

■ Control design

- Stabilization
- Feedback
- Optimal control

■ Optimization

- Static optimization
- Economic variables
- Monitoring

■ Safety

- Failure detection
- Sensor failure

■ Giveaway

An observer is
a soft sensor

Giveaway

Constraint:

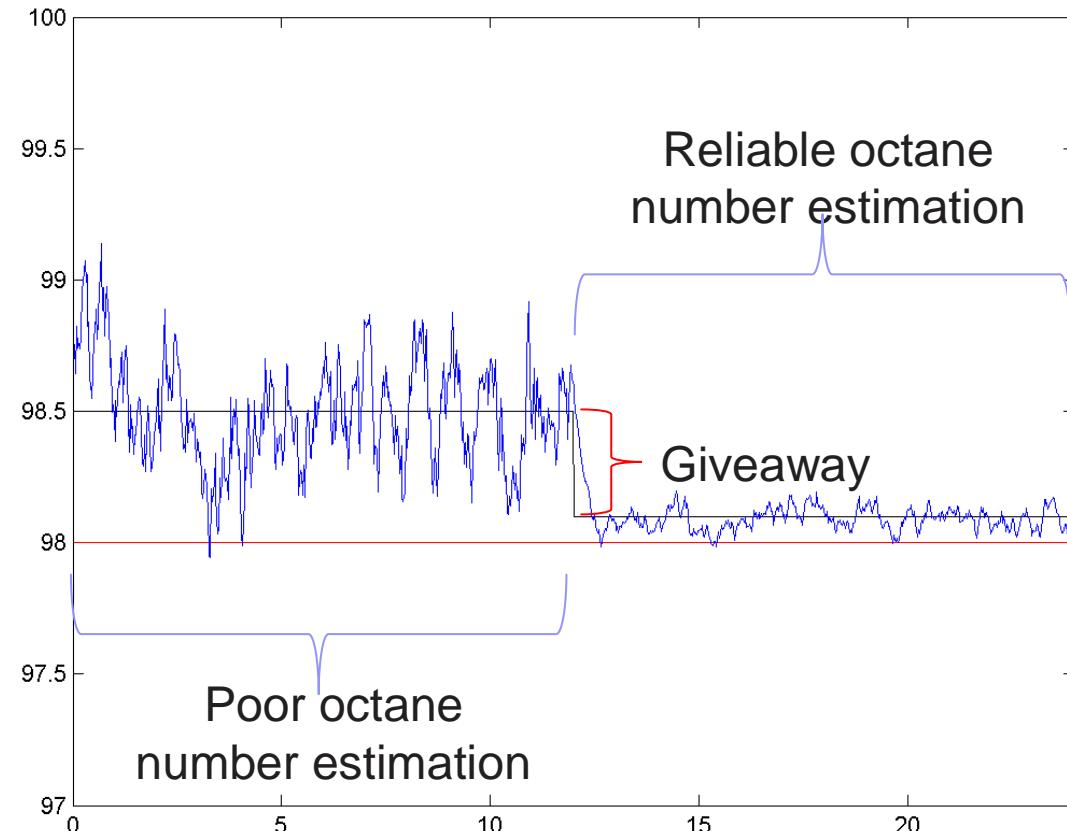
Octane number > 98

Poor observer:

