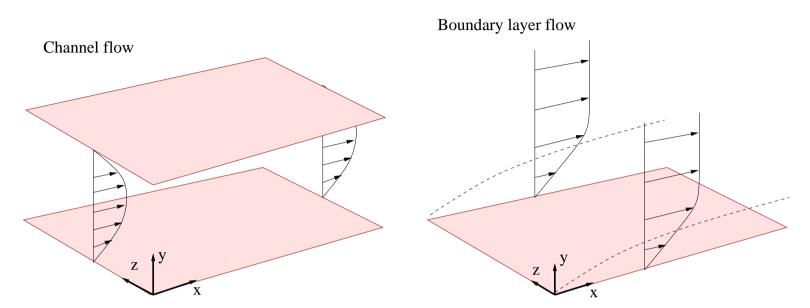
Stochastic disturbances

Flow systems of engineering interest are often exposed to disturbances that are erratic, unpredictable, and thus conveniently described by their statistics.

- wall roughness
- Free-stream turbulence
- Acoustic waves



Navier–Stokes equations



$$\begin{cases} \partial_t u + u \partial_x u + v \partial_y u + w \partial_z u = -\partial_x p + \Delta u / Re, \\ \partial_t v + u \partial_x v + v \partial_y v + w \partial_z v = -\partial_y p + \Delta v / Re, \\ \partial_t w + u \partial_x w + v \partial_y w + w \partial_z w = -\partial_z p + \Delta w / Re, \\ \partial_x u + \partial_y v + \partial_z w = 0 \end{cases} + \mathsf{BC}$$

Fourier transform in homogeneous direction. State space formulation:

 $\dot{q} = Aq$



Statistics

Random vector
$$w = \begin{pmatrix} w_1(t) \\ w_2(t) \\ \vdots \\ w_N(t) \end{pmatrix}$$
, *W*
Covariance matrix:

, White noise if:
$$Ew_i(t)\overline{w_j(t')} = W_{ij}\delta(t-t')$$

Covariance matrix:

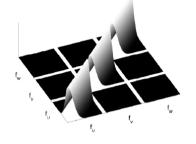
$$W \triangleq Eww^{H} = \begin{pmatrix} E|w_{1}|^{2} & Ew_{1}\overline{w_{2}} & \dots & Ew_{1}\overline{w_{N}} \\ Ew_{2}\overline{w_{1}} & E|w_{2}|^{2} & \vdots \\ \vdots & & \ddots & \vdots \\ Ew_{N}\overline{w_{1}} & \dots & \dots & E|w_{N}|^{2} \end{pmatrix}$$

Diagonal elements: variance Off-diagonal elements: covariance



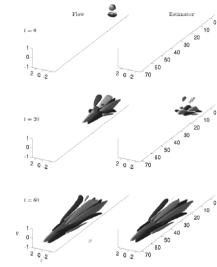
Estimation in laminar channel flow

Simple covariance model:



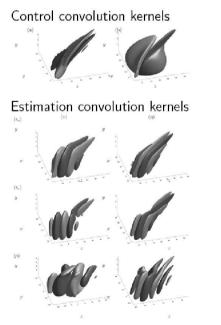
Estimation convolution kernels:

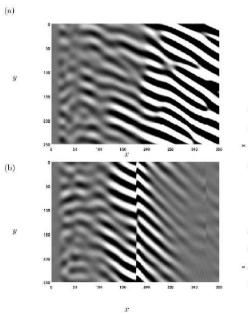


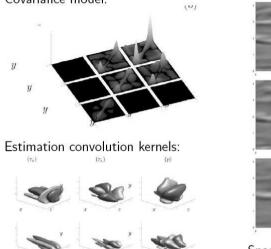


Estimation of initial condition

Estimation/Control of swept boundary layer

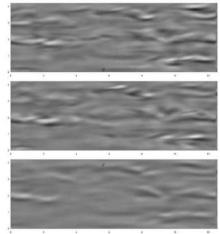




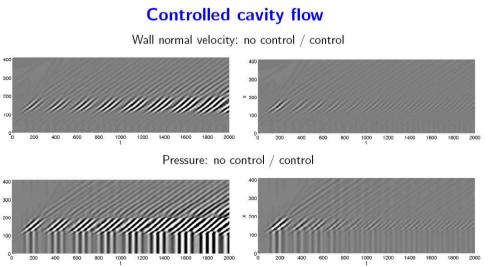


Covariance model:

Estimation in turbulent channel flow



Snapshot of flow/estimated flow



Wave growth: no control /control



1) Stochastic flow systems

 $\dot{q} = Aq + w, \quad \operatorname{cov}(w) = W$

stochastic excitation \rightarrow stochastic state

q should now be described by its covariance matrix P.

