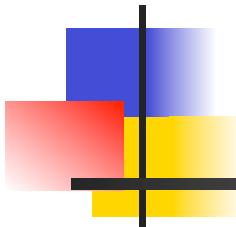
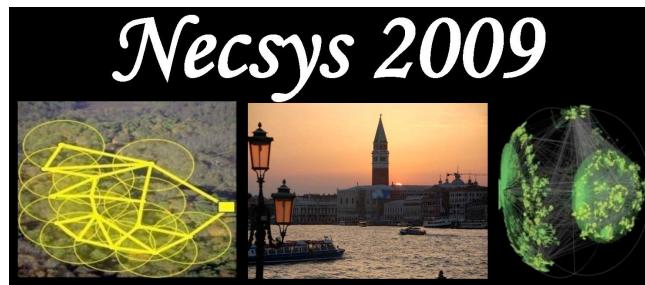


Networked Control Systems subject to packet loss and random delay.



Part II: Random delay and distributed estimation



Luca Schenato
University of Padova
Necsys'09, Tutorial day, 26 September 2009, Venice



Networked Control Systems

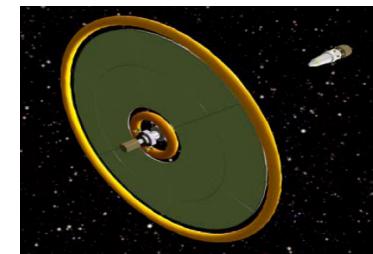
Drive-by-wire systems



Swarm robotics



Smart structures: adaptive space telescope



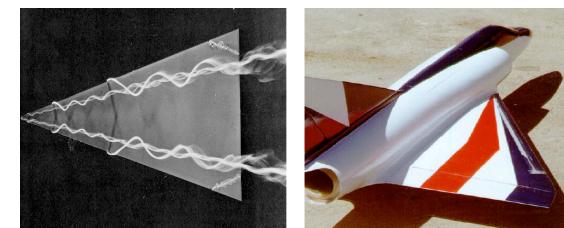
Wireless Sensor Networks



Traffic Control: Internet and transportation

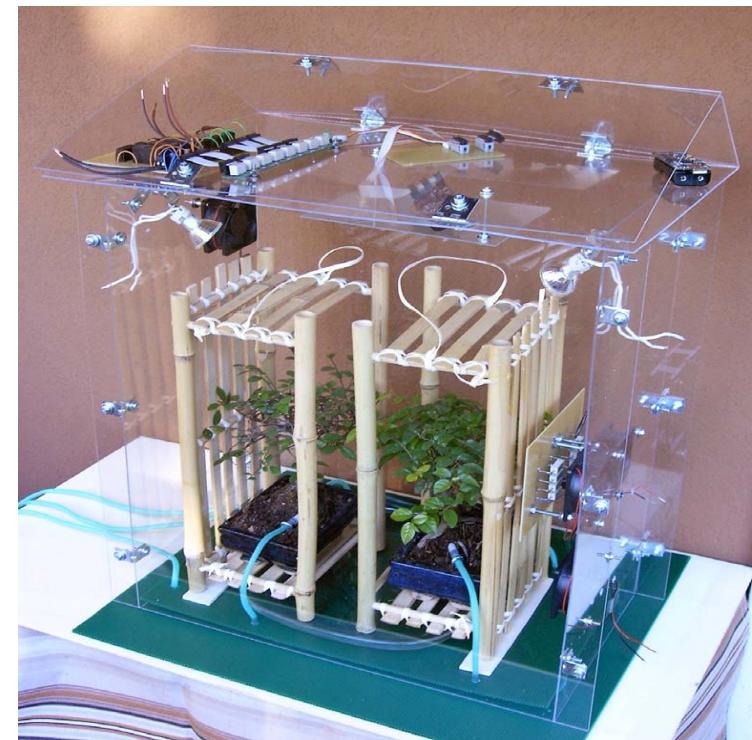
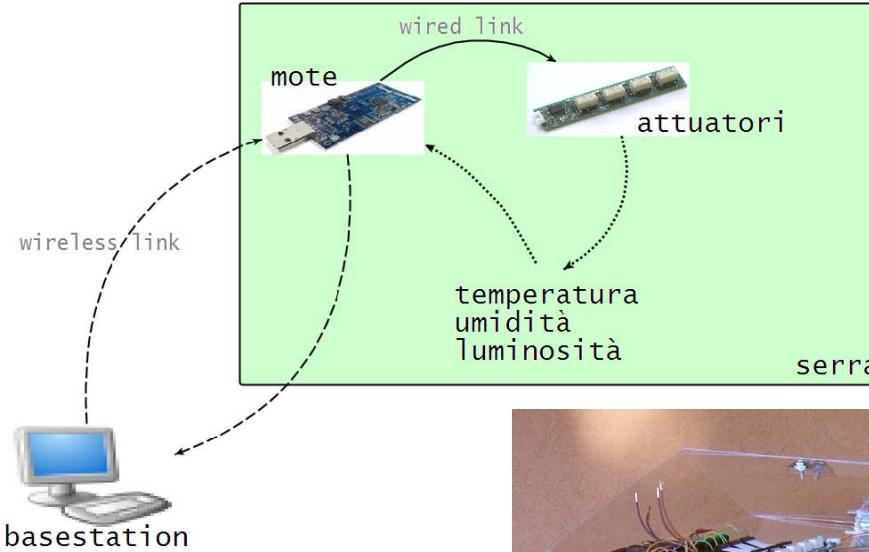


Smart materials: sheets of MEMS sensors and actuators



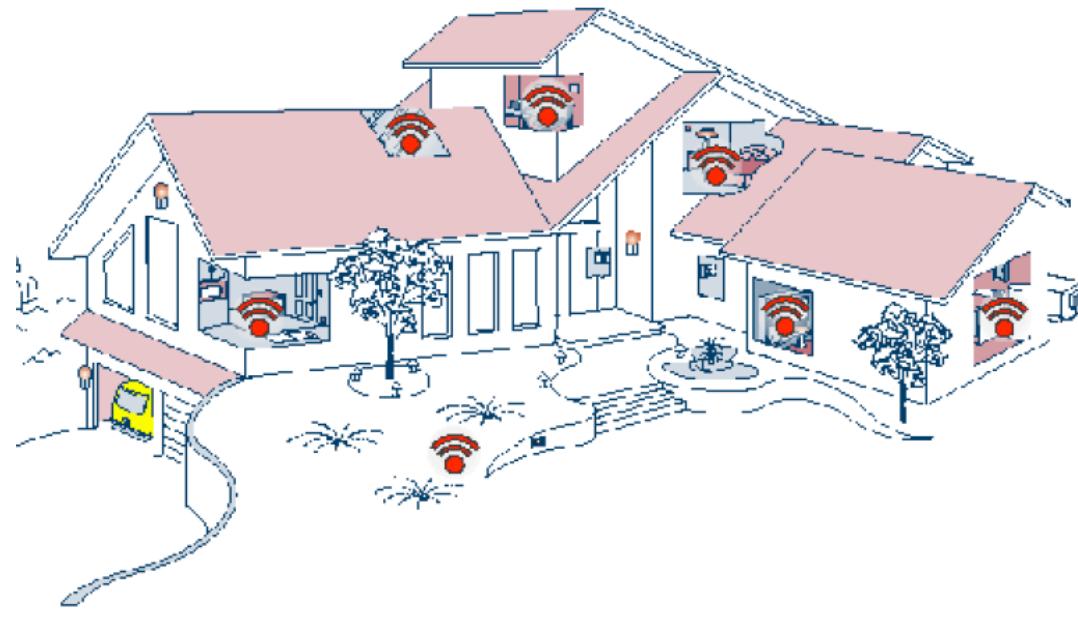
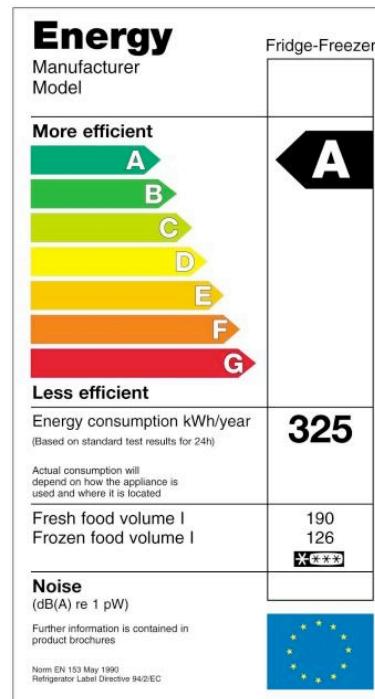
**NCSs: physically distributed dynamical systems
interconnected by a communication network**

Smart greenhouses and building climate control



- Distributed estimation
- Distributed control
- Control under packet loss & random delay
- Sensor fusion
- Distributed time synchronization

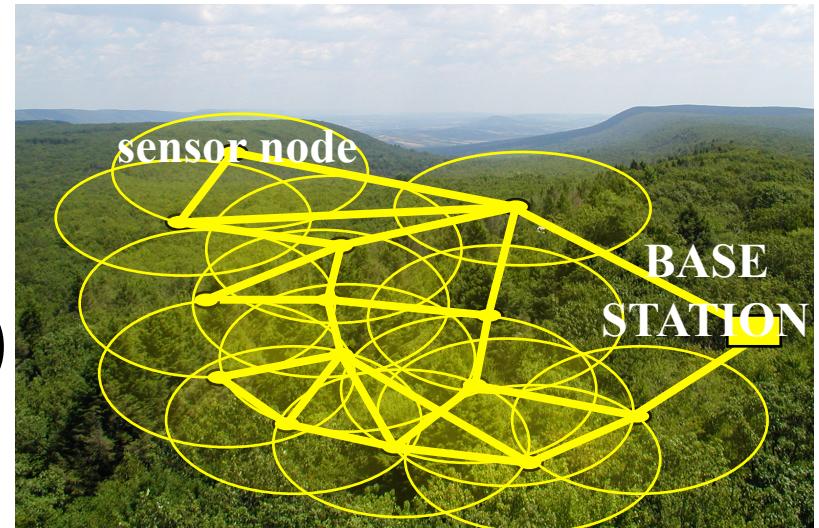
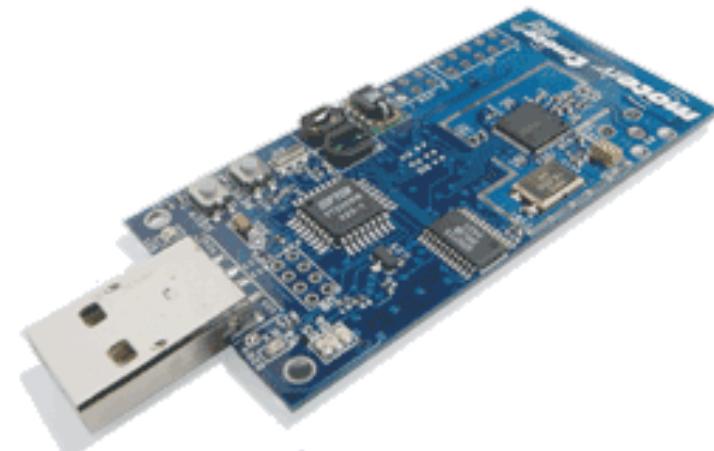
ThermoEfficiency Labeling



- Building thermodynamics model identification
- Sensor selection for identification
- Optimal sensor placement

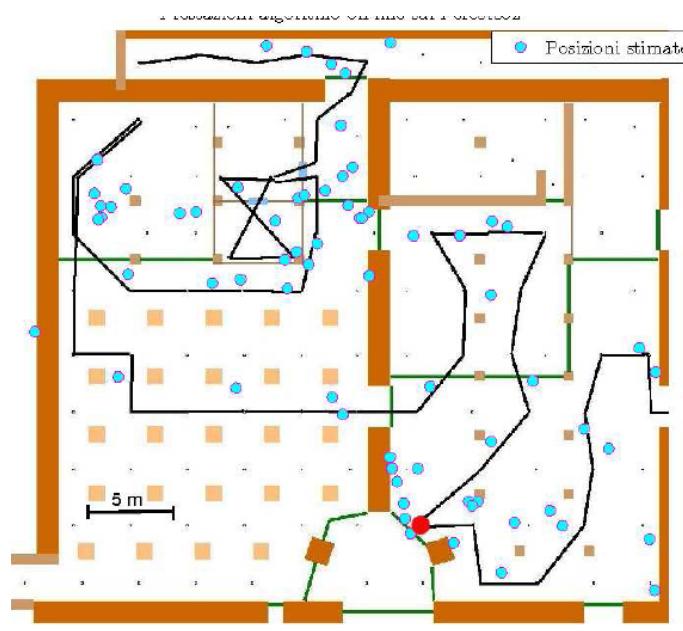
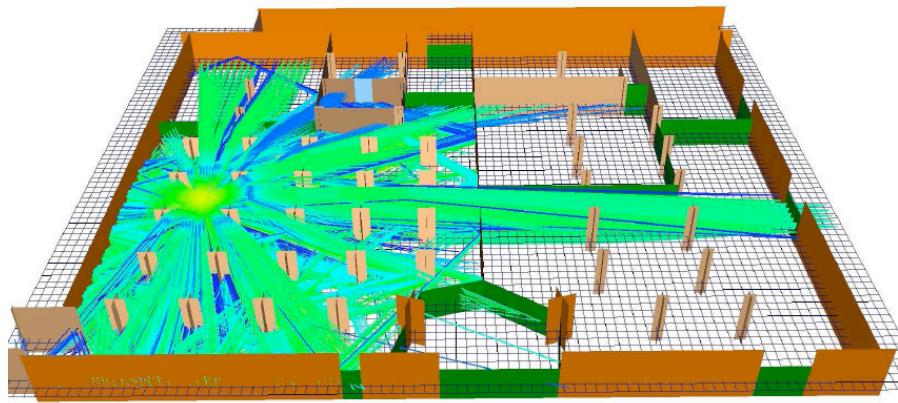
Wireless Sensor Actuator Networks (WSANs)

- Small devices
 -  Controller, Memory
 - Wireless radio
 - Sensors & Actuators
 - Batteries
- Inexpensive
- Multi-hop communication
- Programmable (micro-PC)



Necsys09, Tutorial Day on NCS, 26rd Sept 2009, Venice, Italy

Distributed Localization and Tracking with WSNs



FIRE Eye From Moteiv

- Rescue system with wirelessly networked sensors and electronic maps
- Delivers critical information to firefighters during an emergency
- Cooperation between Chicago Fire Department, Moteiv and UC Berkley engineers
- Monitors occupancy, smoke, light and fire
- Tracks emergency crew inside the building and displays the details inside the firefighter's mask