Control target 98.5

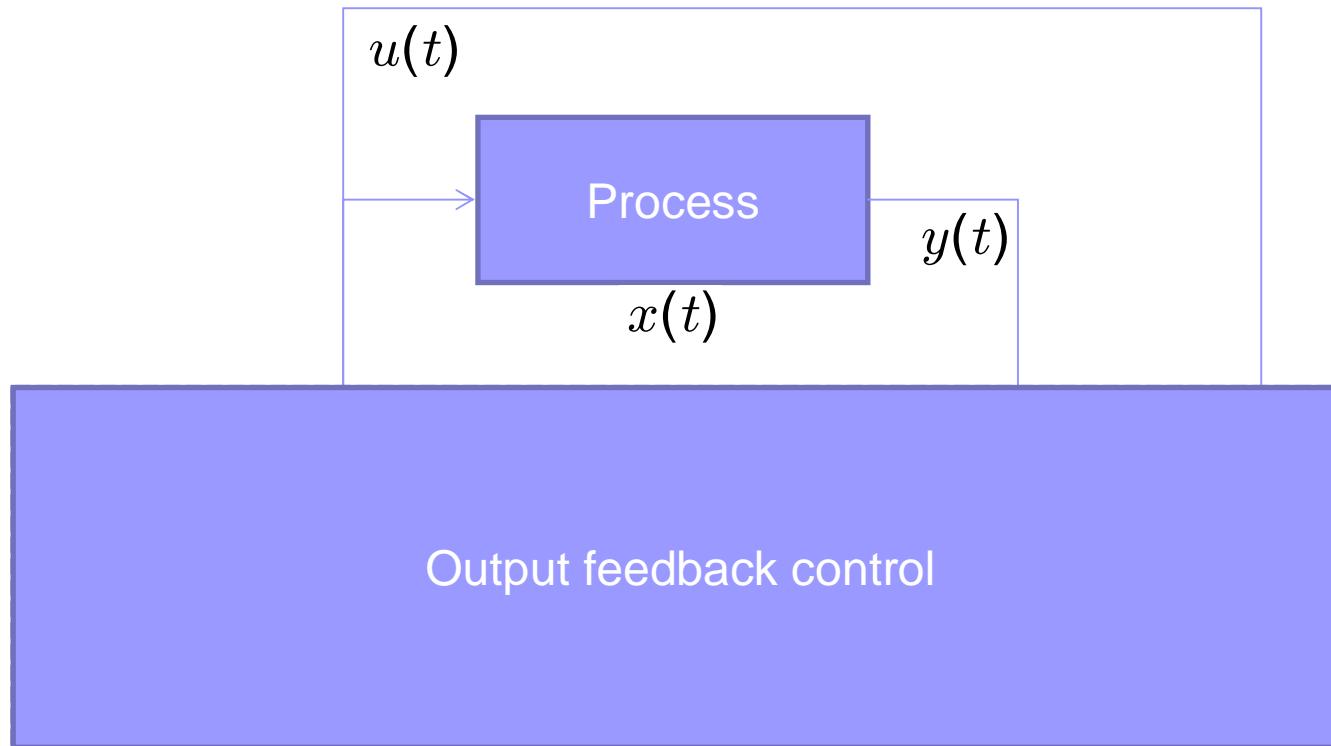
Good observer:

