On Constrained Moving-Horizon Observers in Presence of Bounded Non Gaussian Noises

Mazen Alamir[1]

[1]CNRS, Gipsa-Lab, University of Grenoble

CIFA2012, July 4-6, Grenoble-France

The problem

State estimation of LTI systems

Construct a dynamic state observer for the LTI-System

$$x^+ = Ax + Bu + G\nu$$
$$y = Cx + Hw$$

- ν and w are bounded noises with known bounds

The problem

State estimation of LTI systems

Construct a dynamic state observer for the LTI-System

$$x^+ = Ax + Bu + G\nu$$
$$y = Cx + Hw$$

- ν and w are bounded noises with known bounds
- $E\{\nu_i^2\}$ and $E\{w_i^2\}$ are known **But not** $E\{\nu_i\nu_j\}$ and $E\{w_iw_j\}$

The problem

State estimation of LTI systems

Construct a dynamic state observer for the LTI-System

$$x^+ = Ax + Bu + G\nu$$
$$y = Cx + Hw$$

- ν and w are bounded noises with known bounds
- $E\{\nu_i^2\}$ and $E\{w_i^2\}$ are known **But not** $E\{\nu_i\nu_j\}$ and $E\{w_iw_j\}$
- ν and w are **not necessarily independent** ($E\{\nu_i w_j\} \neq 0$))

The problem

State estimation of LTI systems

Construct a dynamic state observer for the LTI-System

$$x^+ = Ax + Bu + G\nu$$
$$y = Cx + Hw$$

- ν and w are bounded noises with known bounds
- $E\{\nu_i^2\}$ and $E\{w_i^2\}$ are known **But not** $E\{\nu_i \nu_j\}$ and $E\{w_i w_j\}$
- ν and w are **not necessarily independent** ($E\{\nu_i w_j\} \neq 0$))
- Estimation is **used in control**. [$u = K(\hat{x})$]

The problem

State estimation of LTI systems

Construct a dynamic state observer for the LTI-System

$$x^+ = Ax + Bu + G\nu$$
$$y = Cx + Hw$$

- ν and w are bounded noises with known bounds
- $E\{\nu_i^2\}$ and $E\{w_i^2\}$ are known **But not** $E\{\nu_i\nu_j\}$ and $E\{w_iw_j\}$
- ν and w are **not necessarily independent** ($E\{\nu_i w_j\} \neq 0$))
- Estimation is **used in control**. [$u = K(\hat{x})$]
- State is known to satisfy $Ax \leq B$

Some bemols on Kalman Filter

- Constraints [Rao and Rawlings, Automatica 2001]

Some bemols on Kalman Filter

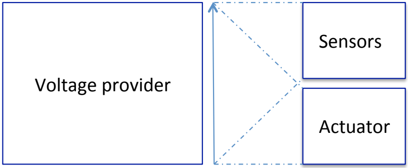
- Constraints
- Optimality is questionable

Some bemols on Kalman Filter

- Constraints
- Optimality is questionable
  - Sensor signals are bounded

Some bemols on Kalman Filter

- Constraints
- Optimality is questionable
  - Sensor signals are bounded
  - ν and w may be **coupled**



The feeding voltage noise is simultaneously injected in sensors and actuators

Some bemols on Kalman Filter

- Constraints
- Optimality is questionable
  - Sensor signals are bounded
  - ν and w may be **coupled**

More generally,

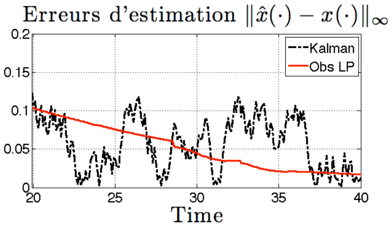
$u = -K\hat{x}$, if not perfectly measured, the output noise is re-injected in the state equation

Some bemols on Kalman Filter

- Constraints
- Optimality is questionable
  - Sensor signals are bounded
  - ν and w may be **coupled**
  - $E\{\nu_i\nu_j\}$, $E\{w_iw_j\}$ are never known [and hence arbitrarily chosen]

Some bemols on Kalman Filter

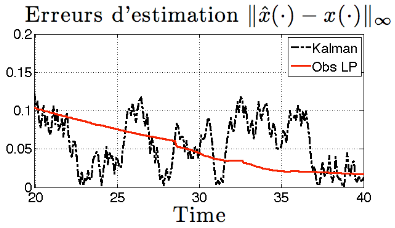
- Constraints
- Optimality is questionable
  - Sensor signals are bounded
  - ν and w may be **coupled**
  - $E\{\nu_i\nu_j\}$, $E\{w_iw_j\}$ are never known [and hence arbitrarily chosen]
- In observer based control, minimizing the variance of $x - \hat{x}$ is not necessarily the best option



Assuming that the L_2 norm of the Kalman-Filter error is lower, would you **really prefer the black curve** to the red when thinking of sending them to actautors ?

Some bemols on Kalman Filter

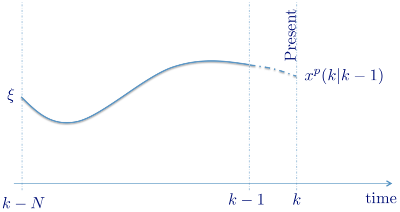
- Constraints
- Optimality is questionable
  - Sensor signals are bounded
  - ν and w may be **coupled**
  - $E\{\nu_i\nu_j\}$, $E\{w_iw_j\}$ are never known [and hence arbitrarily chosen]
- In observer based control, minimizing the variance of $x - \hat{x}$ is not necessarily the best option



Assuming that the L_2 norm of the Kalman-Filter error is lower, would you **really prefer the black curve** to the red when thinking of sending them to actau-tors ?