FIRE EYE **moteiv**

Technology for Innovators™

TEXAS INSTRUMENTS

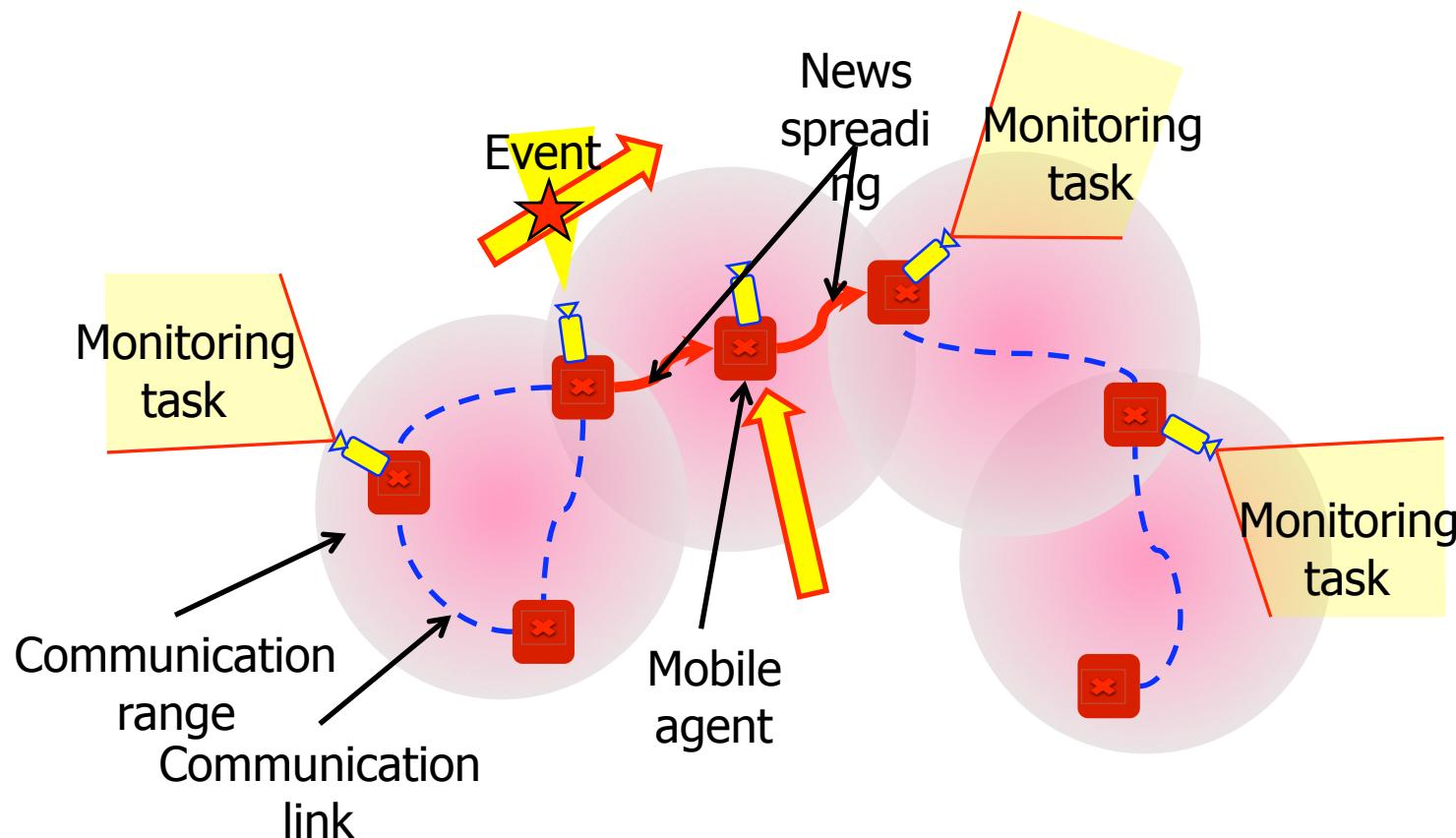


- Indoor radio signal modeling
- Real-time localization
- Distributed tracking
- Coordination

Multi-camera surveillance systems

■ Rationale

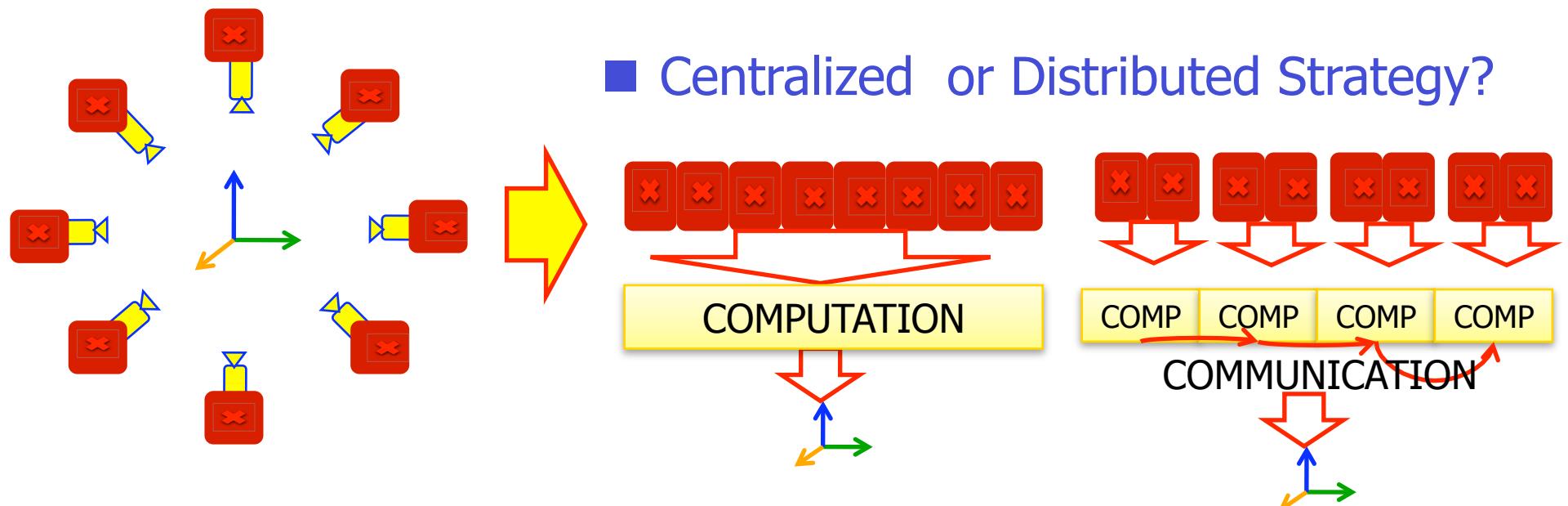
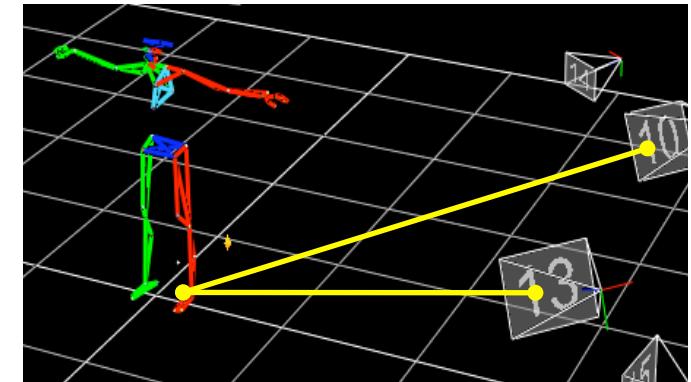
- The Sensor Actor Network is a **multi-agent** **multi-task** **finite-resource** system



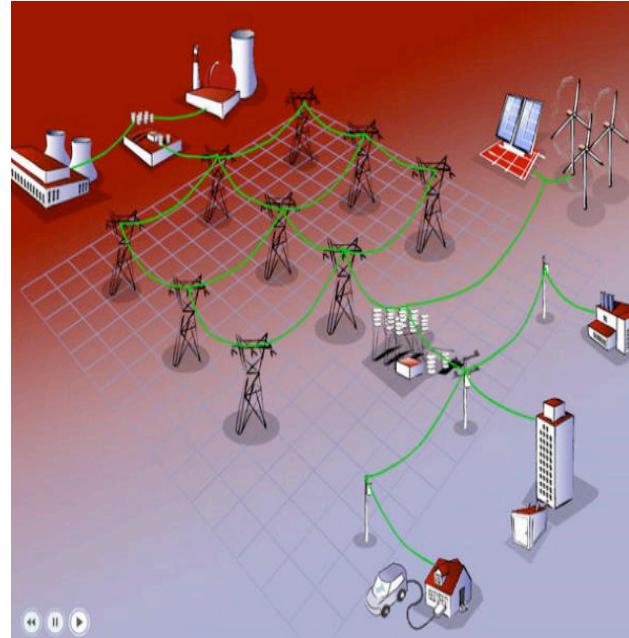
Multi-camera real-time tracking

■ Reconstruction Procedure

- **2D feature point** on the i-th image plane mapped to **ray in 3D space**
- **3D rays** mapped to **3D feature point**



Smart Power Grids

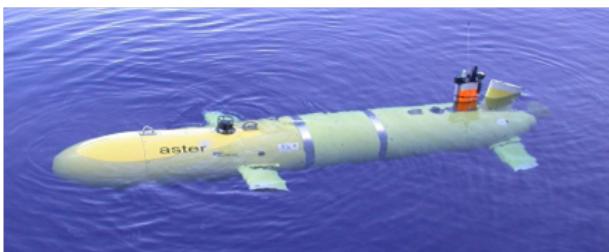
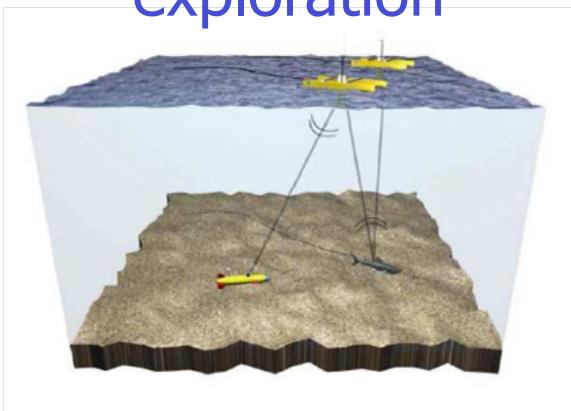


- Foreseeable future
 - Many consumers & producers
 - Cooperation vs greedy behavior
 - Network topology not known and dynamic
 - Need for distributed estimation and control