Control target 98.1

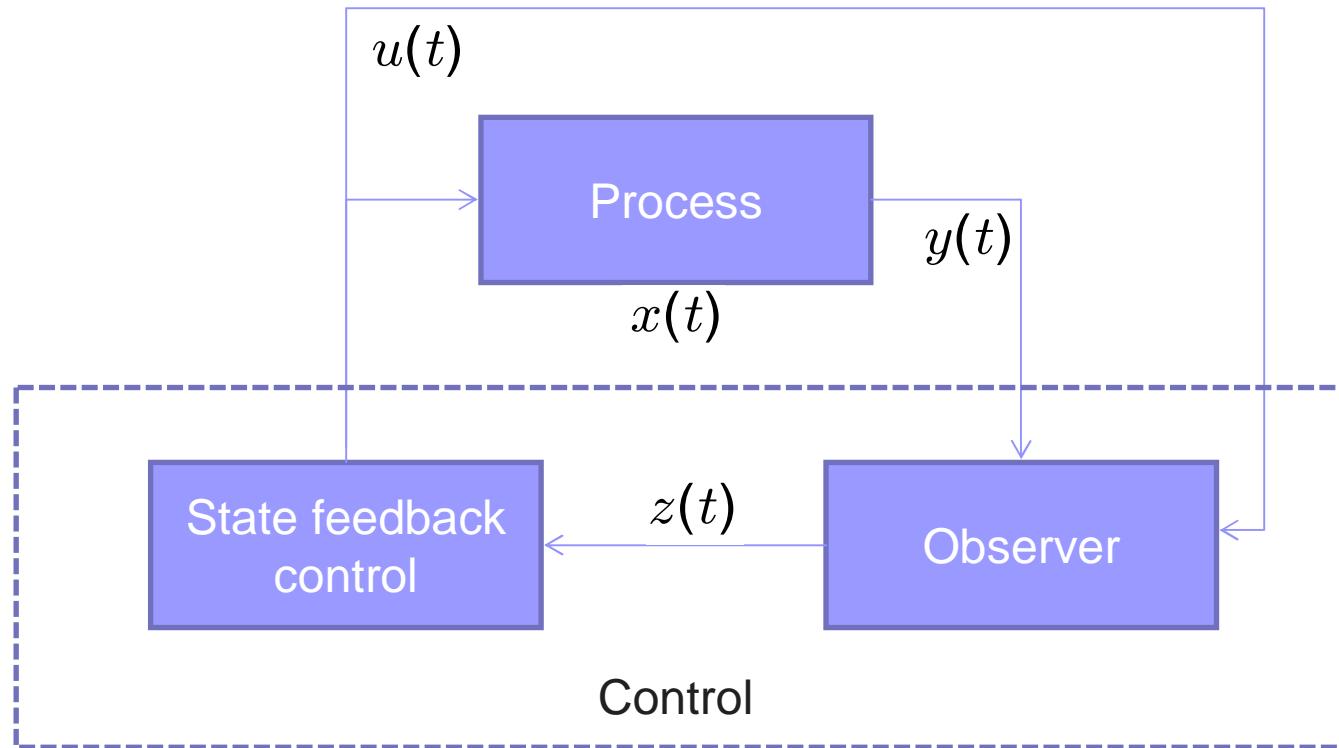


Same remark for a good controller...