$\Longrightarrow$ Even without the constraint-related issue, there is room for novel thoughts

Kalman-like approach

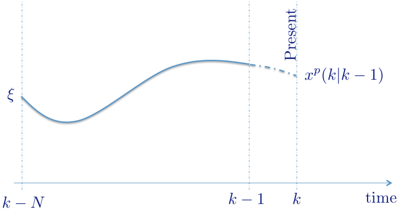


Solve unconstrained quadratic confidence trade-off

$$\min_{\xi}\left[\|\hat{x}(k|\xi)-x^p(k|k-1)\|^2_{Q_s}+\sum_{i=-\infty}^{k}\|\hat{y}(i|\xi)-y_m(i)\|^2_{Q_y}\right]$$

- Q_s and Q_y depend on $E\{\nu\nu^T\}$ and $E\{ww^T\}$
- Recursive LS implementation $\leftrightarrow$ Kalman updating rules

The proposed approach

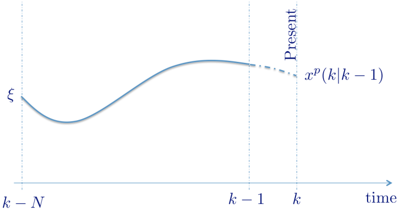


Compute the closest admissible state to the expected one

$$\min_{\eta^{(1)}\geq 0,\eta^{(2)}\geq 0,z=(\xi,\tilde{\nu},\tilde{w})} \left[\sum_{i=1}^{n}(\eta_i^{(1)}+\eta_i^{(2)})\right] \quad \text{under}$$

- $y^p(k|z) = y_m(k)$
- $\hat{x}(k|z) - x^p(k|k-1) = \eta^{(1)} - \eta^{(2)}$
- Temporal constraints on $\tilde{\nu}$ and $\tilde{w}$ [Kolmogorov-Pokhorov]
- Knowledge-base constraints on the state $Ax \leq B$

The proposed approach



Compute the closest admissible state to the expected one

$$\min_{\eta^{(1)}\geq 0,\eta^{(2)}\geq 0, z=(\xi,\tilde{\nu},\tilde{w})}\Big[\sum_{i=1}^{n}(\eta_i^{(1)}+\eta_i^{(2)})\Big] \quad \text{under}$$

- $y^p(k|z) = y_m(k)$
- $\hat{x}(k|z) - x^p(k|k-1) = \eta^{(1)} - \eta^{(2)}$
- Temporal constraints on $\tilde{\nu}$ and $\tilde{w}$ **[Kolmogorov-Pokhorov]**
- Knowledge-base constraints on the state $Ax \leq B$

Some Definitions & Notation

Consider N random independent varables $\{V_i\}_{i=1}^N$ satisfying $E(V_i) = 0$ and denote by σ_N^2 their sum of variances:

$$\sigma_N^2 := \sum_{i=1}^{N} E(V_i^2)$$

Assume that

$$(\forall i \in \{1, \dots, N\}) \qquad |V_i| \leq \bar{V}$$

and denote their partial sum by :

$$S_N := \sum_{i=1}^{N} V_i$$

Kolmogorov-Pokhorov Inequalities [Stout-74]

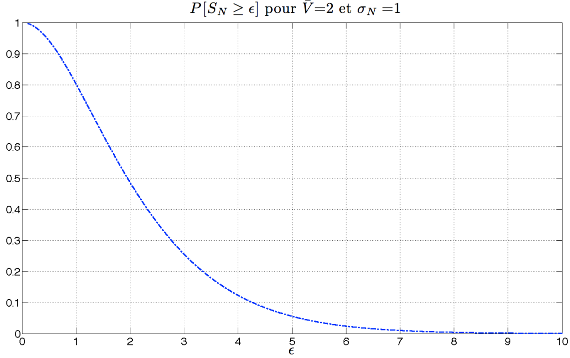
The following inequality is satisfied for all $\epsilon > 0$:

$$Pr\Big[|S_N| \geq \epsilon\sigma_N\Big] \leq \exp\Big(-\frac{\epsilon\sigma_N}{2\bar{V}} \cdot \sinh^{-1}(\frac{\epsilon\bar{V}}{2\sigma_N})\Big)$$

Kolmogorov-Pokhorov Inequalities [Stout-74]

The following inequality is satisfied for all $\epsilon > 0$:

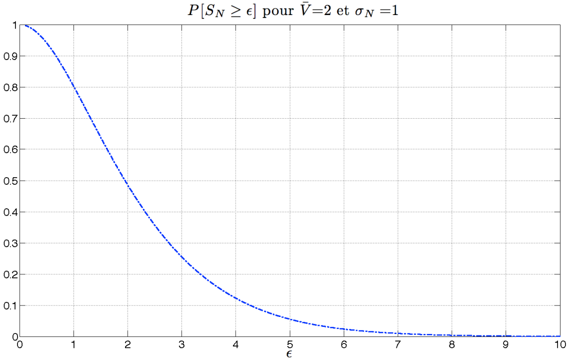
$$Pr\Big[|S_N| \geq \epsilon\sigma_N\Big] \leq \exp\Big(-\frac{\epsilon\sigma_N}{2\bar{V}}\cdot\sinh^{-1}(\frac{\epsilon\bar{V}}{2\sigma_N})\Big)$$



Kolmogorov-Pokhorov Inequalities [Stout-74]

The following inequality is satisfied for all $\epsilon > 0$:

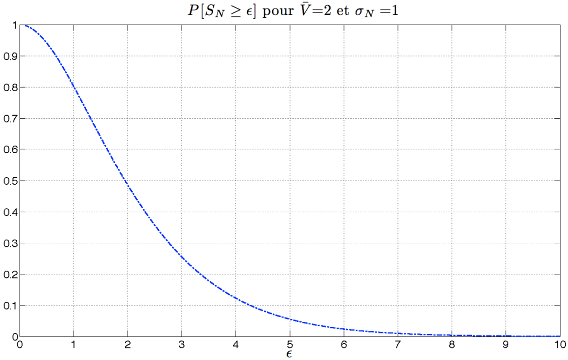
$$Pr\Big[|S_N| \geq \epsilon\sigma_N\Big] \leq \exp\Big(-\frac{\epsilon\sigma_N}{2\bar{V}} \cdot \sinh^{-1}(\frac{\epsilon\bar{V}}{2\sigma_N})\Big) =: \eta$$



Kolmogorov-Pokhorov Inequalities [Stout-74]

The following inequality is satisfied for all $\epsilon > 0$:

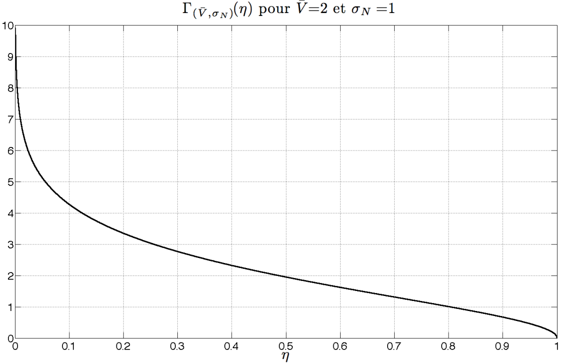
$$Pr\Big[|S_N| \geq \epsilon\sigma_N\Big] \leq \Gamma^{-1}_{(\bar{V},\sigma_N)}(\epsilon) =: \eta$$



Kolmogorov-Pokhorov Inequalities [Stout-74]

The following inequality is satisfied for all $\epsilon > 0$:

$$Pr\left[|S_N| \geq \Gamma_{(\bar{V},\sigma_N)}(\eta) \cdot \sigma_N\right] \leq \eta$$



Kolmogorov-Pokhorov Inequalities [Stout-74]

The following inequality is satisfied for all $\epsilon > 0$:

$$Pr\Big[|S_N| \geq \Gamma_{(\bar{V},\sigma_N)}(\eta)\cdot \sigma_N\Big] \leq \eta$$

For all N, the following is satisfied with a probability of $(1-\eta)\%$

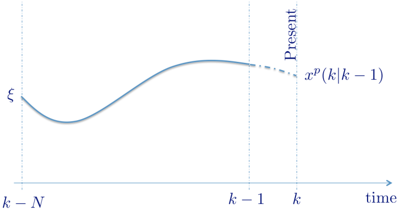
$$\forall s \in \{1,\dots,n_\nu\}$$

$$\left|\sum_{l=0}^{N-1} \nu_s(k+l)\right| \leq \Gamma_{(\bar{\nu}_s,\sqrt{NQ_\nu(s,s)})}(\eta)\cdot\sqrt{N\cdot Q_\nu(s,s)}$$

$$\forall s \in \{1,\dots,n_w\}$$

$$\left|\sum_{l=0}^{N-1} w_s(k+l)\right| \leq \Gamma_{(\bar{w}_s,\sqrt{NQ_w(s,s)})}(\eta)\cdot\sqrt{N\cdot Q_w(s,s)}$$

The proposed approach



Compute the closest admissible state to the expected one

$$\min_{\eta^{(1)}\geq 0,\eta^{(2)}\geq 0,z=(\xi,\tilde{\nu},\tilde{w})} \left[\sum_{i=1}^{n}(\eta_i^{(1)}+\eta_i^{(2)})\right] \quad \text{under}$$

- $y^p(k|z) = y_m(k)$
- $\hat{x}(k|z) - x^p(k|k-1) = \eta^{(1)} - \eta^{(2)}$
- Temporal constraints on $\tilde{\nu}$ and $\tilde{w}$ **[Kolmogorov-Pokhorov]**
- Knowledge-base constraints on the state $Ax \leq B$

Consider the system

$$
\begin{aligned}
\dot{x} &= A_c x + B_c u + G_c \nu \\
y &= Cx + Hw
\end{aligned}
$$

Consider the system

$$\begin{aligned}\dot{x} &= A_c x + B_c u + G_c \nu \\ y &= Cx + Hw\end{aligned}$$

$$A_c := \begin{pmatrix}-1 & 1 & 0.2\\ 0 & -1 & 3\\ 0.2 & 0.6 & -2.7\end{pmatrix} \;;\; B_c := \begin{pmatrix}1\\1\\2\end{pmatrix}$$

$$G_c := \begin{pmatrix}10 & 0.5\\ -2 & -10\\ 10 & 10\end{pmatrix} \;;\; C := \begin{pmatrix}1 & 1 & 1\end{pmatrix} \;;\; H = 1$$

Consider the system

$$\begin{aligned}\dot{x} &= A_c x + B_c u + G_c \nu \\ y &= Cx + Hw\end{aligned}$$

- $\nu_1 := b_1 \cdot \tanh(e_1)$
- $\nu_2 := b_2 \cdot \tanh(e_2)$
- $w := b_3 \cdot \tanh(e_3)$
- e_i white Gaussian noises
- $(var(e_1), var(e_2), var(e_3)) := (0.5, 0.5, 0.8)$
-
$$\sigma_i^2 := b_i^2 \int_{-\infty}^{\infty} [\frac{e^{-v^2/(2 \cdot var^2(e_i))}}{\sqrt{2\pi} \cdot var(e_i)}] \cdot [\tanh(v)]^2 dv$$

- $(b_1, b_2, b_3) \in \Big\{(0.02, 0.02, 2), (0.2, 0.2, 2)\Big\}$

Consider the system

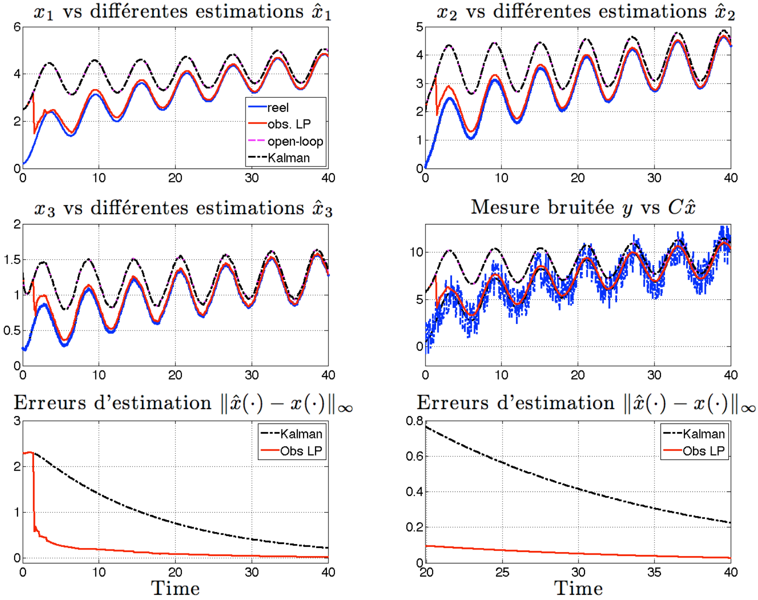
$$
\begin{aligned}
\dot{x} &= A_c x + B_c u + G_c \nu \\
y &= Cx + Hw
\end{aligned}
$$