Coordinated robotics for exploration

Underwater exploration



Planetary exploration

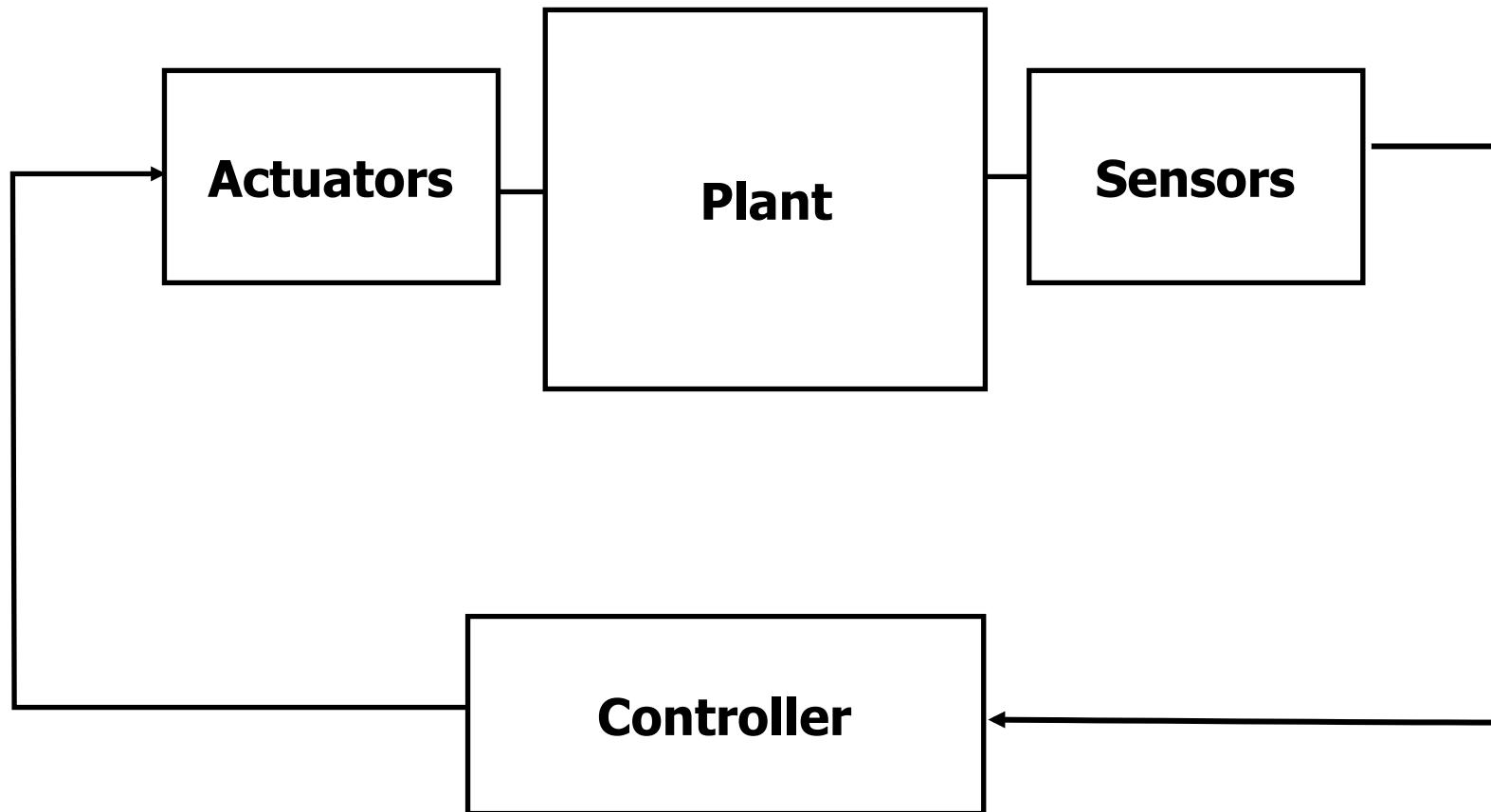


Search & rescue missions



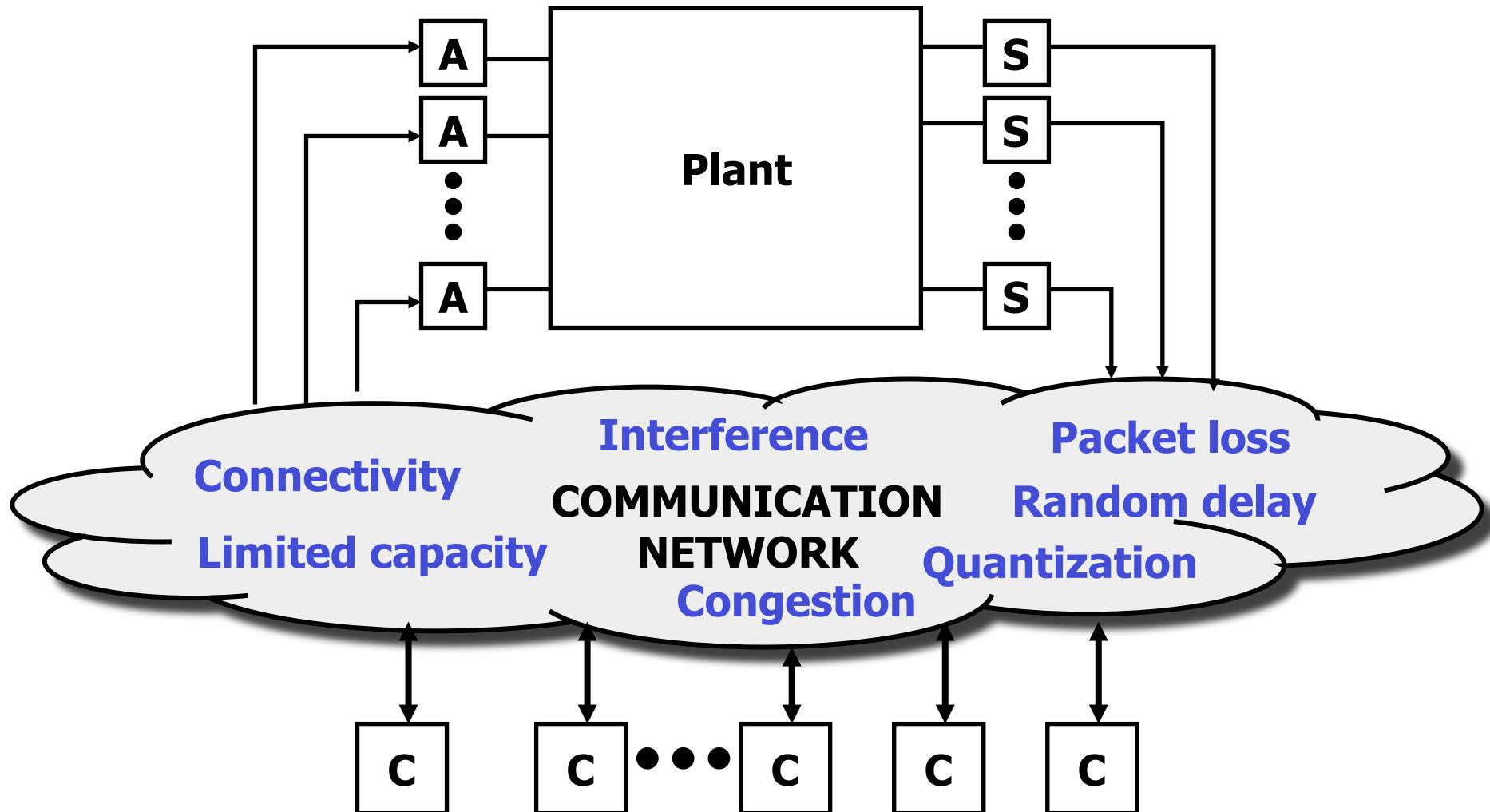
NCSs: what's new for control?

Classical architecture: Centralized structure

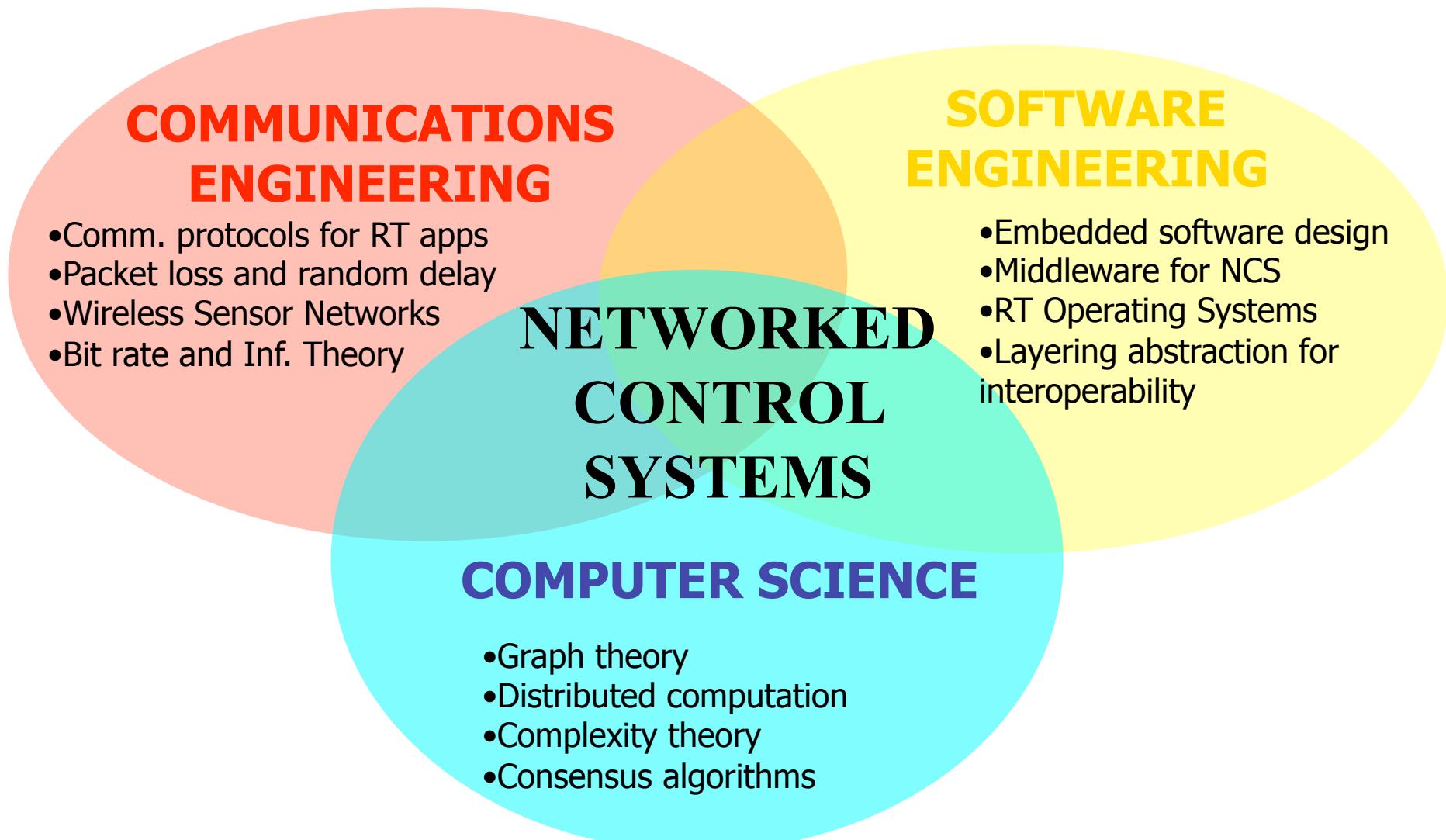


NCSs: what's new for control?

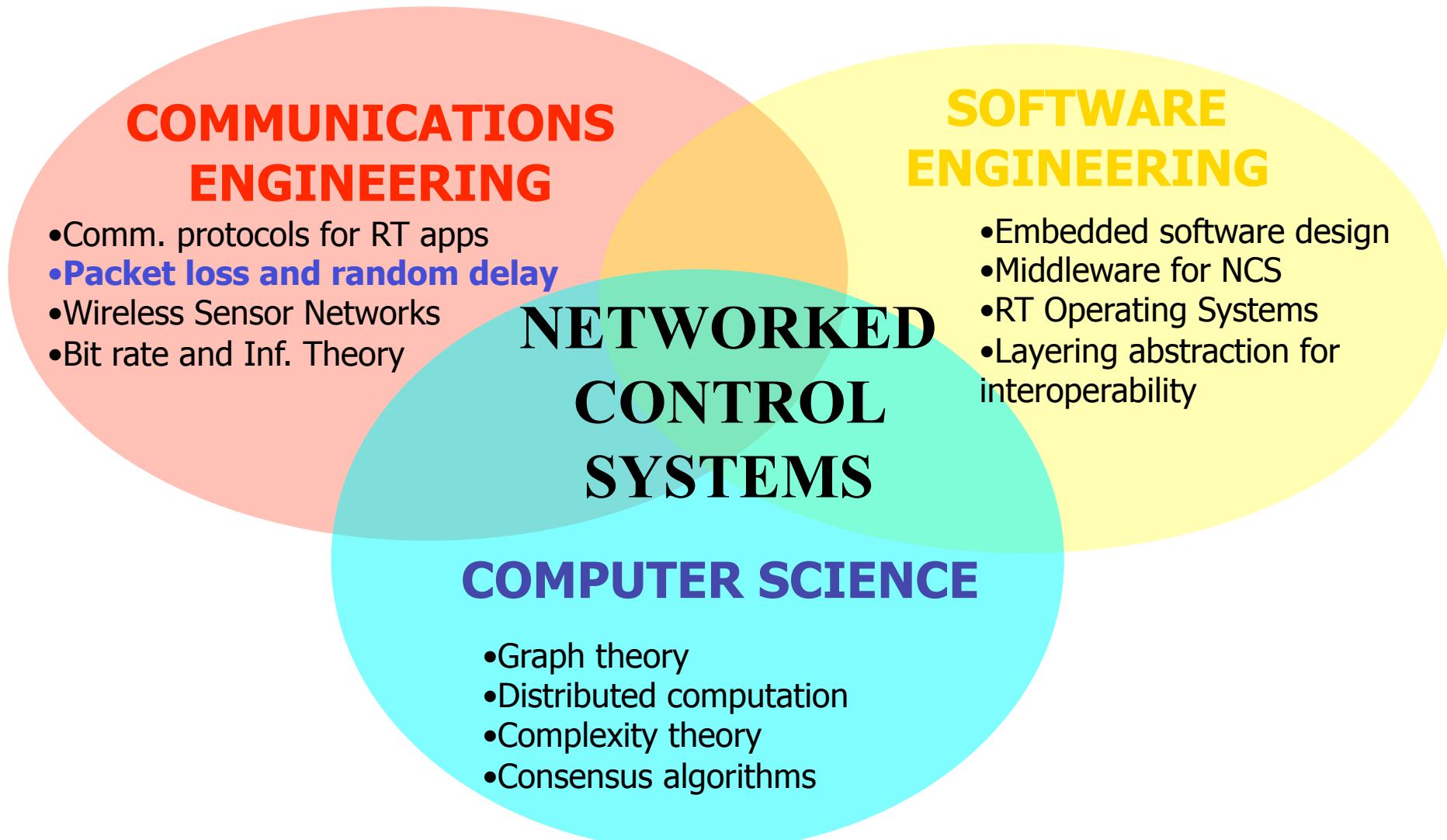
NCSs: Large scale distributed structure



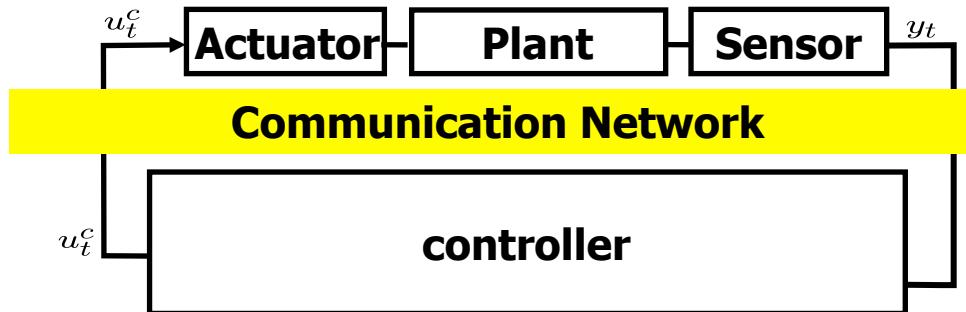
Interdisciplinary research needed



Interdisciplinary research needed

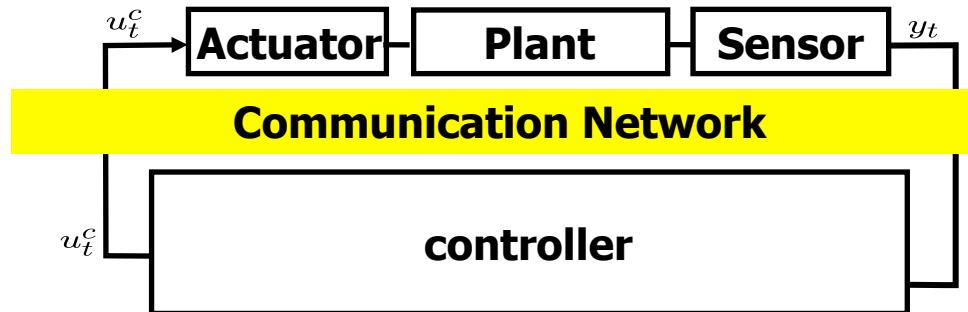


Communication and Control: Modeling with single link



- Infinite bandwidth:
 - Deterministic (worst case)
 - Delay and packet loss is time-varying but measurable to receiver
 - Delay and packet loss is NOT known to receiver
 - Stochastic (mean square)
 - Delay and packet loss are random, but measurable and known stats
 - Finite bandwidth
 - Quantization
 - Power limited transmission
- Problems:
 - Time-varying delay
 - Random packet loss
 - Quantization

Communication and Control: Modeling with single link

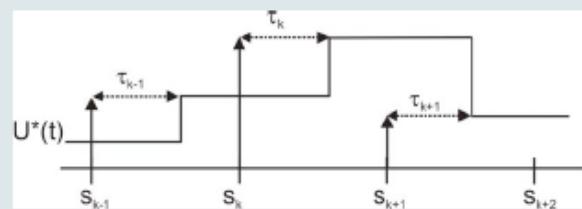
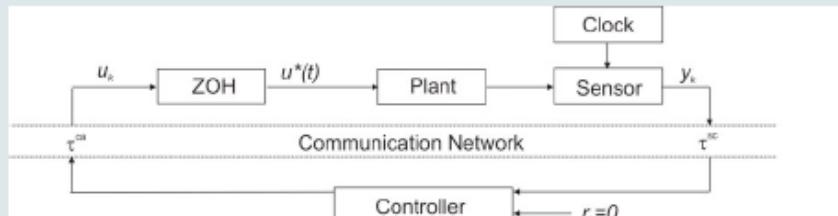


- Infinite bandwidth:
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 - Delay and packet loss are random, but measurable and known stats
- Finite bandwidth
 - Quantization
 - Power limited transmission

Core of this tutorial

Modeling: deterministic with infinite bandwidth

Networked control systems (small delay case: $\tau_k < h$)



$$\begin{aligned} \text{Continuous-time plant: } & \dot{x}(t) = Ax(t) + Bu^*(t) \\ \text{Zero-order hold: } & u^*(t) = u_k, \text{ for } t \in [s_k + \tau_k, s_{k+1} + \tau_{k+1}) \end{aligned}$$

Networked control systems: Model

$$x_{k+1} = e^{Ah}x_k + \int_0^{h-\tau_k} e^{As}dsBu_k + \int_{h-\tau_k}^h e^{As}dsBu_{k-1}$$

Using the augmented state vector $\xi_k = \begin{pmatrix} x_k \\ u_{k-1} \end{pmatrix}$ we obtain

$$\xi_{k+1} = \begin{pmatrix} x_{k+1} \\ u_k \end{pmatrix} = \underbrace{\left(e^{Ah} \quad \int_{h-\tau_k}^h e^{As}dsB \right)}_{=:F(\tau_k)} \begin{pmatrix} x_k \\ u_{k-1} \end{pmatrix} + \underbrace{\left(\int_0^{h-\tau_k} e^{As}dsB \quad I \right)}_{=:G(\tau_k)} u_k$$