Control design



Control design

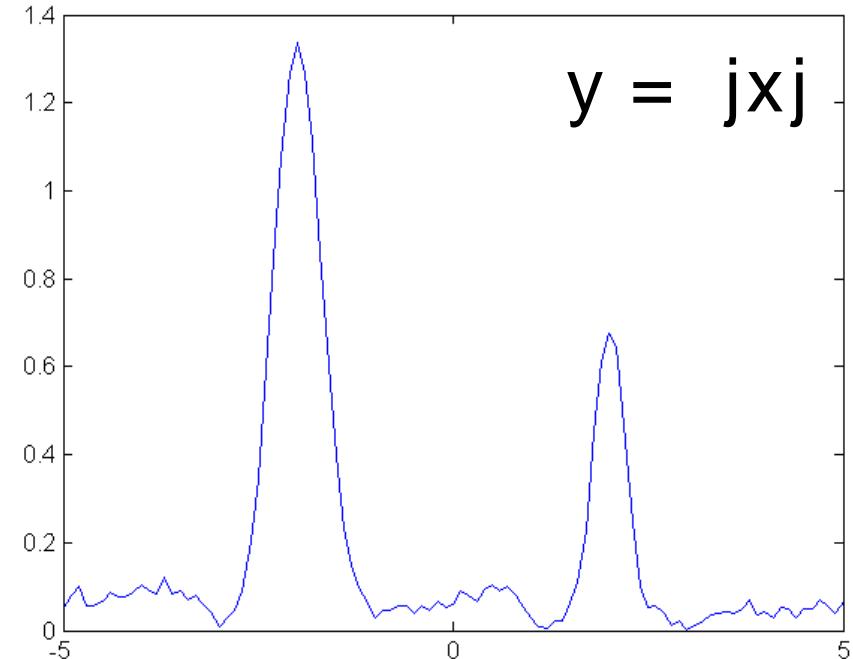
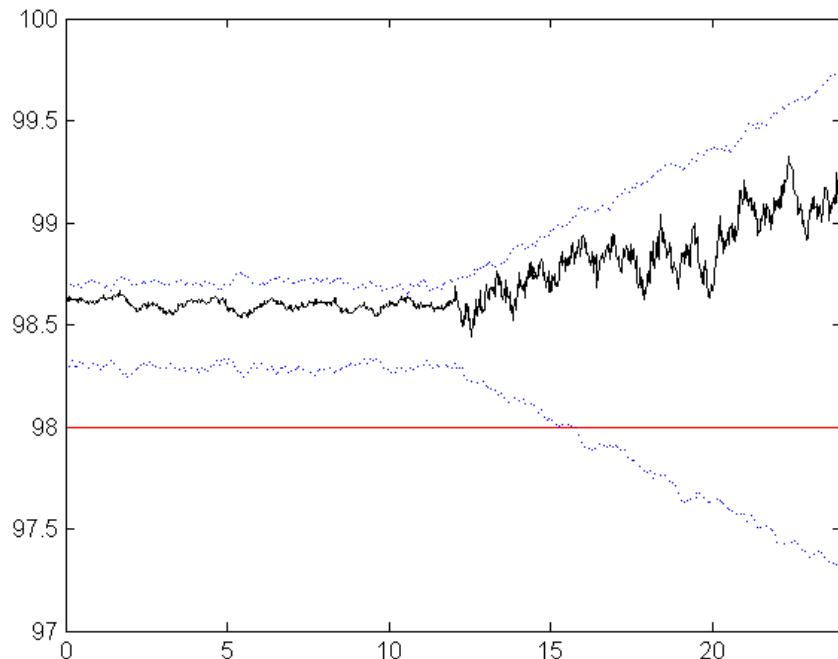