- Sampling period $\tau = 0.1$
- $N_O = 15$
- The control is defined by:

$$
u(t) := \frac{2}{5}\sin(\frac{2\pi t}{6}) + \frac{2}{10}\min\Big\{1, \max\{0.4, b\}\Big\} \qquad (1)
$$

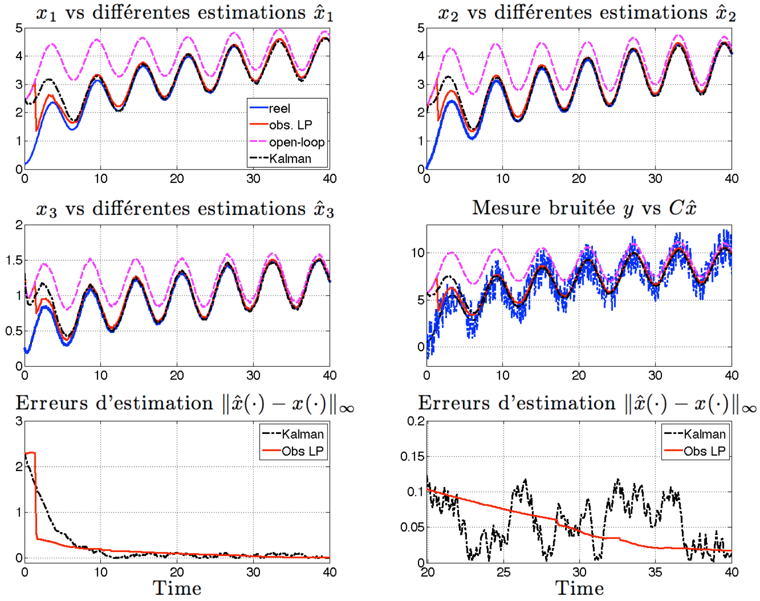
- b is a white noise

- Tune Kalman filter according to σ_i
- No way to consider the bounds
- KP Inequalities threshold $\eta = 0.1$


x_1 vs différentes estimations $\hat{x}_1$
reel
obs. LP
open-loop
Kalman
x_2 vs différentes estimations $\hat{x}_2$
x_3 vs différentes estimations $\hat{x}_3$
Mesure bruitée y vs $C\hat{x}$
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_\infty$
Kalman
Obs LP
Time
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_\infty$
Kalman
Obs LP
Time

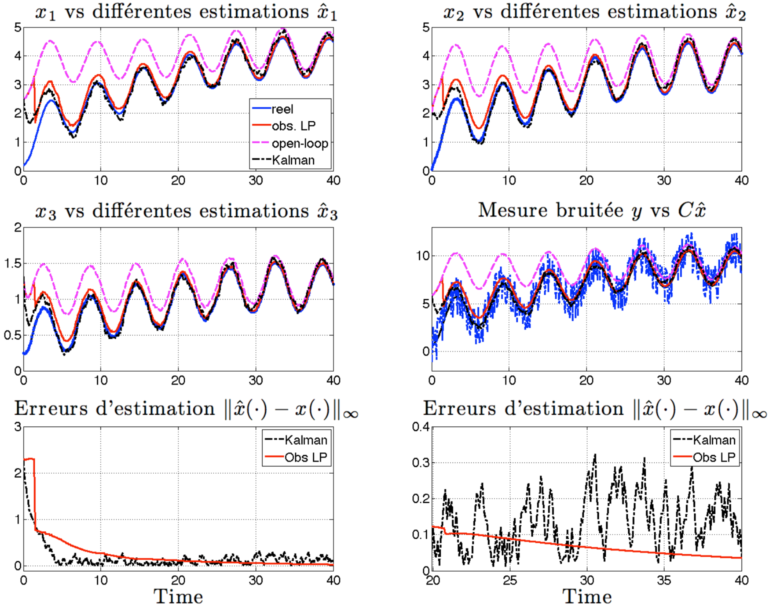
- $\rightarrow$ KF too slow (not enough confidence in measurements)

- Tune Kalman filter according to σ_1, σ_2 and $\sqrt{10^{-5}} \cdot \sigma_3$
- Increase the confidence in output measurements
- KP Inequalities threshold $\eta = 0.1$


x_1 vs différentes estimations $\hat{x}_1$
reel
obs. LP
open-loop
Kalman
x_2 vs différentes estimations $\hat{x}_2$
x_3 vs différentes estimations $\hat{x}_3$
Mesure bruitée y vs $C\hat{x}$
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_\infty$
Kalman
Obs LP
Time
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_\infty$
Kalman
Obs LP
Time

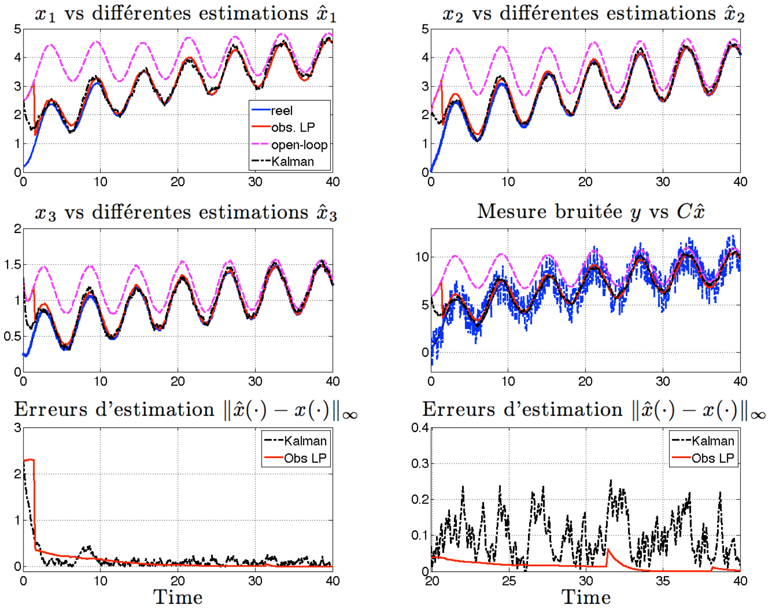
- KF is $\rightarrow$ still too slow (not enough confidence in measurements)