Model with delay:

$$\xi_{k+1} = F(\tau_k)\xi_k + G(\tau_k)u_k$$

time-varying system with parametric uncertainty

$$\tau_k \in [\tau_{\min}, \tau_{\max}]$$

Modeling: deterministic with infinite bandwidth

Model with delay:

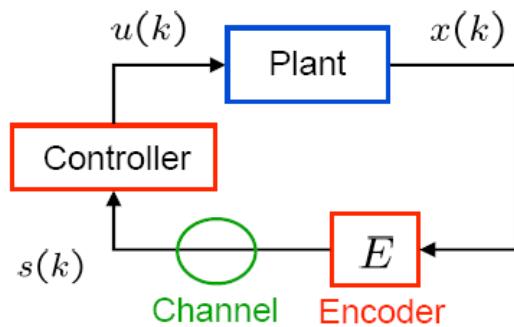
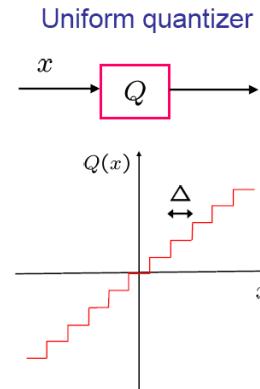
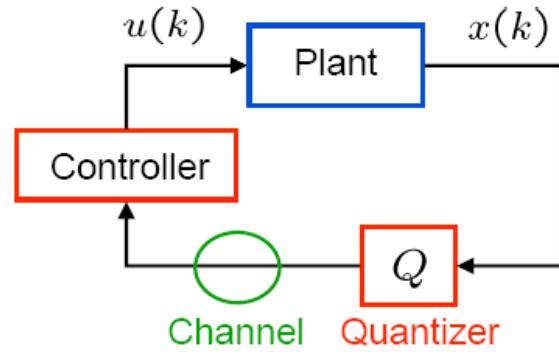
$$\xi_{k+1} = F(\tau_k)\xi_k + G(\tau_k)u_k$$

time-varing system with parametric uncertainty

$$\tau_k \in [\tau_{\min}, \tau_{\max}]$$

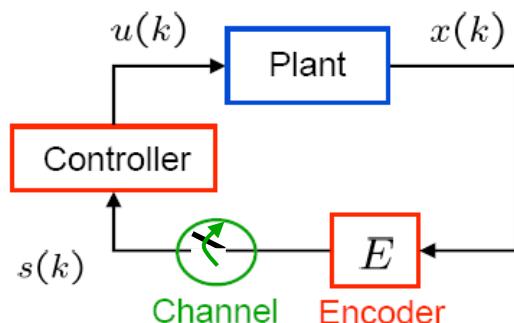
- If $\underline{\lambda}_k$ is known, then **LQG-like approach**: optimal time-varying control $u_k = K(\underline{\lambda}_k) \approx_k$ Nilson (1998)
- If $\underline{\lambda}_k$ is unknown, then **robust control approach**: worst case analysis with constant control $u_k = K \approx_k$ Zhang (2001), Montestruque (2004), Naghshtabrizi (2006), Cloosterman (2009)
- Most results concern stability and not performance

Modeling of finite bandwidth: rate limited



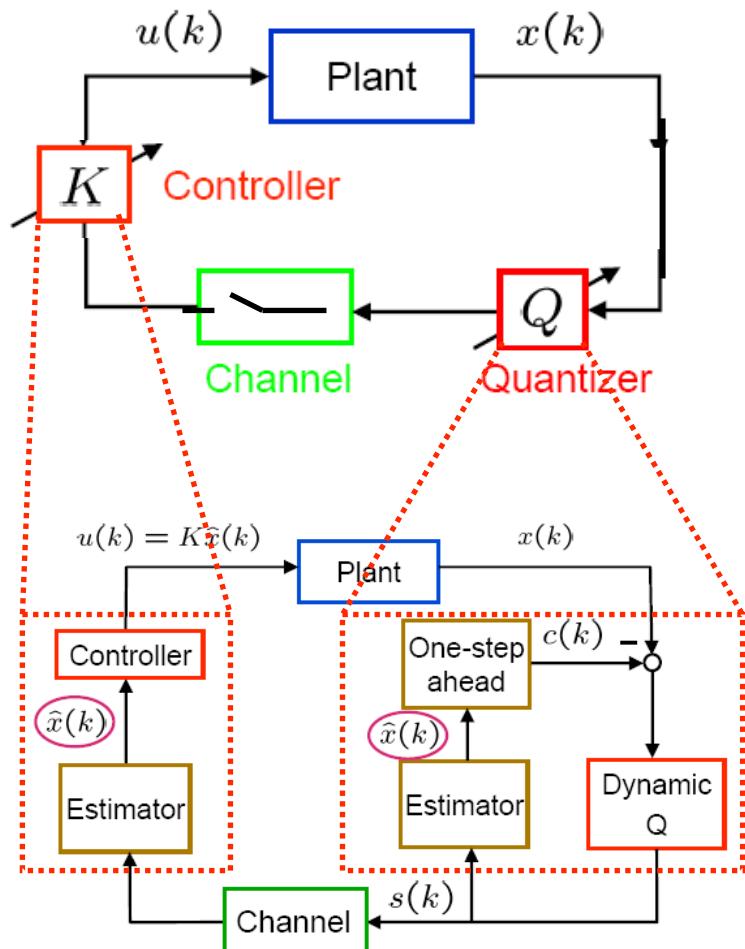
$$s(k) = E_k(x(k), \dots, x(0), s(k-1), \dots, s(0))$$

Encoder, i.e. a smart quantizer, can be designed (time-varying)



Packet loss = erasure channel

Modeling of finite bandwidth: rate limited

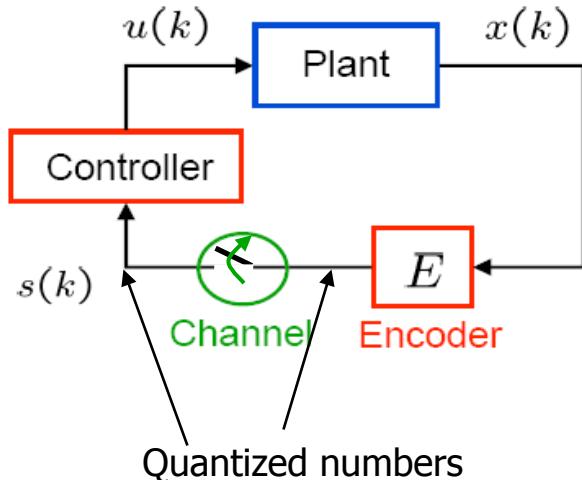


- Problems:
 - Coarseness of quantizer
 - Bit rate
 - Packet loss
- Approach:
 - Design (complex) time-varying encoder/controller
- Main results
 - Bit rate $R > \sum_i \log_2 |\lambda_i^u(A)|$
 - Packet loss $\rightarrow \alpha < \frac{1}{\prod_i |\lambda_i^u|^2}$
 - Coarseness $|\chi| \rho_c = \frac{\gamma_c + 1}{\gamma_c - 1} \quad \gamma_c = \sqrt{\frac{1 - \alpha}{\frac{1}{\prod_i |\lambda_i^u|^2} - \alpha}}$

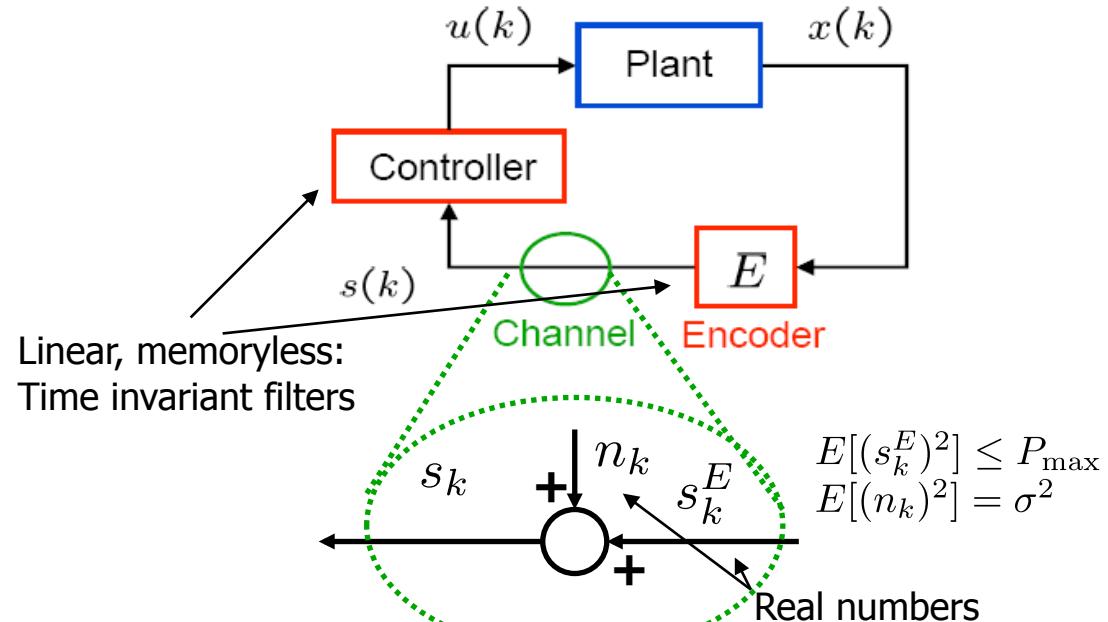
Nair & Evans (2004), Tatikonda et al (2004), Matveev & Savkin (2004), Yuksel & Basar (2006), Ishii et al. (2008), Elia & Mitter (2001), Fu & Xie (2005), Ishii & Francis (2002), Elia (2005)

Modeling of finite bandwidth: signal-to-noise limited

Bit Rate limited



Signal-to-noise limited



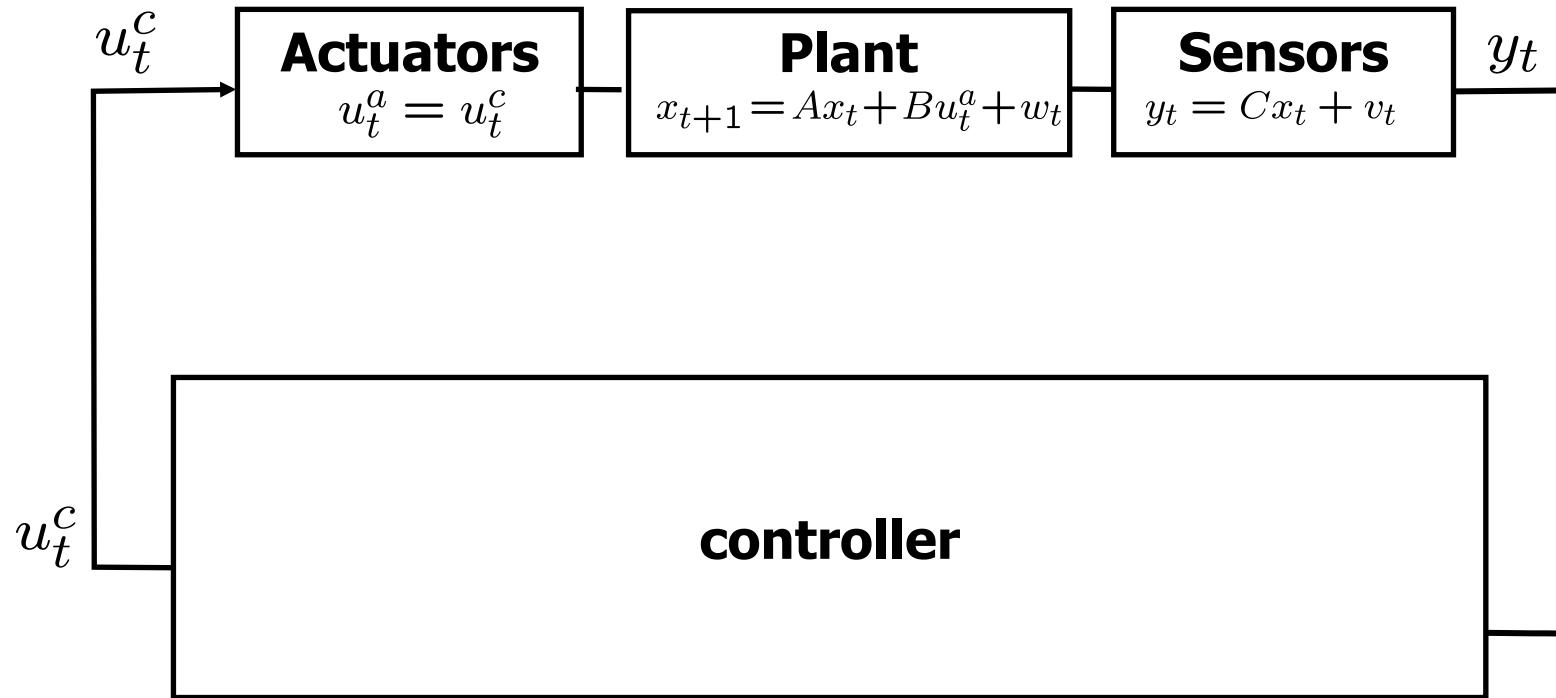
- Takes into account finite bandwidth
- Mathematically clean
- Provide performance bounds

Elia (2004), Martins & Dahleh (2008), Braslavsky et al 2006), Okano et al. (2009)

Communication and Control: Modeling with single link

Modeling	PROS	CONS
Deterministic + infinite bandwidth	<ul style="list-style-type: none">■ easy to implement■ good for delay	<ul style="list-style-type: none">■ worst case packet loss■ no performance bounds
Stochastic + infinite bandwidth	<ul style="list-style-type: none">■ performance bounds■ good for packet loss	<ul style="list-style-type: none">■ time synch required
Rate limited (quantization)	<ul style="list-style-type: none">■ more realistic■ links with info theory	<ul style="list-style-type: none">■ hard to implement■ no performance bounds
Signal-to-noise-ratio (SNR) limited	<ul style="list-style-type: none">■ more realistic■ clean results	<ul style="list-style-type: none">■ coder/decoder to be designed