How to get P from A and W?



Lyapunov equation

Explicit state solution:

$$\dot{q} = Aq + w \quad \Rightarrow \quad q(t) = \int_{\tau=0}^{\infty} e^{A(t-\tau)} w(\tau) \mathrm{d}\tau + e^{At} q_0$$

State covariance:

$$\underbrace{Eq(t)q(t)^{H}}_{P(t,t)} = \int_{0}^{\infty} \int_{0}^{\infty} e^{A(t-\tau)} \underbrace{Ew(\tau)w(\tau')^{H}}_{Ew(\tau)w(\tau')} e^{A^{H}(t-\tau')} d\tau d\tau'$$
$$= \int_{0}^{\infty} e^{A(t-\tau)} W e^{A^{H}(t-\tau)} d\tau$$

Differentiating this convolution integral:

$$\dot{P} = AP + PA^H + W$$



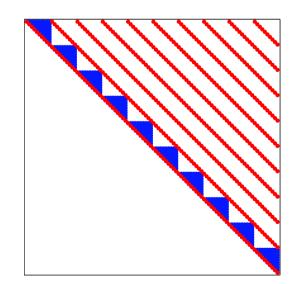
Numerical solution of the Lyapunov equation

Solve: $AX + XA^H + W = 0$

- 1. Schur decomposition $A = UA'U^H$, $\rightarrow A'$ upper diagonal, U orthogonal.
- 2. Resulting equation $A' \stackrel{X'}{U^H X U} + \stackrel{X'}{U^H X U} A'^H + \stackrel{W'}{U^H W U} = 0$
- 3. Use Kronecker product \otimes

$$A \otimes B \triangleq \begin{pmatrix} a_{11}B & a_{12}B & \dots & a_{1m}B \\ a_{21}B & a_{22}B & \dots & a_{2m}B \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1}B & a_{n2}B & \dots & a_{nm}B \end{pmatrix}$$

$$\operatorname{vec}(A'X' + X'A'^{H} + W') = 0$$
$$= \underbrace{(I \otimes A' + \overline{A'} \otimes I)}_{\mathcal{F}} \operatorname{vec}(X') + \operatorname{vec}(W')$$