- Tune Kalman filter according to σ_1, σ_2 and $\sqrt{10^{-6}} \cdot \sigma_3$
- Increase the confidence in output measurements
- KP Inequalities threshold $\eta = 0.1$

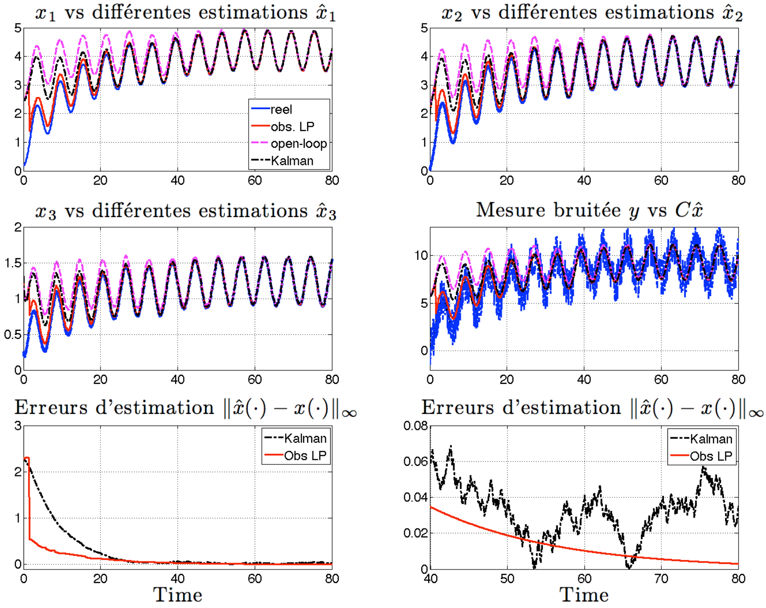

x_1 vs différentes estimations $\hat{x}_1$
reel
obs. LP
open-loop
Kalman
x_2 vs différentes estimations $\hat{x}_2$
x_3 vs différentes estimations $\hat{x}_3$
Mesure bruitée y vs $C\hat{x}$
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_\infty$
Kalman
Obs LP
Time
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_\infty$
Kalman
Obs LP
Time

- $\rightarrow$ KF is quite fast but too sensitive to noise

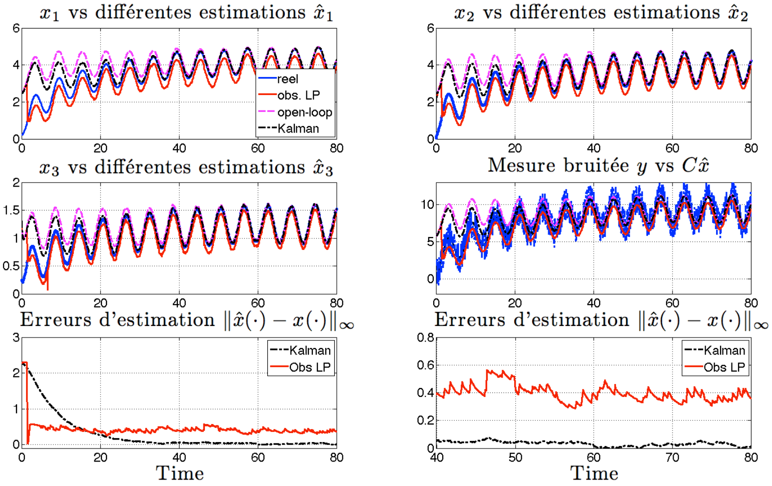
- Tune Kalman filter according to σ_1, σ_2 and $\sqrt{10^{-6}} \cdot \sigma_3$
- KP Inequalities threshold increased from $\eta = 0.1$ to $\eta = 0.4$


x_1 vs différentes estimations $\hat{x}_1$
reel
obs. LP
open-loop
Kalman
x_2 vs différentes estimations $\hat{x}_2$
x_3 vs différentes estimations $\hat{x}_3$
Mesure bruitée y vs $C\hat{x}$
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_\infty$
Kalman
Obs LP
Time
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_\infty$
Kalman
Obs LP
Time

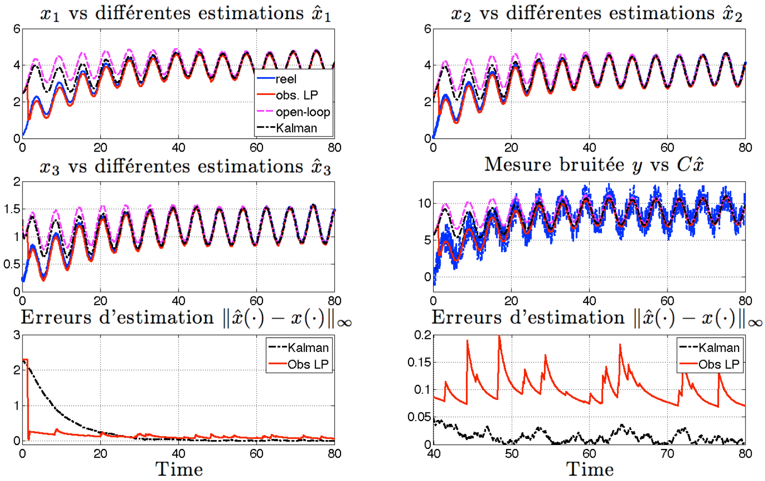
- Choose a good trade-off for Kalman filter according to σ_1, σ_2 and $\sqrt{10^{-4}} \cdot \sigma_3$
- Reset the KP Inequalities threshold to $\eta = 0.1$
- Let's compare the asymptotic behavior ...


x_1 vs différentes estimations $\hat{x}_1$
reel
obs. LP
open-loop
Kalman
x_2 vs différentes estimations $\hat{x}_2$
x_3 vs différentes estimations $\hat{x}_3$
Mesure bruitée y vs $C\hat{x}$
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_\infty$
Kalman
Obs LP
Time
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_\infty$
Kalman
Obs LP
Time