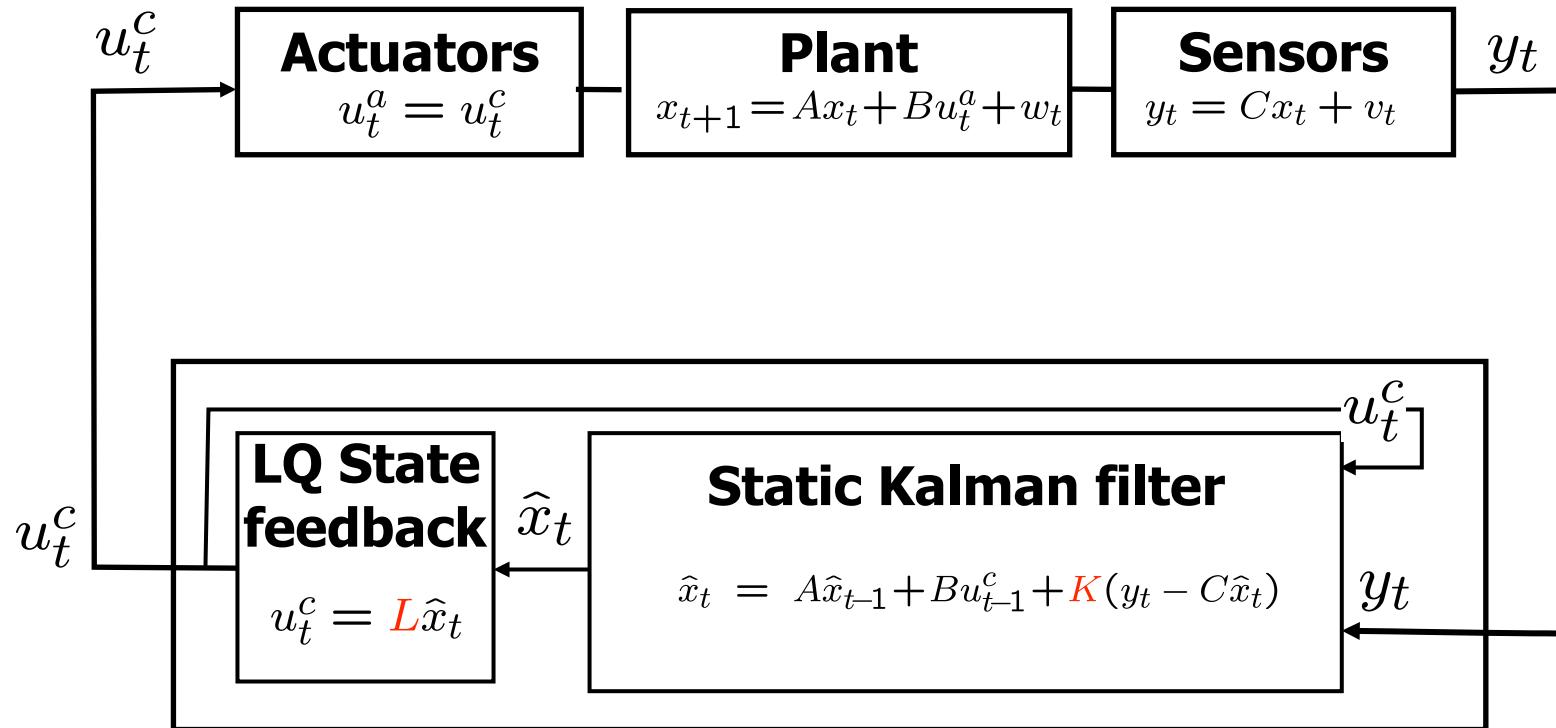
Optimal LQG



$$\min_{u_1^c, \dots, u_T^c} J = \sum_{t=1}^T E[x_t^T W x_t + u_t^T U u_t], \quad T \rightarrow \infty$$

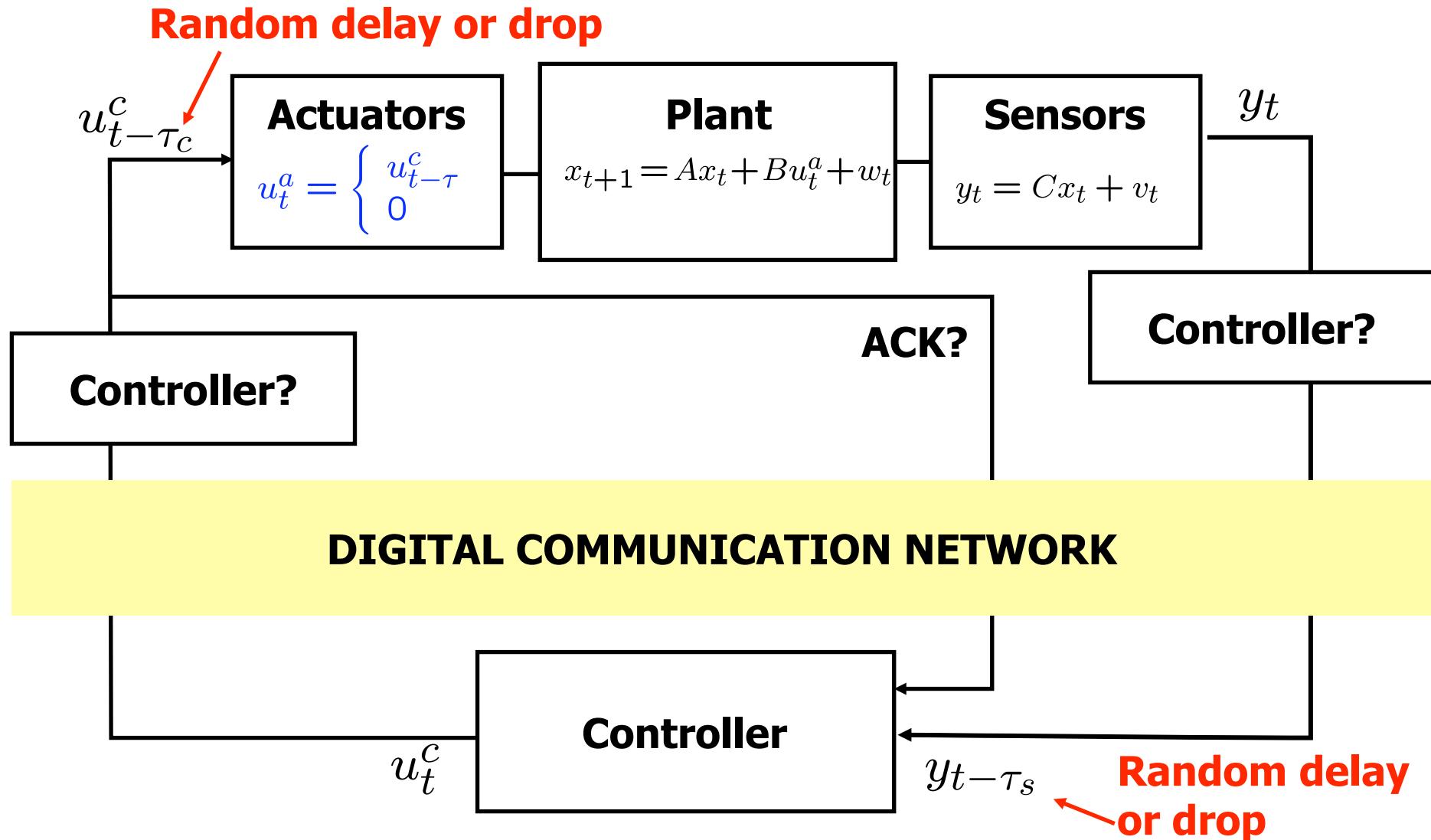
Sensors and actuators are co-located, i.e. no delay nor loss

Optimal LQG

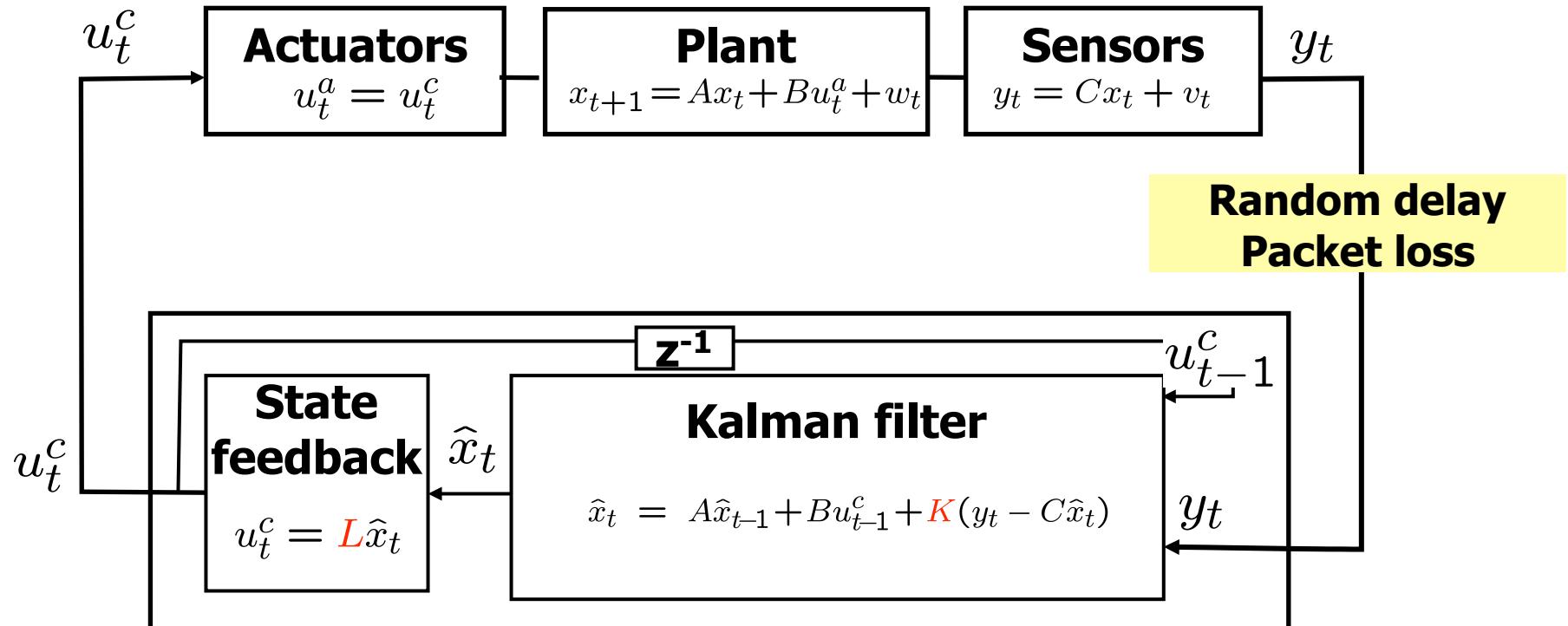


1. **Separation principle holds:** Optimal controller = Optimal estimator design + Optimal state feedback design
2. Closed Loop system **always stable** (under standard reach./det. hypotheses)
3. Gains K, L are constant solution of **Algebraic Riccati Equations**

Optimal LQG control over DCN



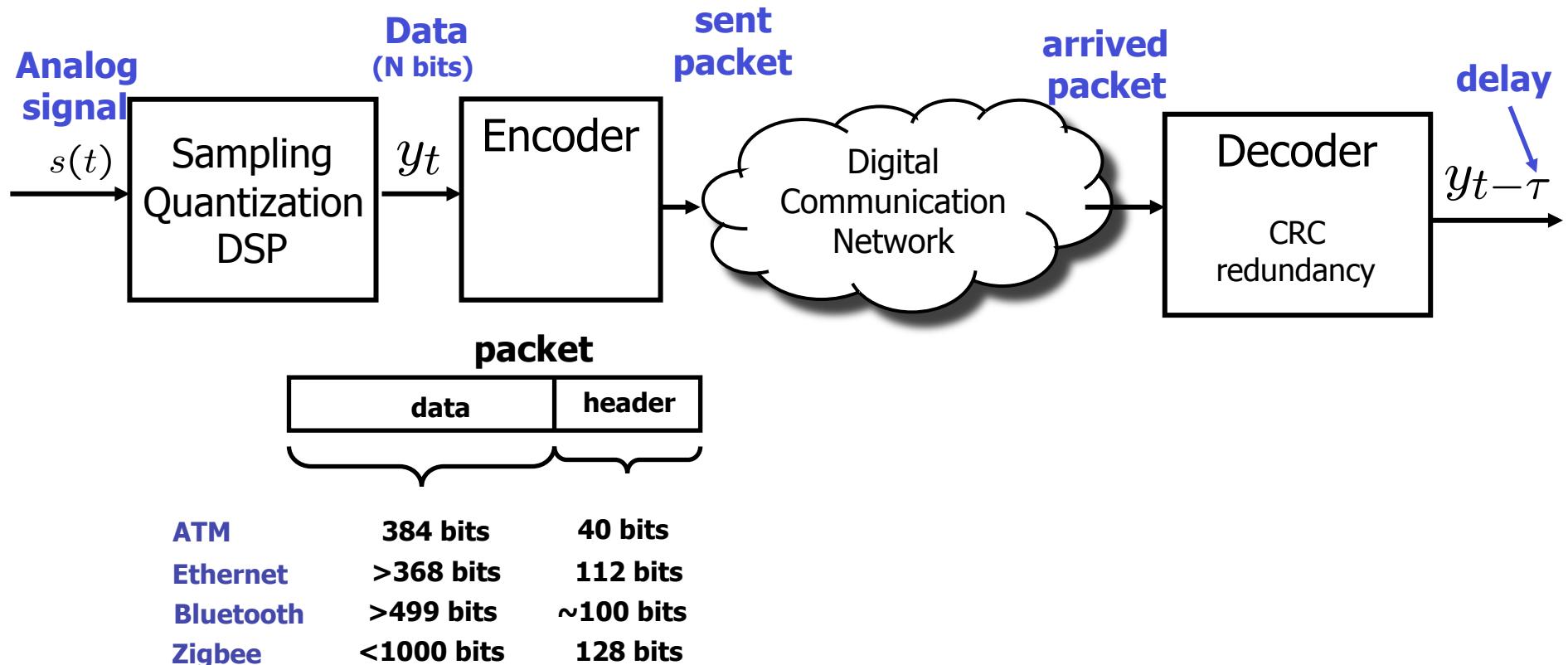
Some consideration on the separation principle



$$\hat{x}_t = E[x_t | y_t, y_{t-1}, \dots, y_0, u_{t-1}^a, \dots, u_1^a]$$

if $(u_{t-1}^a, \dots, u_1^a)$ known $\implies e_t = x_t - \hat{x}_t = f(y_t, y_{t-1}, \dots, y_1, y_0)$

Modeling of Digital Communication Network (DCN)