 ${\mathcal F}$ has upper diagonal structure

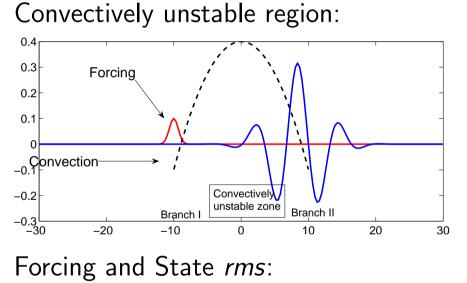
4. Solve by backward substitution

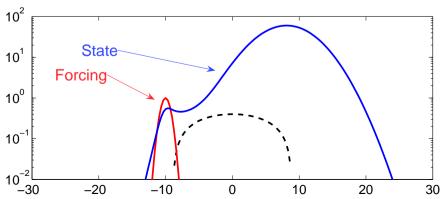


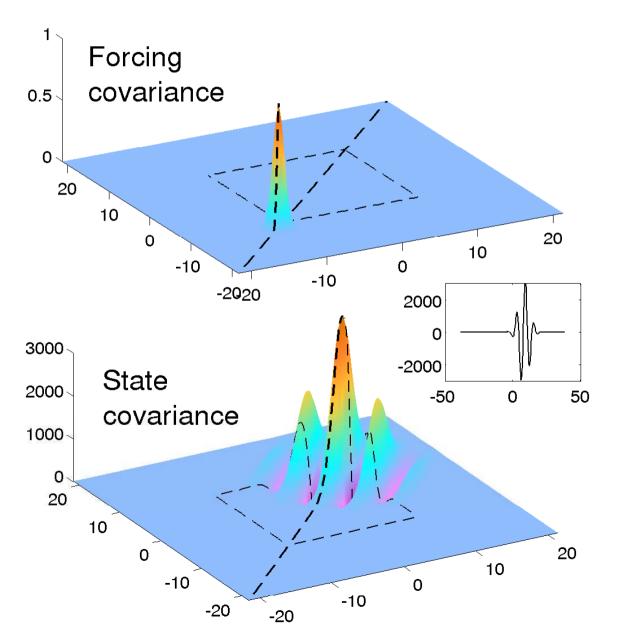
1D example: Ginzburg-Landau

$$\dot{q} + Uq_x = \gamma q_{xx} + \mu(x)q$$

Excitations: $w(x,t) = f(x)\lambda(t)$, $\lambda \in \mathbb{R}$ is white noise, $E|w|^2 = 1$.



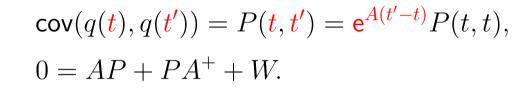


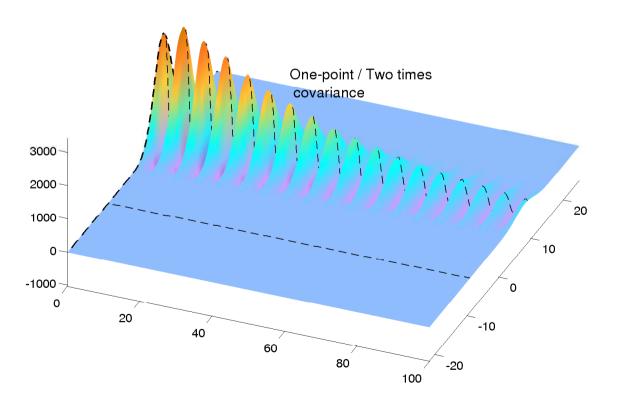


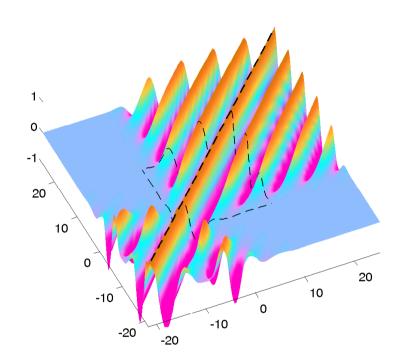


1D example: Ginzburg-Landau

One point/Two times covariance:







Two points correlation

(normalized to unit *rms*):

$$\operatorname{corr}(q_i, q_j) = E \frac{q_i \overline{q_j}}{|q_i| |q_j|} = \tilde{P}_{ij}$$