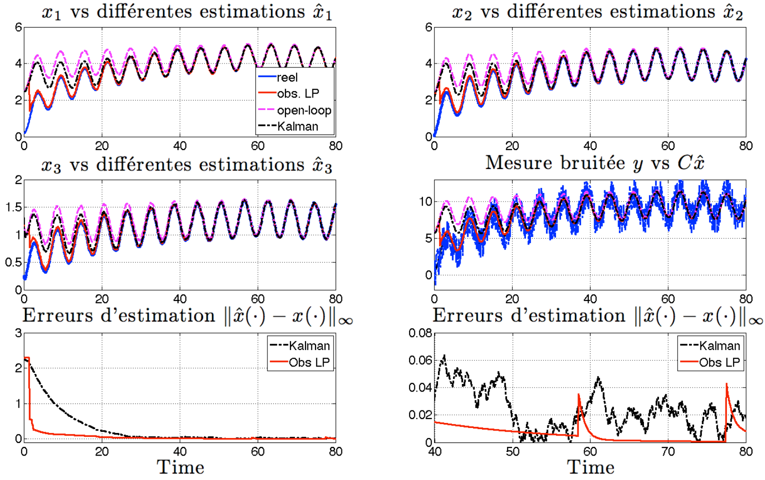
- Choose a good trade-off for Kalman filter according to σ_1, σ_2 and $\sqrt{10^{-4}} \cdot \sigma_3$
- Reset the KP Inequalities threshold to $\eta = 0.95$
- Let's compare the asymptotic behavior ...


x_1 vs différentes estimations $\hat{x}_1$
reel
obs. LP
open-loop
Kalman
x_2 vs différentes estimations $\hat{x}_2$
x_3 vs différentes estimations $\hat{x}_3$
Mesure bruitée y vs $C\hat{x}$
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_\infty$
Kalman
Obs LP
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_\infty$
Kalman
Obs LP
Time
Time

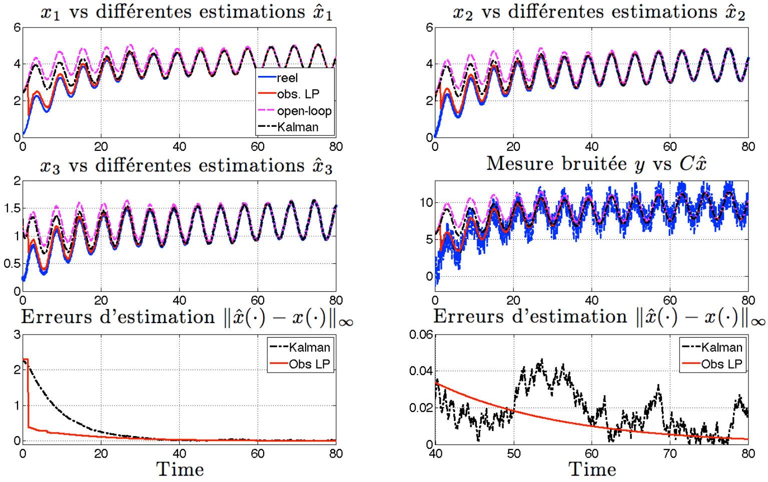
- Choose a good trade-off for Kalman filter according to σ_1, σ_2 and $\sqrt{10^{-4}} \cdot \sigma_3$
- Reset the KP Inequalities threshold to $\eta = 0.6$
- Let's compare the asymptotic behavior ...


x_1 vs différentes estimations $\hat{x}_1$
reel
obs. LP
open-loop
Kalman
x_2 vs différentes estimations $\hat{x}_2$
x_3 vs différentes estimations $\hat{x}_3$
Mesure bruitée y vs $C\hat{x}$
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_\infty$
Kalman
Obs LP
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_\infty$
Kalman
Obs LP
Time
Time

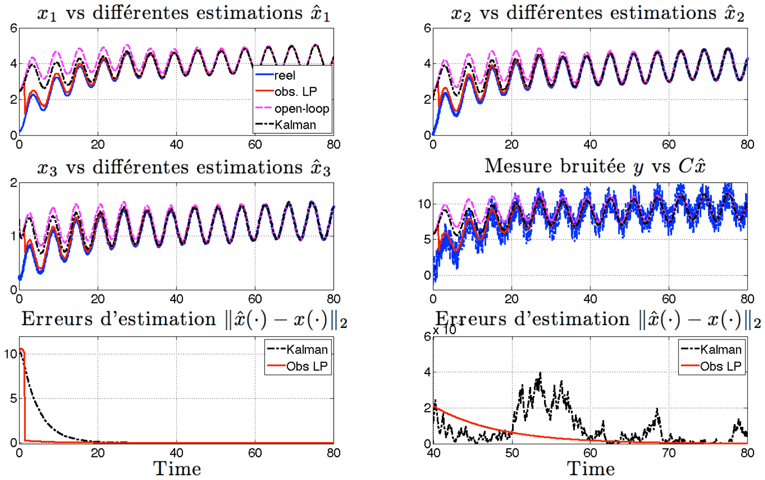
- Choose a good trade-off for Kalman filter according to σ_1, σ_2 and $\sqrt{10^{-4}} \cdot \sigma_3$
- Reset the KP Inequalities threshold to $\eta = 0.2$
- Let's compare the asymptotic behavior ...


x_1 vs différentes estimations $\hat{x}_1$
reel
obs. LP
open-loop
Kalman
x_2 vs différentes estimations $\hat{x}_2$
x_3 vs différentes estimations $\hat{x}_3$
Mesure bruitée y vs $C\hat{x}$
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_\infty$
Kalman
Obs LP
Time
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_\infty$
Kalman
Obs LP
Time