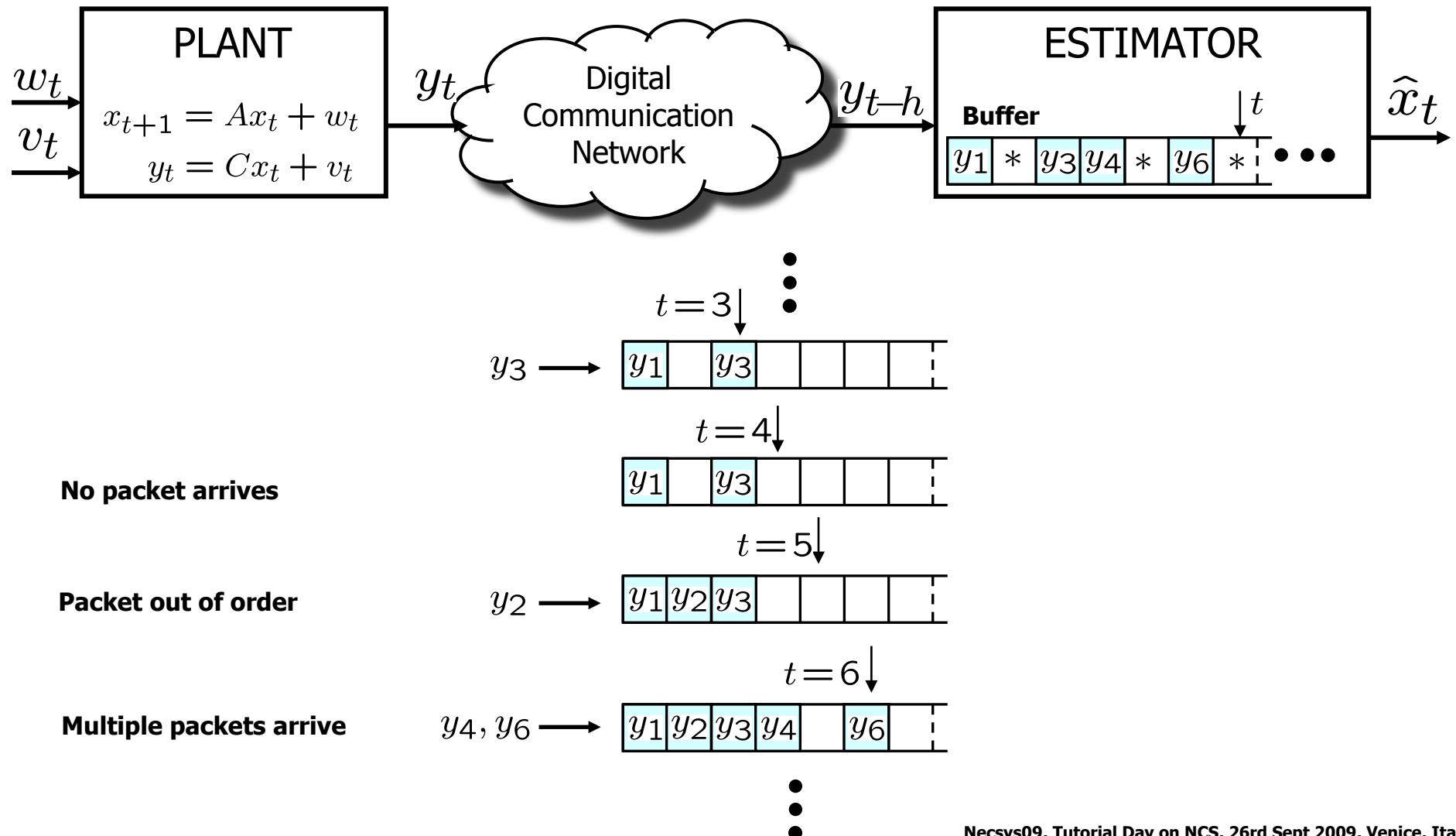


Assumptions:

- (1) Quantization noise << sensor noise
- (2) Packet-rate limited (\neq bit-rate)
- (3) No transmission noise (data corrupted = dropped packet)
- (4) Packets are time-stamped

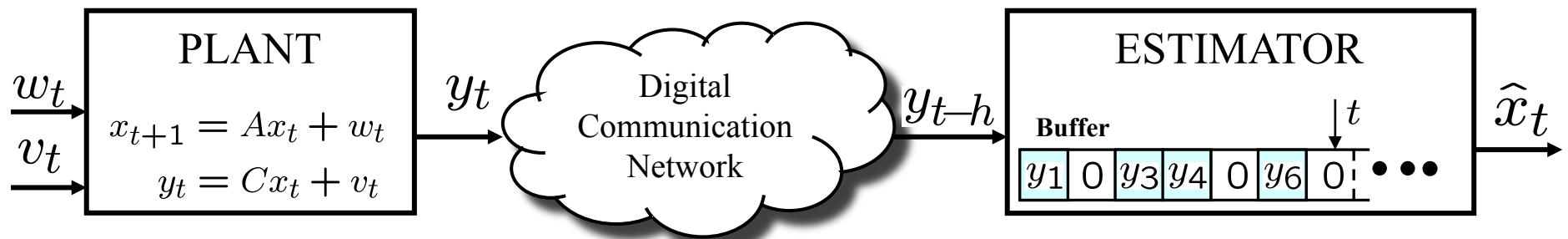
Random delay
 &
 Packet loss
 at receiver

Estimation modeling



Minimum variance estimation

$\hat{x}_t = \mathbb{E}[x_t | \{y_k\}]$ available at estimator at time t]



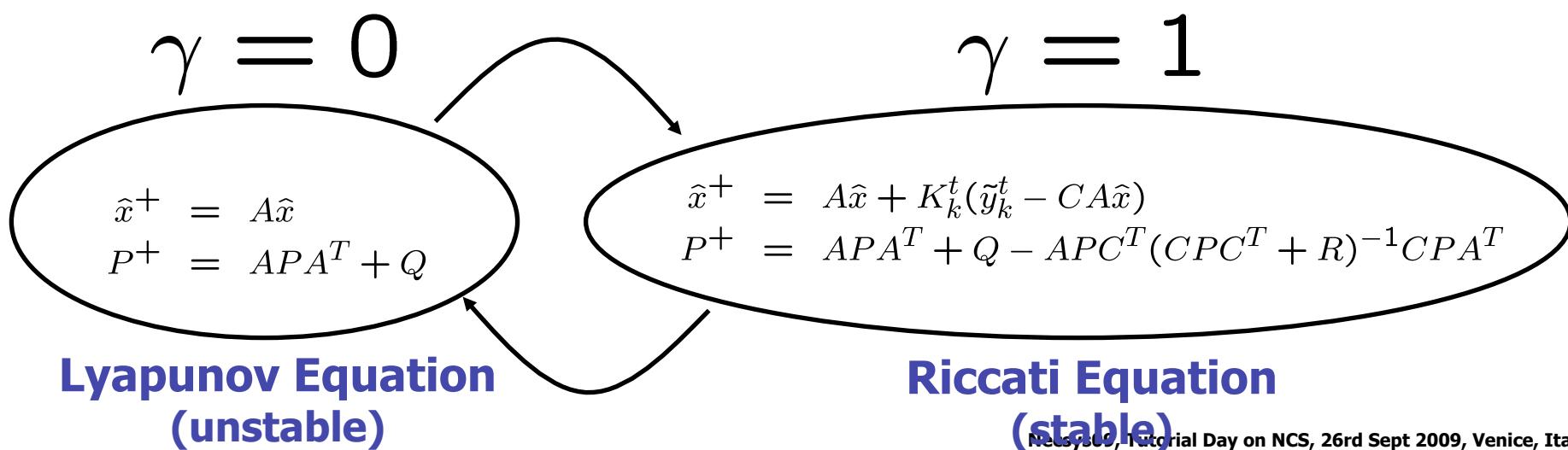
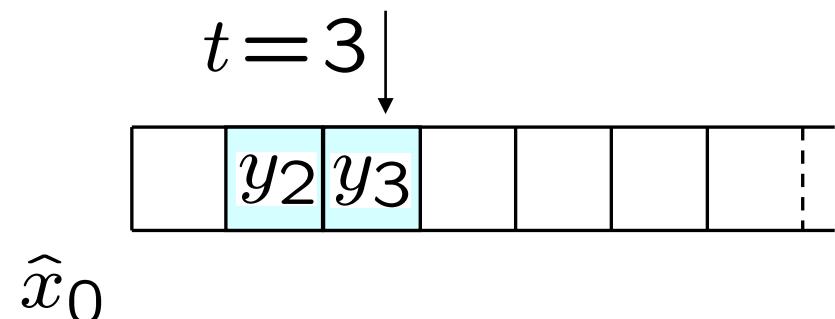
$$\gamma_k^t = \begin{cases} 1 & \text{if } y_k \text{ arrived before or at time } t, \quad t \geq k \\ 0 & \text{otherwise} \end{cases}$$

$$\tilde{y}_k = \gamma_k^t (Cx_k + v_k) = \textcolor{red}{C}_k^t x_k + u^t$$

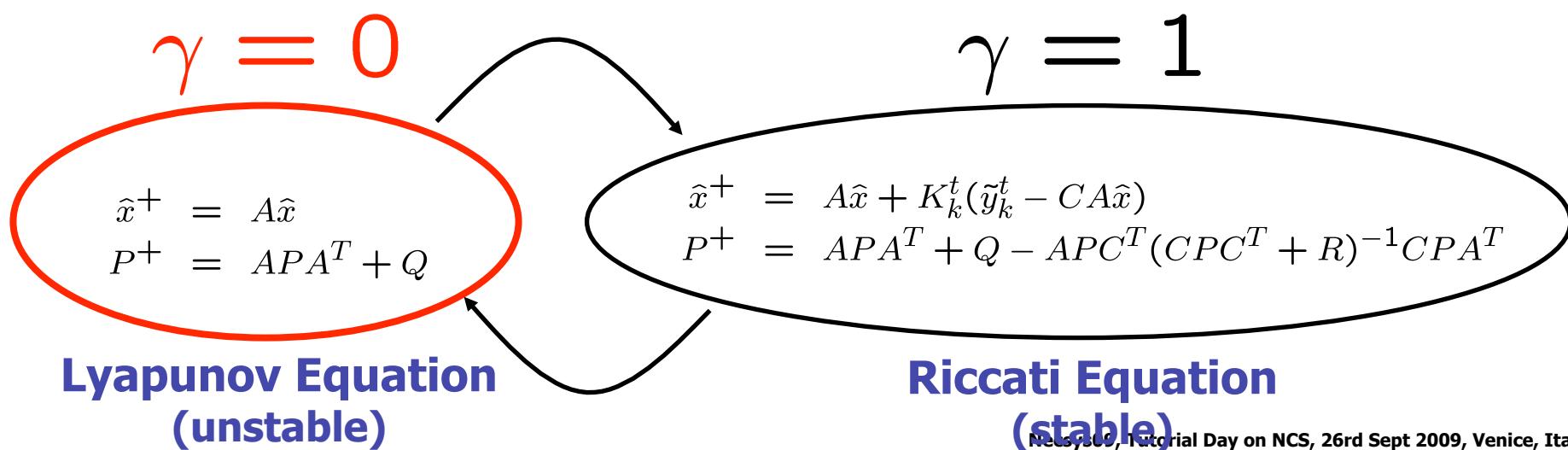
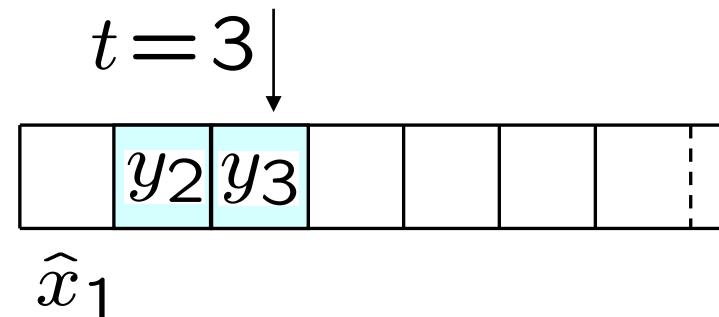
**Kalman
time-varying
linear system**

$$\hat{x}_t = \mathbb{E}[x_t | \tilde{y}_1, \dots, \tilde{y}_t, \gamma_1^t, \dots, \gamma_t^t]$$

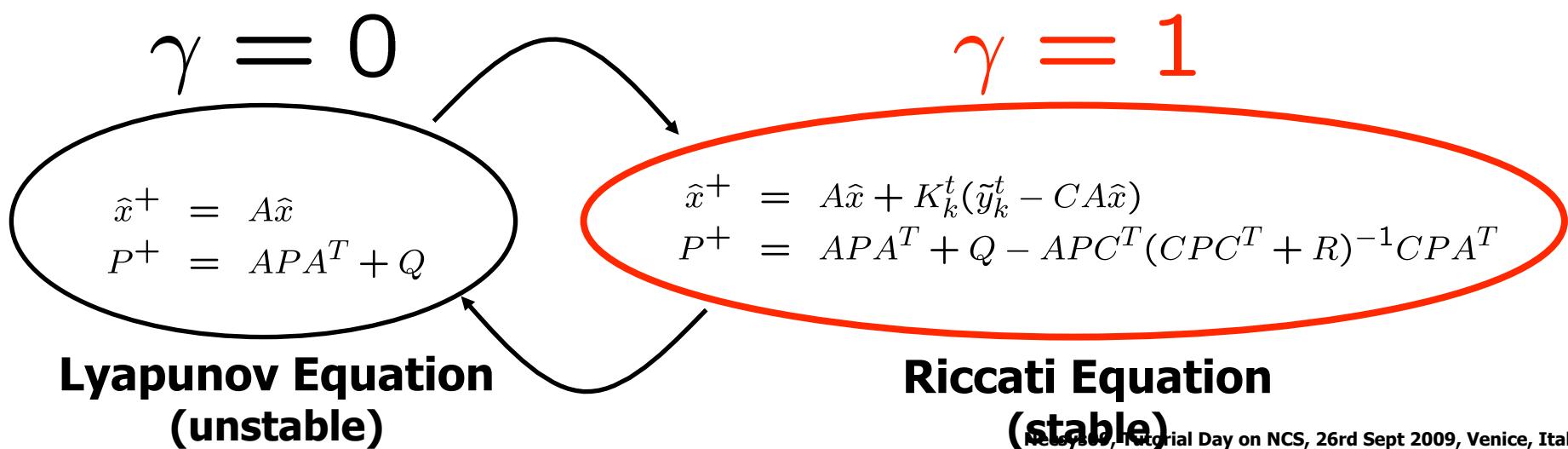
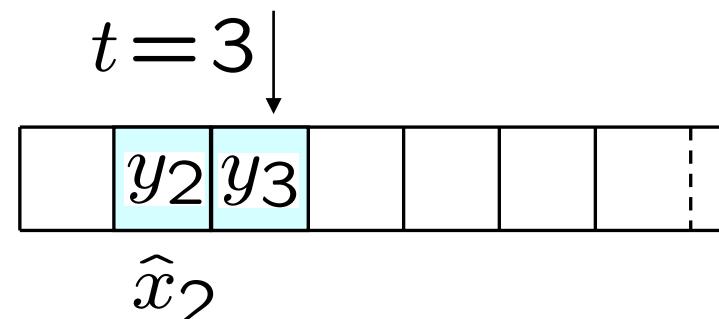
Minimum variance estimation