2) Control of stochastic flow systems

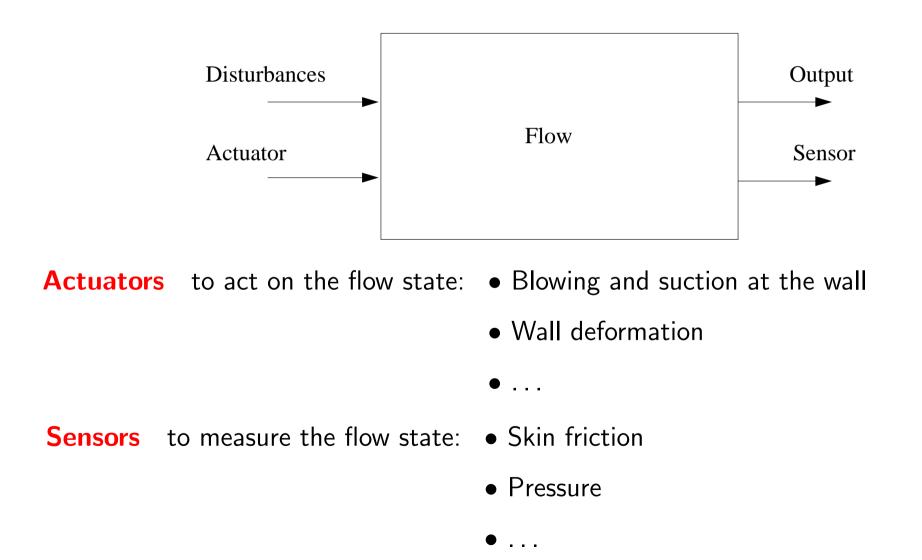
Control to reduce flow rms

 \rightarrow Actuators, sensors, feedback law

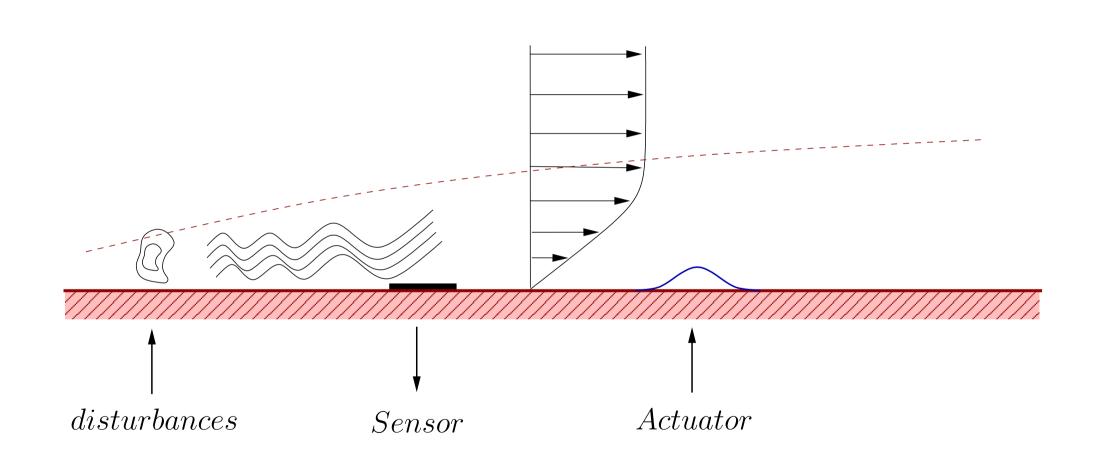
Minimize for stochastic properties



Actuators and sensors

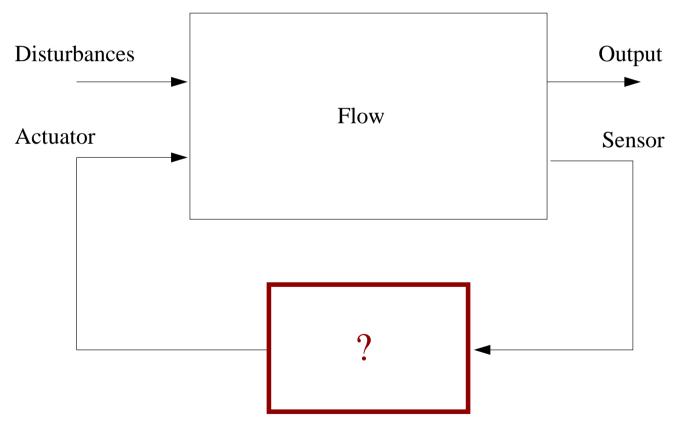








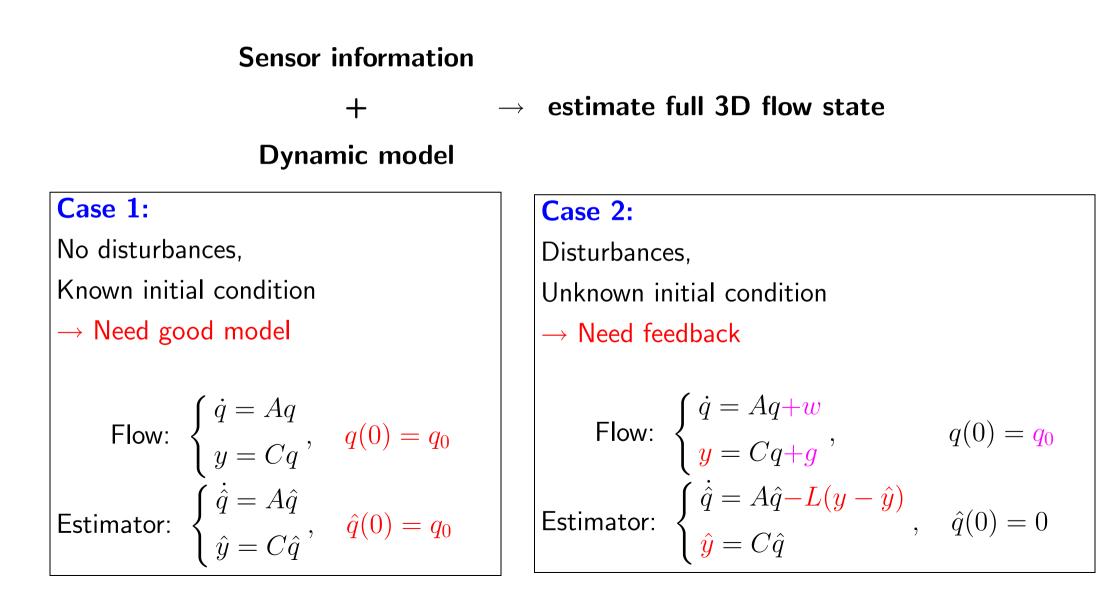
Feedback



Use optimization for the feedback law



Estimation





Control and estimation

system
$$\begin{cases} \dot{q} = Aq + w + Bu, \\ y = Cq + g \end{cases}$$
, estimator
$$\begin{cases} \dot{\hat{q}} = A\hat{q} - L(y - \hat{y}), \\ \hat{y} = C\hat{q} \end{cases}$$

Full information control: Feedback: u = KqClosed loop: $\dot{q} = \underbrace{(A+BK)}_{A_c} q+w$ $A_c = A + BK$ is stable?

Estimation:
Estimation error
$$\tilde{q} = q - \hat{q}$$
:
 $\dot{\tilde{q}} = \underbrace{(A+LC)}_{A_e} \tilde{q} + w - Lg$
 $A_e = A + LC$ is stable?

. •

Output feedback control: $u = K\hat{q}$.

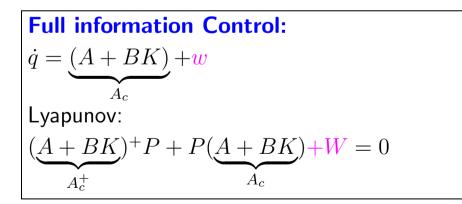


Lyapunov equations for control and estimation systems

Mean energy= integral of *rms*

 $E_K = \mathsf{Tr}(P)$

System is sensitive or unstable \rightarrow large energetic response to external disturbances



Estimation:

$$\dot{\tilde{q}} = \underbrace{(A + LC)}_{A_e} \tilde{q} + w - Lg$$
Lyapunov:

$$\underbrace{(A + LC)}_{A_e} \tilde{P} + \tilde{P} \underbrace{(A + LC)}_{A_e^+}^{+} + W + \alpha^2 LL^+ = 0$$