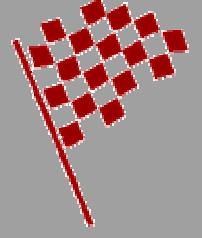
$u(x(t))$ has been replaced by $u(z(t))$
since $x(t)$ is unknown

Monitoring, confidence intervals,...

... any measurement of observer accuracy, as a physical sensor.

- Interval observers (Gouze, Rapaport, ...)
- Kalman filtering (Kalman, Bucy, ...)
- Nonlinear filtering (DMZ, Clark, Davis, Pardoux, ...)
- ...





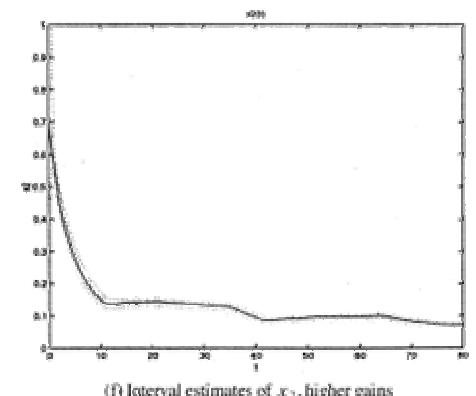
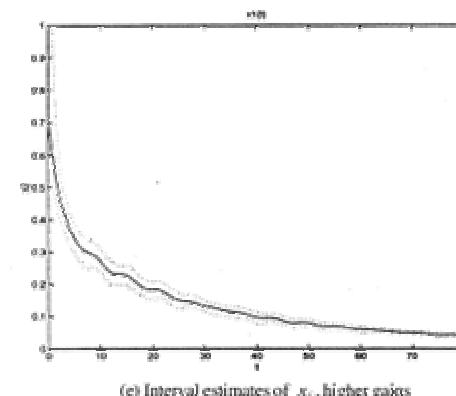
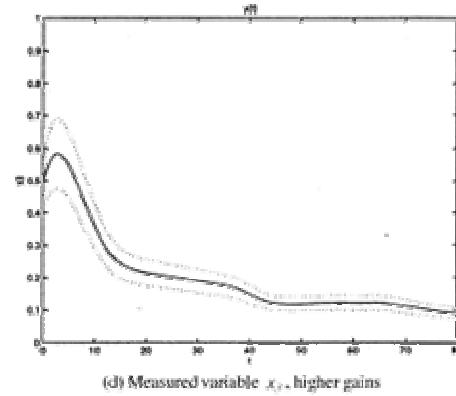
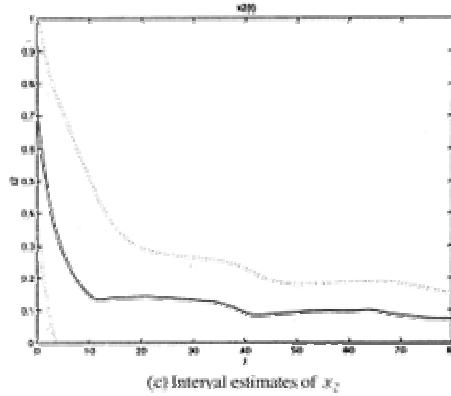
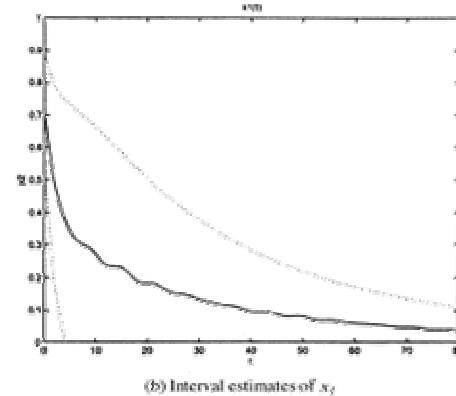
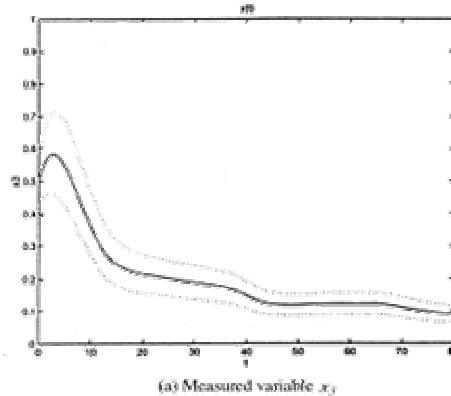
Population of larvae (biomass x_1), juveniles (x_2) and adults (x_3).

$$\begin{cases} \dot{x}_1 = -\alpha_1 x_1 - m_1 x_1 + \frac{a(t)x_3}{b+x_3} \\ \dot{x}_2 = \alpha_1 x_1 - \alpha_2 x_2 - m_2 x_2 \\ \dot{x}_3 = \alpha_2 x_2 - m_3 x_3 - c(t) x_3 \\ y = x_3 \end{cases}$$

$c(t)$ represents an harvesting effort on the adult population.

α_i, m_i, a, b, c poorly known: just some intervals...