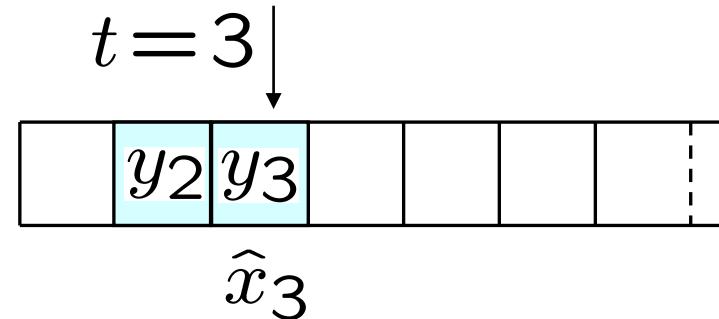
Minimum variance estimation



Minimum variance estimation

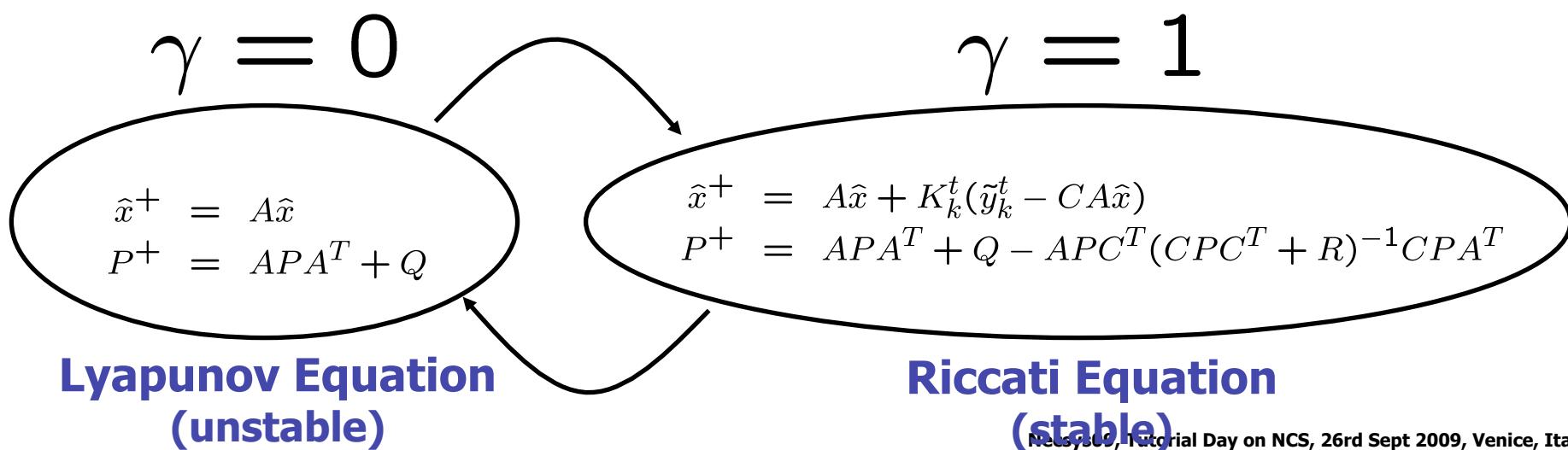
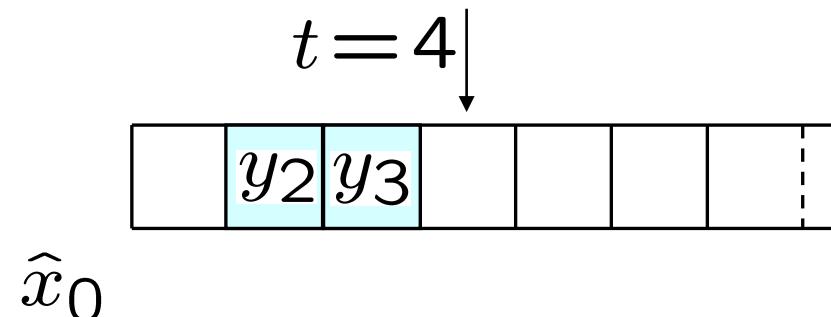


Minimum variance estimation

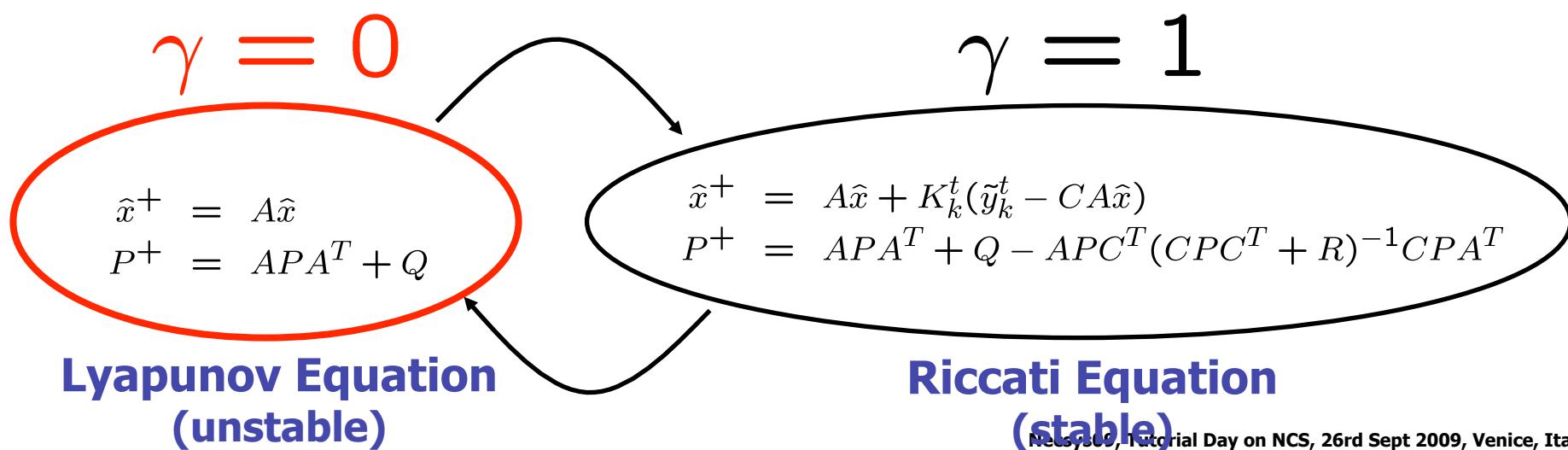
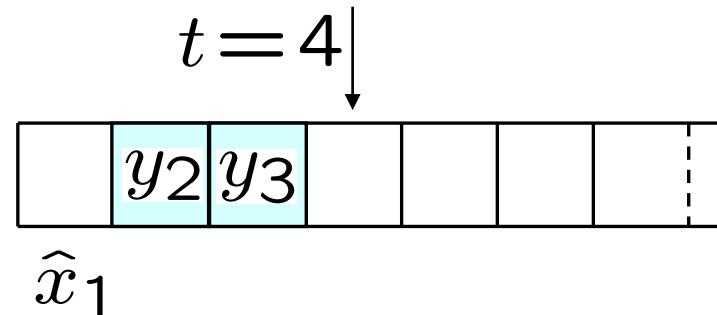


The diagram illustrates the relationship between the Lyapunov Equation and the Riccati Equation. It features two ovals: a black one on the left labeled "Lyapunov Equation (unstable)" containing the equations $\hat{x}^+ = A\hat{x}$ and $P^+ = APA^T + Q$, and a red one on the right labeled "Riccati Equation (stable)" containing the equations $\hat{x}^+ = A\hat{x} + K_k^t(\tilde{y}_k^t - CA\hat{x})$ and $P^+ = APA^T + Q - APC^T(CPC^T + R)^{-1}CPA^T$. Arrows indicate a flow from the Lyapunov oval to the Riccati oval, representing the transformation process.

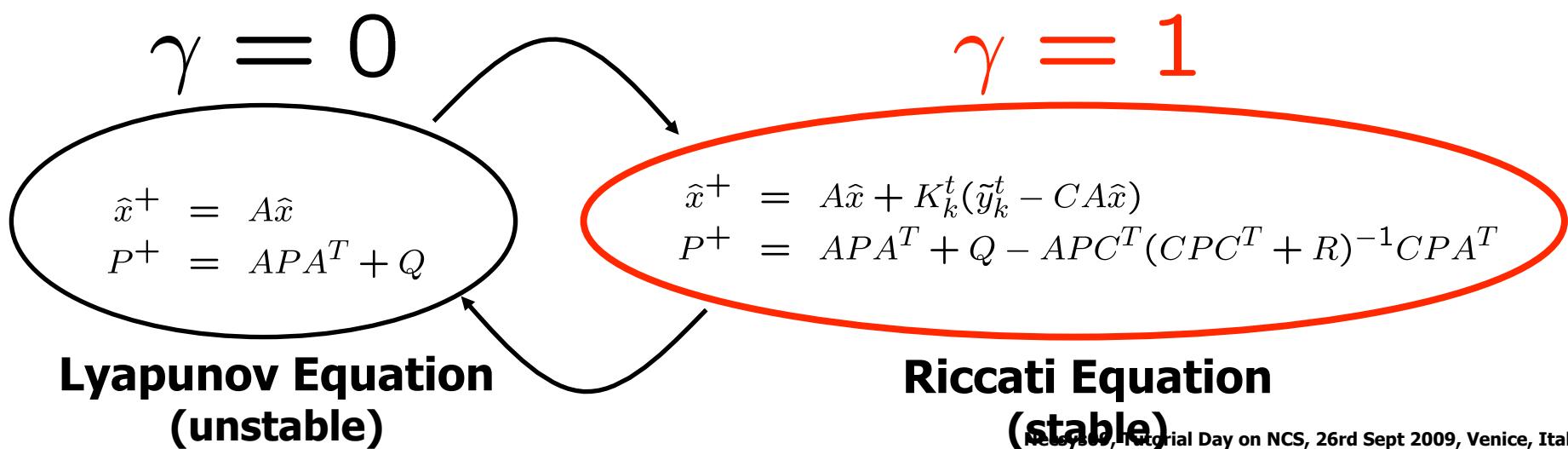
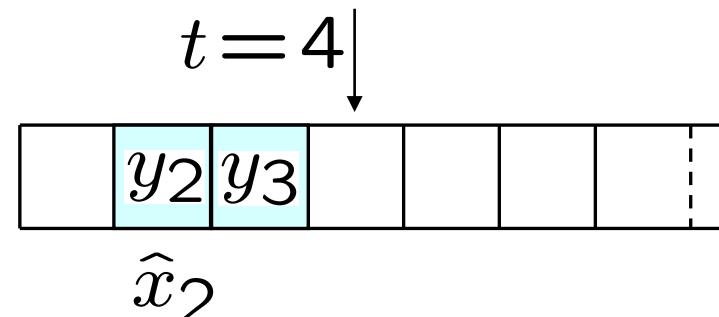
Minimum variance estimation



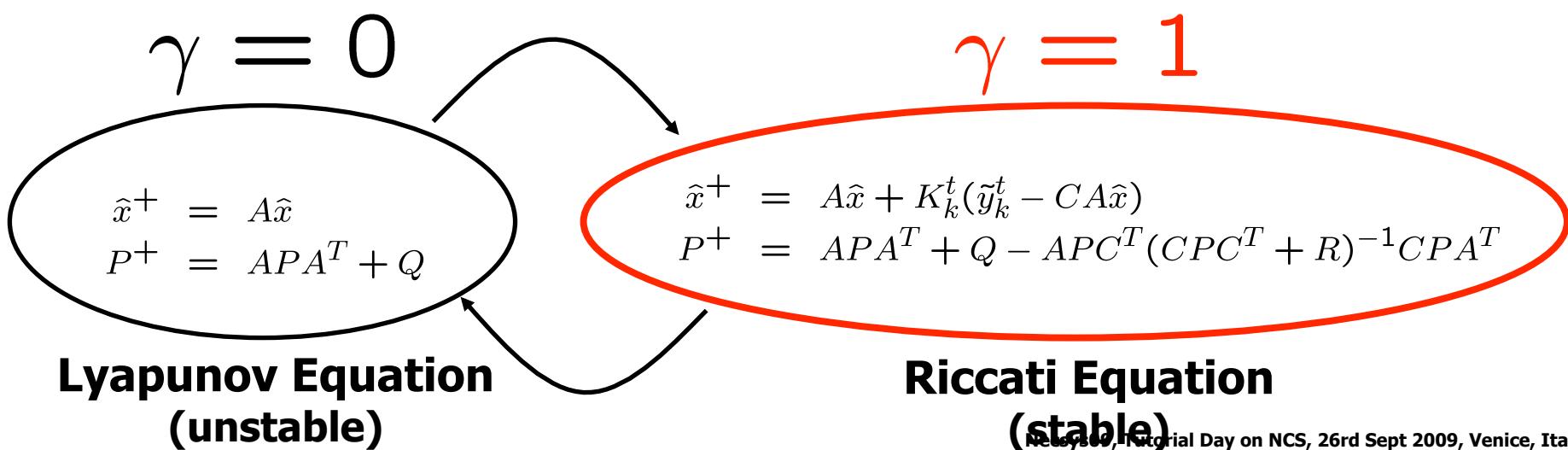
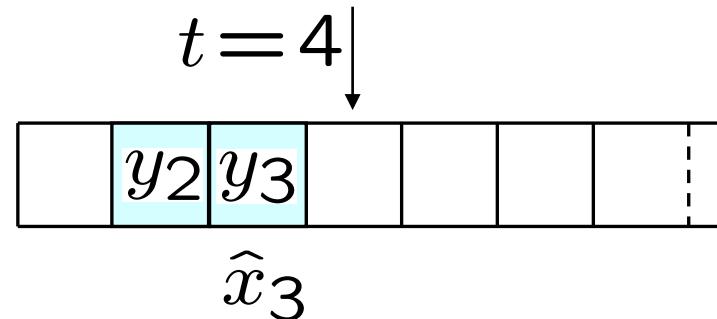
Minimum variance estimation



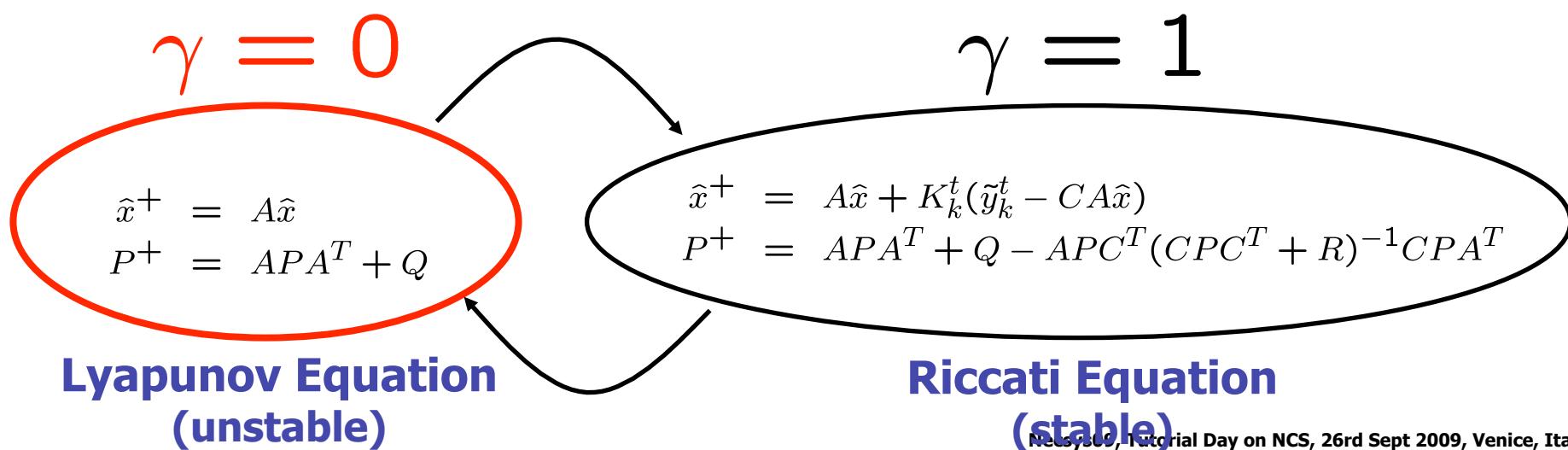
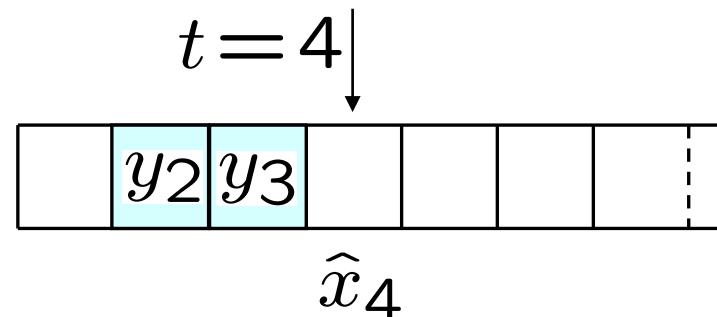
Minimum variance estimation