Now: find optimal feedback K and L



Optimization

Constrained minimisation \rightarrow Lagrange multiplier Λ Minimax problem for Lagrangians \mathscr{L}_c and \mathscr{L}_e .

	Objective	Constraint
Control: minimize $E(q ^2 + \ell^2 u ^2) = \operatorname{Tr}(PQ + \ell^2 KPK^+)$		$((A+BK)P+P(A+BK)^{+}+W)$
	$\nabla_{\Lambda} \mathscr{L}_c = 0 $	$A^+\Lambda + \Lambda A - \Lambda B B^+\Lambda/\ell^2 + Q.$
	$\nabla_P \mathscr{L}_c = 0 \left\{ \Rightarrow \left\{ \begin{array}{c} K = 0 \\ K = 0 \end{array} \right\} \right\}$	$A^{+}\Lambda + \Lambda A - \Lambda B B^{+}\Lambda/\ell^{2} + Q,$ $B^{+}\Lambda/\ell^{2}.$
$ Kq ^2$	$\nabla_{K}\mathscr{L}_{c}=0\int \qquad (\Pi$	
	Objective	Constraint
Estimation: minimize $E(\underbrace{\ q - \hat{q}\ ^2}_{\ \tilde{q}\ ^2}) = \operatorname{Tr}(\tilde{P})$	$\mathscr{L}_{e} = \operatorname{Tr}(\tilde{P}) + \operatorname{Tr}[\Lambda((A + LC)\tilde{P})]$	$\tilde{P} + \tilde{P}(A + LC)^{+} + \alpha^{2}LL^{+} + W)]$
	$\nabla_{\Lambda} \mathscr{L}_e = 0$	$-A\tilde{P}+\tilde{P}A^+-\tilde{P}C^+C\tilde{P}/\alpha^2+W$
	$\nabla_{\tilde{P}}\mathscr{L}_e = 0 \left\{ \Rightarrow \left\{ \begin{array}{c} 0 \\ 0 \end{array} \right\} \right\}$	$= A\tilde{P} + \tilde{P}A^{+} - \tilde{P}C^{+}C\tilde{P}/\alpha^{2} + W$ $= -\tilde{P}C^{+}/\alpha^{2}.$
	$\nabla_{\mathbf{r}} \mathscr{Q} = 0$	$= -P O^{\alpha} / \alpha$.