Interval observers II

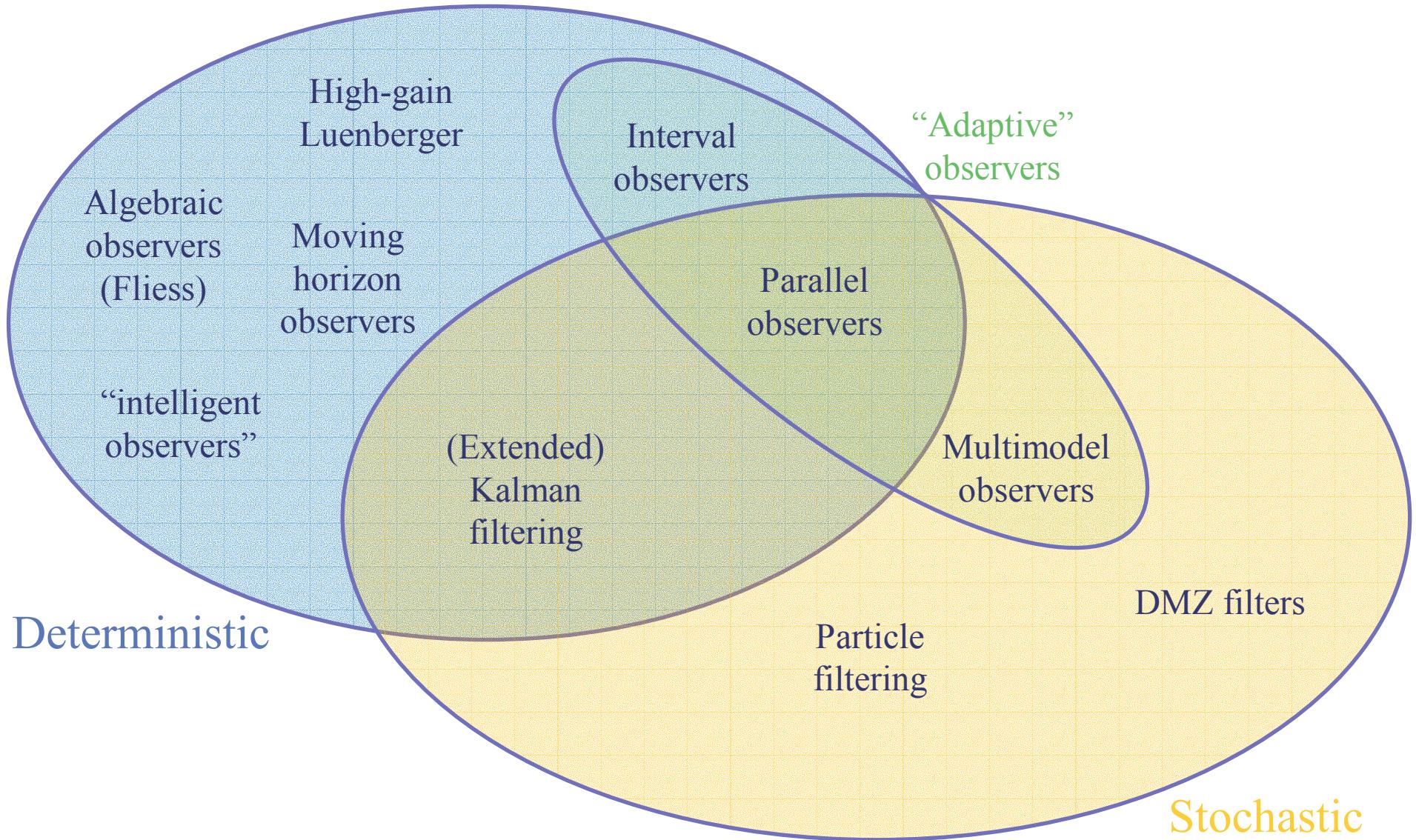
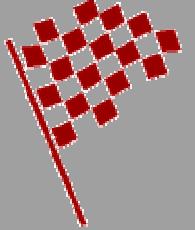


Interval observer
=

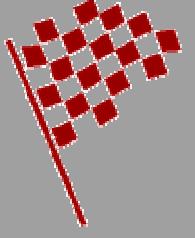
Worst case observer

Gouze–Rapaport–Hadj-Sadok, "Interval observers for uncertain biological systems".

Different kind of observers



Nonlinear filtering



$$\begin{cases} \frac{dx}{dt} = f(x, u) \\ y = h(x, u) \end{cases}$$

Deterministic system and observer

$\frac{dz}{dt} = \dots$ with $\| z(t) - x(t) \| \rightarrow 0$ as t goes to infinity.