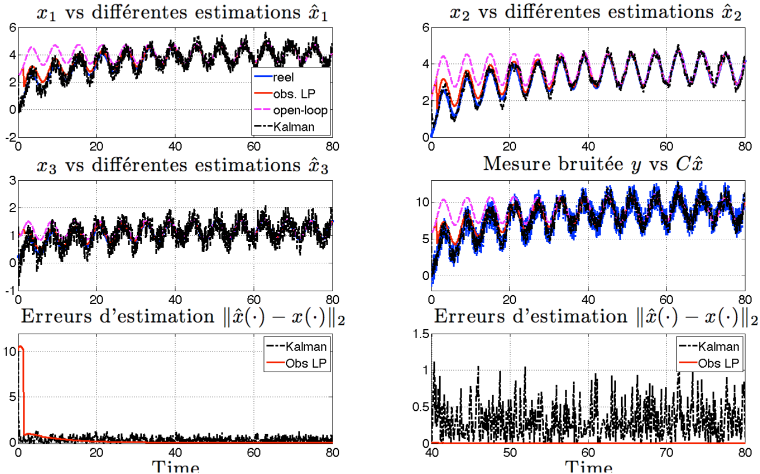
- Choose a good trade-off for Kalman filter according to σ_1, σ_2 and $\sqrt{10^{-4}} \cdot \sigma_3$
- Reset the KP Inequalities threshold to $\eta = 0.1$
- Let's compare the asymptotic behavior ...


x_1 vs différentes estimations $\hat{x}_1$
reel
obs. LP
open-loop
Kalman
x_2 vs différentes estimations $\hat{x}_2$
x_3 vs différentes estimations $\hat{x}_3$
Mesure bruitée y vs $C\hat{x}$
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_\infty$
Kalman
Obs LP
Time
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_\infty$
Kalman
Obs LP
Time

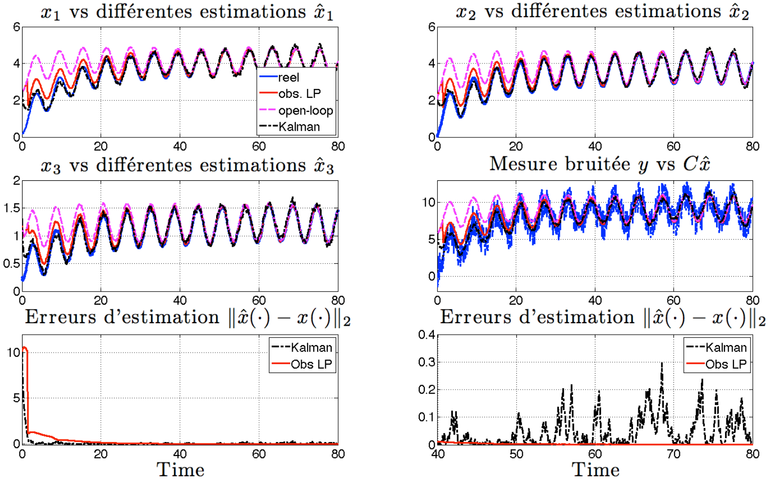
- Choose a good trade-off for Kalman filter according to σ_1, σ_2 and $\sqrt{10^{-4}} \cdot \sigma_3$
- Reset the KP Inequalities threshold to $\eta = 0.1$
- Let's compare the asymptotic behavior ...


x_1 vs différentes estimations $\hat{x}_1$
reel
obs. LP
open-loop
Kalman
x_2 vs différentes estimations $\hat{x}_2$
x_3 vs différentes estimations $\hat{x}_3$
Mesure bruitée y vs $C\hat{x}$
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_2$
Kalman
Obs LP
Time
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_2$
Kalman
Obs LP
Time

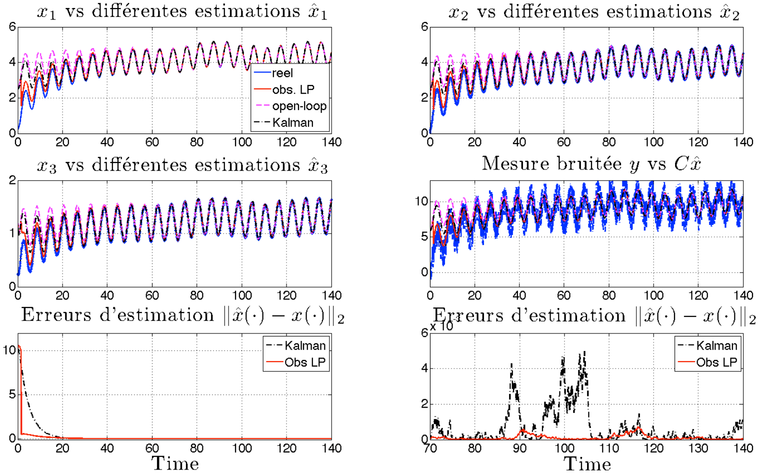
- Choose a good trade-off for Kalman filter according to $\sigma_1 = 0.2$, $\sigma_2 = 0.2$ and $\sqrt{10^{-4}} \cdot \sigma_3$
- Reset the KP Inequalities threshold to $\eta = 0.1$
- Let's compare the asymptotic behavior ...


x_1 vs différentes estimations $\hat{x}_1$
reel
obs. LP
open-loop
Kalman
x_2 vs différentes estimations $\hat{x}_2$
x_3 vs différentes estimations $\hat{x}_3$
Mesure bruitée y vs $C\hat{x}$
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_2$
Kalman
Obs LP
Time
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_2$
Kalman
Obs LP
Time

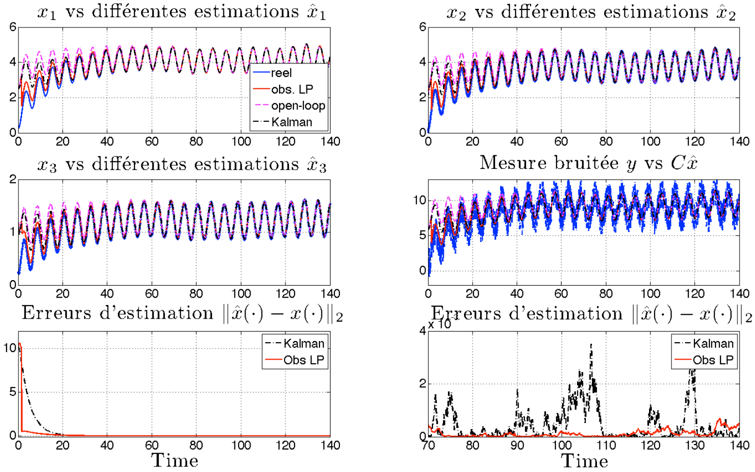
- Choose a good trade-off for Kalman filter according to $\sigma_1 = 0.2$, $\sigma_2 = 0.2$ and $\sqrt{10^{-2}} \cdot \sigma_3$
- Reset the KP Inequalities threshold to $\eta = 0.1$
- Let's compare the asymptotic behavior ...