Same structure for control and estimation \rightarrow two Riccati equations



Numerical solution of Riccati equation

Solve: $A^H X + XA + XBB^H X + Q = 0$

1. Build Hamiltonian:
$$\mathscr{H} = \begin{pmatrix} A & BB^H \\ -Q & -A^H \end{pmatrix}$$

2. Schur decomposition $\mathscr{H} = USU^H$, $\rightarrow S$ upper triangular, U orthogonal

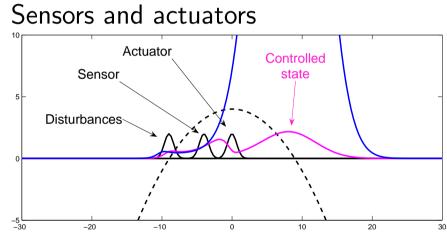
3. Order Schur decomposition to decompose stable/unstable subspaces:

$$S = \begin{pmatrix} S_{11} & S_{12} \\ 0 & S_{22} \end{pmatrix}, \ U = \begin{pmatrix} U_{11} & U_{12} \\ U_{21} & U_{22} \end{pmatrix}$$

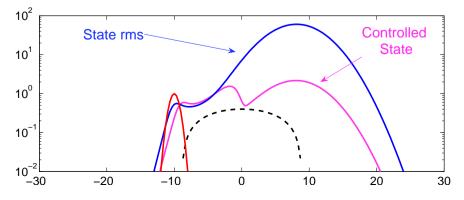
4. Solve $X = U_{21}U_{11}^{-1}$

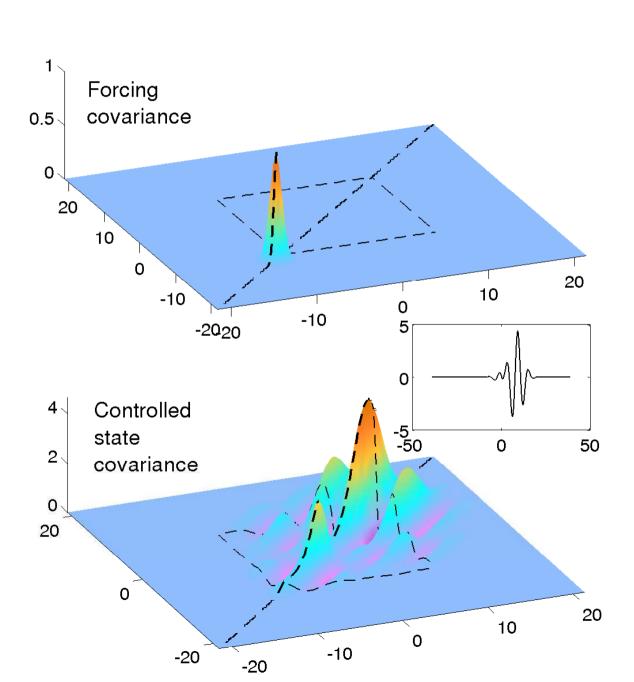
1D example: Controlled Ginzburg-Landau

$$\begin{cases} \dot{q} + Uq_x = \gamma q_{xx} + \mu(x)q + b(x)u(t) \\ y(t) = \int_x c(x)q(x)dx \end{cases}$$



Forcing and controlled state *rms*:







Summary

- Stochastic disturbances, stochastic systems
- Covariance matrices
- Lyapunov equation
- Sensors/Actuators/Feedback
- Optimization on the Lyapunov equation