Stochastic system and filter

$$\begin{cases} dX(t) = f(X(t), u) dt + Q^{\frac{1}{2}} dW(t) \\ dY(t) = h(X(t), u) dt + R^{\frac{1}{2}} dV(t) \end{cases}$$

Probability law of $X(t)$ knowing $Y(s)$ for s from 0 to t .

Fokker-Planck equation

$$dX(t) = f(X(t), u) dt + Q^{\frac{1}{2}} dW(t)$$

$$\frac{d}{dt} p(t, x) = L^* p(t, x) dt$$

where

$$L = \frac{1}{2} \sum_{i,j=1}^n Q_{i,j} \frac{\partial^2}{\partial x_i \partial x_j} + \sum_{i=1}^n f_i(x, u) \frac{\partial}{\partial x_i}$$

Then

$$E [\phi(X(t))] = \frac{\int \phi(x) p(t, x) dx}{\int p(t, x) dx}$$

Duncan-Mortensen-Zakaï equation

$$\begin{cases} dX(t) = f(X(t), u) dt + Q^{\frac{1}{2}} dW(t) \\ dY(t) = h(X(t), u) dt + R^{\frac{1}{2}} dV(t) \end{cases}$$

$$\frac{d}{dt} p(t, x) = L^* p(t, x) dt + h(x, u) p(t, x) dY(t)$$

where

$$L = \frac{1}{2} \sum_{i,j=1}^n Q_{i,j} \frac{\partial^2}{\partial x_i \partial x_j} + \sum_{i=1}^n f_i(x, u) \frac{\partial}{\partial x_i}$$

Then

$$E [\phi(X(t)) \mid \mathcal{F}_t^Y] = \frac{\int \phi(x) p(t, x) dx}{\int p(t, x) dx}$$

$$\begin{cases} dX(t) = f(X(t), u) dt + Q^{\frac{1}{2}} dW(t) \\ Y_k = C(u)X(t_k) + R^{\frac{1}{2}} V(k) \end{cases}$$

Un-normalized discrete-time DMZ equation:

$$q(t_k, x) = \int f_{Y_k}^{X(t_k)=x}(y_k) f_{X(t_k)}^{X(t_{k-1})=\xi}(x) p(t_{k-1}, \xi) d\xi$$

where

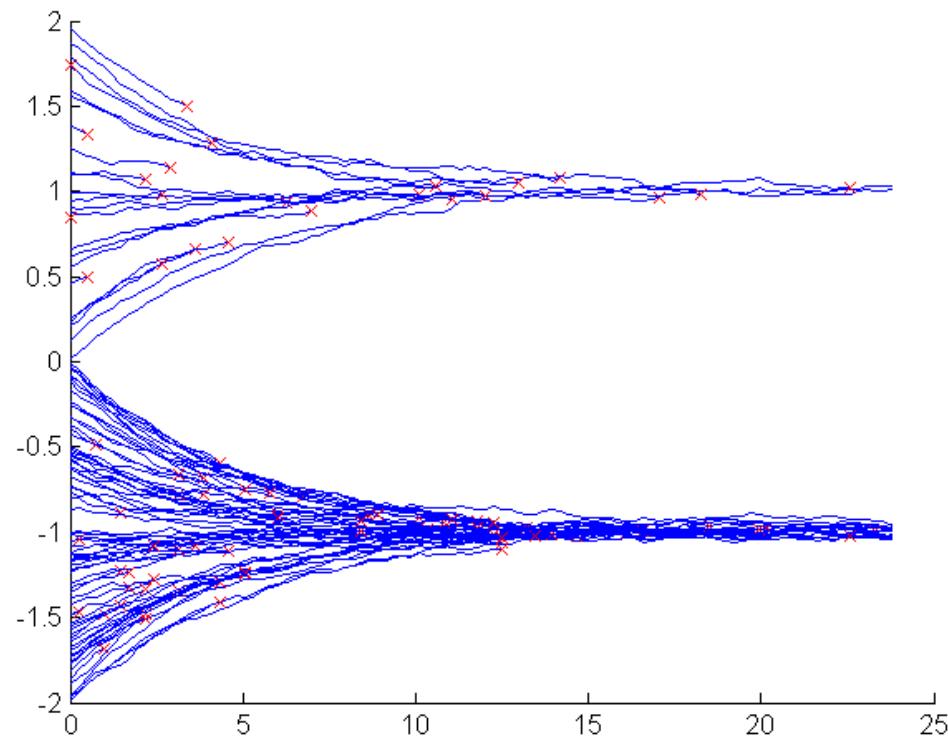
$$p(t_k, x) = \frac{1}{\int f_{Y_k}^{Y^{k-1}=y^{k-1}}(y_k)} q(t_k, x) = \frac{q(t_k, x)}{\int q(t_k, \xi) d\xi}$$