x_1 vs différentes estimations $\hat{x}_1$
reel
obs. LP
open-loop
Kalman
x_2 vs différentes estimations $\hat{x}_2$
x_3 vs différentes estimations $\hat{x}_3$
Mesure bruitée y vs $C\hat{x}$
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_2$
Kalman
Obs LP
Time
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_2$
Kalman
Obs LP
Time

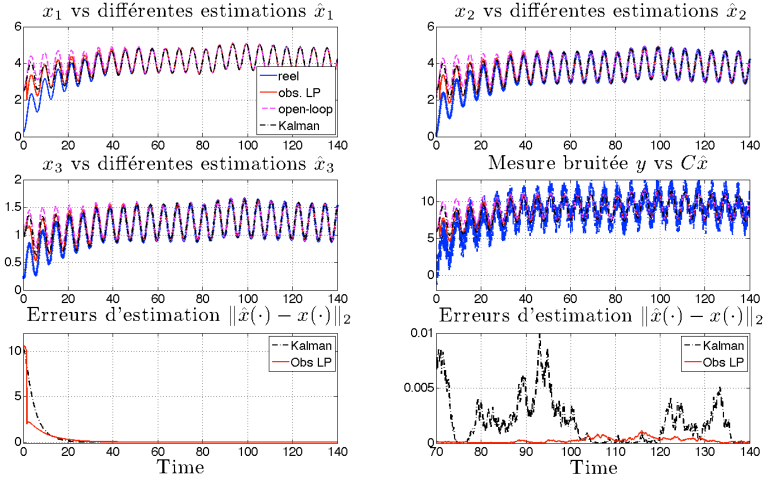
- Choose a good trade-off for Kalman filter according to $\sigma_1 = 0.2$, $\sigma_2 = 0.2$ and σ_3
- Reset the KP Inequalities threshold to $\eta = 0.1$
- Let's compare the asymptotic behavior ...


x_1 vs différentes estimations $\hat{x}_1$
reel
obs. LP
open-loop
Kalman
x_2 vs différentes estimations $\hat{x}_2$
x_3 vs différentes estimations $\hat{x}_3$
Mesure bruitée y vs $C\hat{x}$
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_2$
Kalman
Obs LP
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_2$
x 10
Kalman
Obs LP
Time
Time

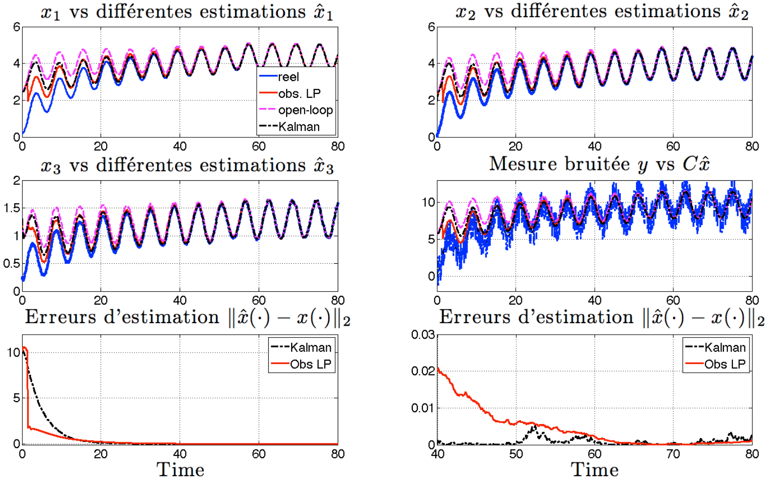
- Choose a good trade-off for Kalman filter according to $\sigma_1 = 0.2$, $\sigma_2 = 0.2$ and σ_3
- Reset the KP Inequalities threshold to $\eta = 0.1$
- Let's compare the asymptotic behavior ...


x_1 vs différentes estimations $\hat{x}_1$
reel
obs. LP
open-loop
Kalman
x_2 vs différentes estimations $\hat{x}_2$
x_3 vs différentes estimations $\hat{x}_3$
Mesure bruitée y vs $C\hat{x}$
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_2$
Kalman
Obs LP
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_2$
x 10
Kalman
Obs LP
Time
Time

- Choose a good trade-off for Kalman filter according to $\sigma_1 = 0.2$, $\sigma_2 = 0.2$ and σ_3
- Reset the KP Inequalities threshold to $\eta = 0.025$
- Let's compare the asymptotic behavior ...


x_1 vs différentes estimations $\hat{x}_1$
reel
obs. LP
open-loop
Kalman
x_2 vs différentes estimations $\hat{x}_2$
x_3 vs différentes estimations $\hat{x}_3$
Mesure bruitée y vs $C\hat{x}$
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_2$
Kalman
Obs LP
Erreurs d'estimation $\|\hat{x}(\cdot) - x(\cdot)\|_2$
Kalman
Obs LP
Time
Time

- Choose a good trade-off for Kalman filter according to $\sigma_1 = 0.2$, $\sigma_2 = 0.2$ and σ_3
- Reset the KP Inequalities threshold to $\eta = 0.025$
- Let's compare the asymptotic behavior . . .


x1 vs différentes estimations x̂1
reel
obs. LP
open-loop
Kalman
x2 vs différentes estimations x̂2
x3 vs différentes estimations x̂3
Mesure bruitée y vs Cx̂
Erreurs d'estimation ‖x̂(·) − x(·)‖2
Kalman
Obs LP
Time
Erreurs d'estimation ‖x̂(·) − x(·)‖2
Kalman
Obs LP
Time

- Preliminary work
- Solution particularly appealing for observer-based control
- KP-like related curves can be obtained experimentally
- More investigation is needed regarding
  - Stability assessment
  - The impact of observation horizon
  - The KP inequalities threshold
- Are the qualitative conclusions general ?