DMZ equation \Leftrightarrow Reject-composition
Dirac approximation

$$q(t, x) \simeq \sum_{i=1}^{N(k)} \delta_{Z_i(t)}(x)$$

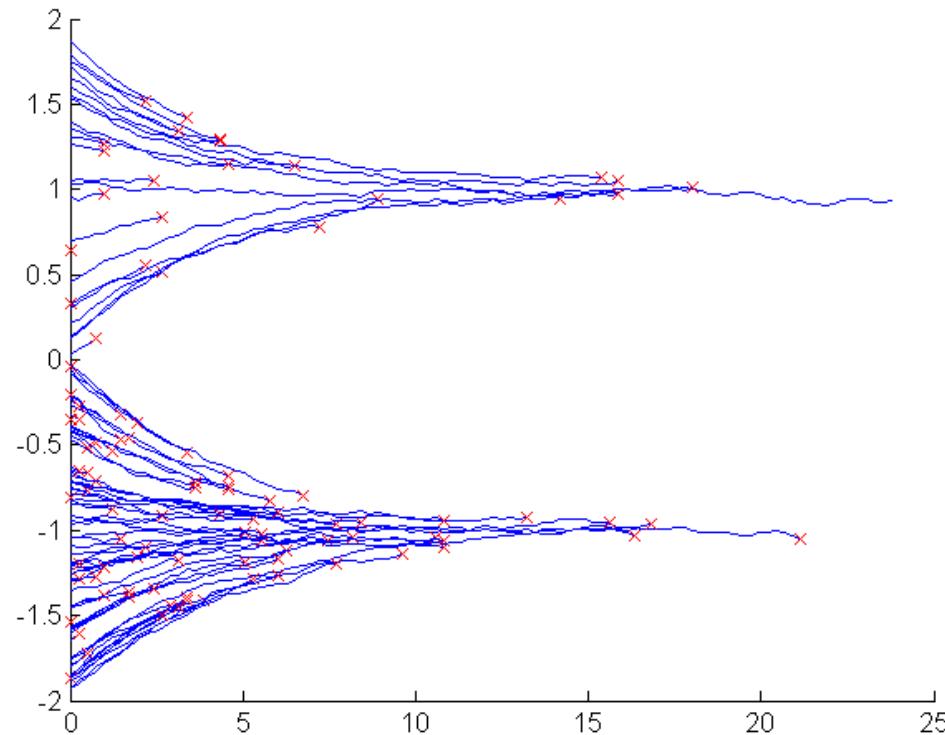
where $Z_i(t)$ denotes particles.

Particle filtering II



Filtering
=
Killing

Particle filtering II



Filtering
=
Killing

But sometimes,
no survivals !

Weighted sum of Dirac approximation

$$q(t, x) \simeq \sum_{i=1}^{N(k)} b_i(t) \delta_{Z_i(t)}(x)$$

where

- $Z_i(t)$ denotes particles
- $b_i(t)$ denotes weights

Particle filtering IV

$$P \left(\left\{ \exists i, \frac{b_i(t)}{\sum b_j(t)} > 1 - \varepsilon \right\} \right) \longrightarrow 1 \text{ as } t \rightarrow \infty$$