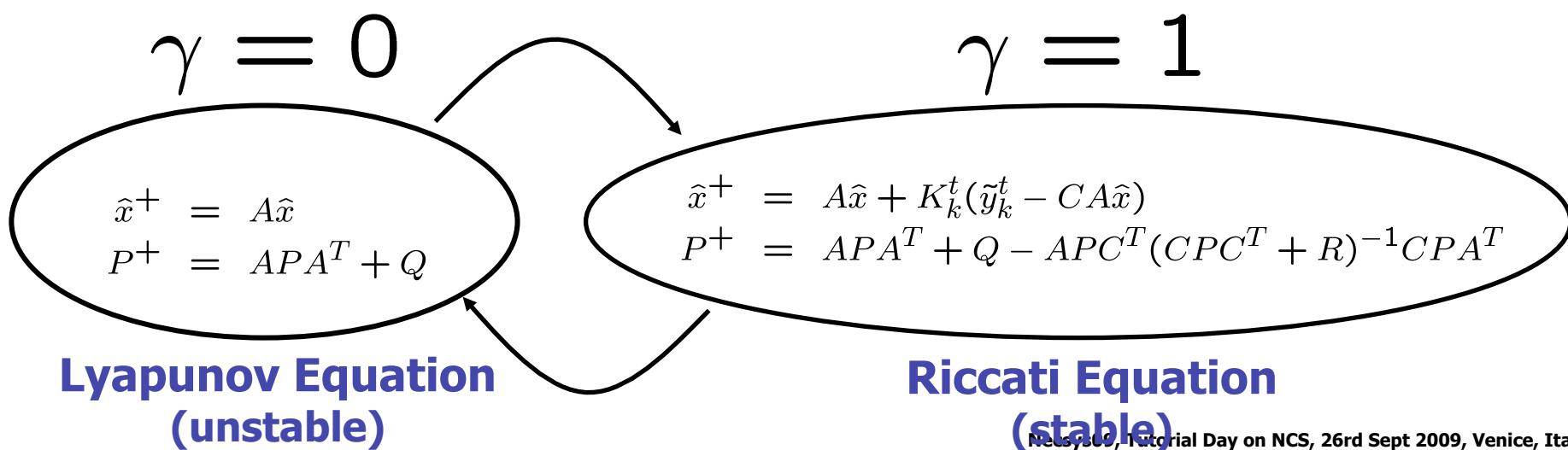
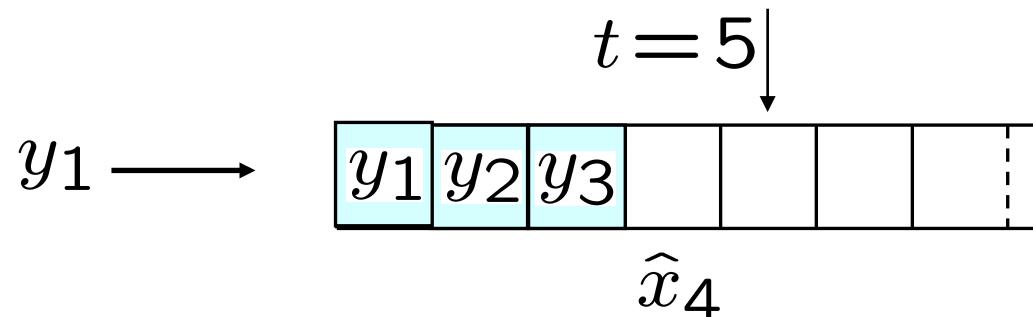
Minimum variance estimation



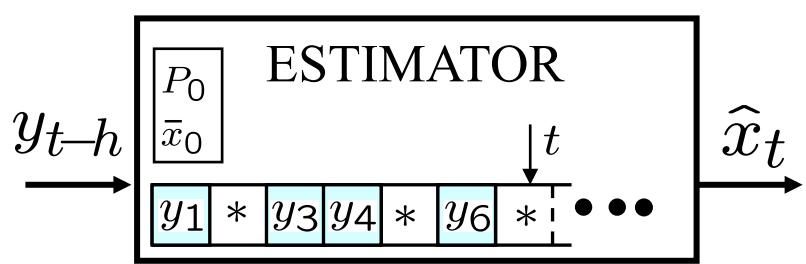
Minimum variance estimation



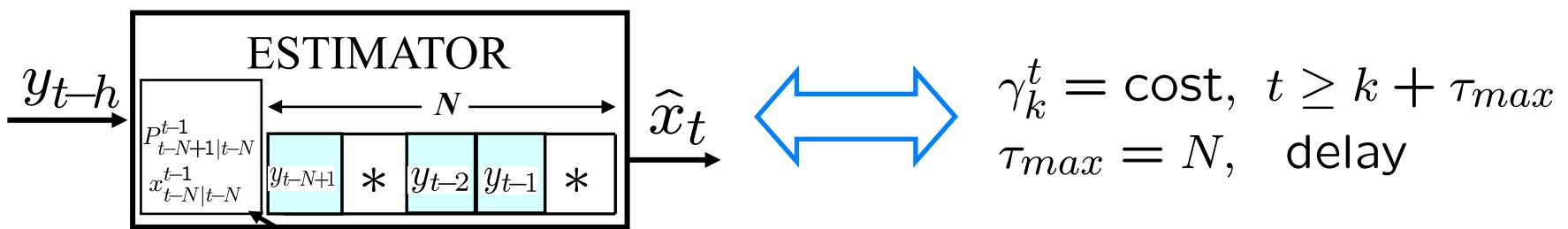
Minimum variance estimation



Properties of Optimal Estimator



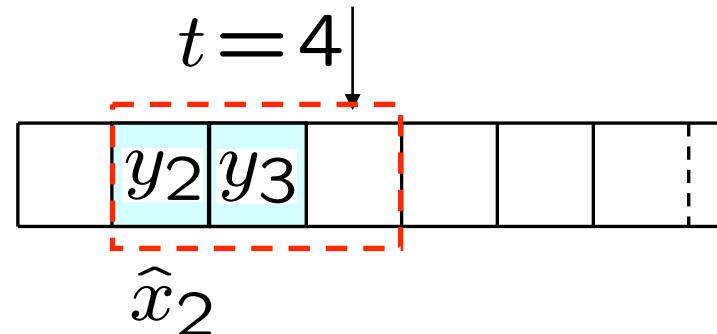
- Optimal for any arrival process
- Stochastic time-varying gain $K_t = K(\gamma_1, \dots, \gamma_t)$
- Stochastic error covariance $P_t = P(\gamma_1, \dots, \gamma_t)$
- Possibly infinite memory buffer
- Inversion of up to t matrices at any time t



$$\begin{aligned}\hat{x}_{t-N|t-N}^{t-1} &\triangleq \hat{x} \\ P_{t-N+1|t-N}^{t-1} &\triangleq P\end{aligned}$$

$$\begin{aligned}\hat{x}^+ &= A\hat{x} + \gamma_{t-N}^t P C^T (C P C^T + R)^{-1} (\tilde{y}_{t-N}^t - C A \hat{x}), \\ P^+ &= A P A^T + Q - \gamma_{t-N}^t A P C^T (C P C^T + R)^{-1} C P A^T\end{aligned}$$

Minimum variance estimation



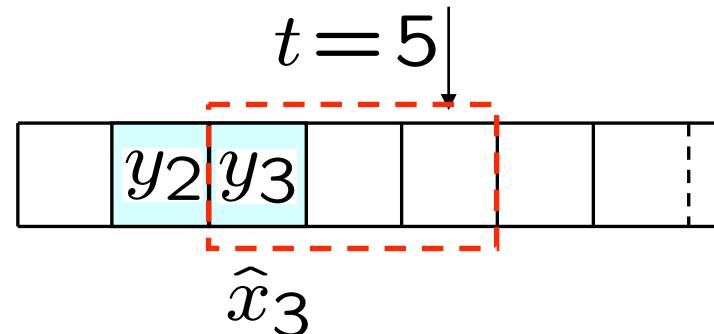
$\gamma = 0$
 $\hat{x}^+ = A\hat{x}$
 $P^+ = APA^T + Q$

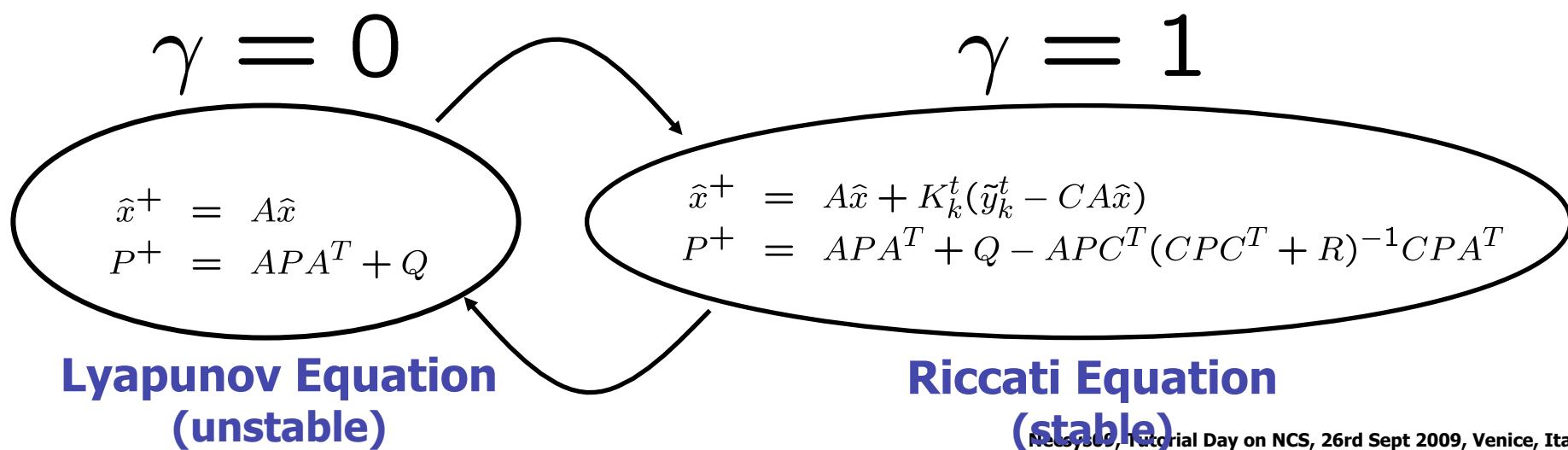
**Lyapunov Equation
(unstable)**

$\gamma = 1$
 $\hat{x}^+ = A\hat{x} + K_k^t(\tilde{y}_k^t - CA\hat{x})$
 $P^+ = APA^T + Q - APC^T(CPC^T + R)^{-1}CPA^T$

**Riccati Equation
(stable)**

Minimum variance estimation





The diagram illustrates the relationship between the Lyapunov and Riccati equations. It shows two ovals: one labeled $\gamma = 0$ containing the Lyapunov equations, and another labeled $\gamma = 1$ containing the Riccati equations. Arrows indicate a flow from the Lyapunov equations towards the Riccati equations.

$\gamma = 0$ $\hat{x}^+ = A\hat{x}$ $P^+ = APA^T + Q$	$\gamma = 1$ $\hat{x}^+ = A\hat{x} + K_k^t(\tilde{y}_k^t - CA\hat{x})$ $P^+ = APA^T + Q - APC^T(CPC^T + R)^{-1}CPA^T$
---	---

Lyapunov Equation (unstable)

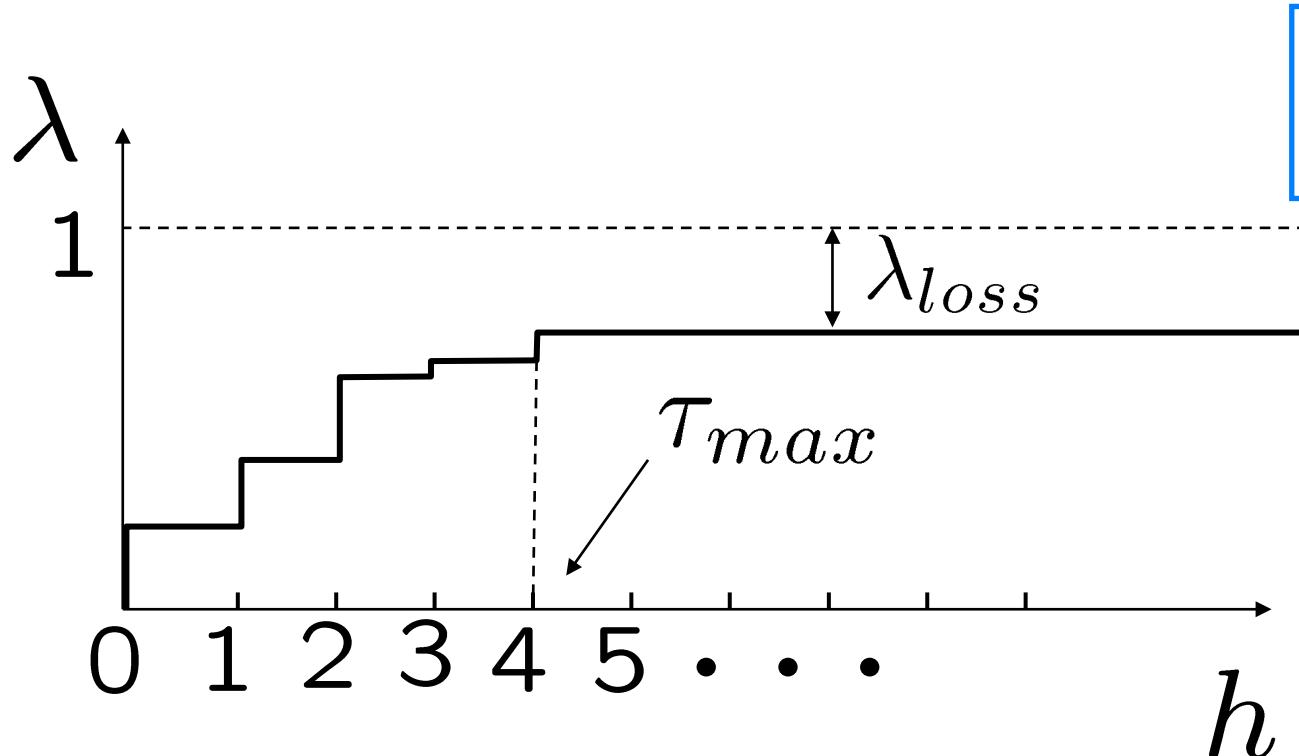
Riccati Equation (stable)

What about stability and performance?

Additional assumption on arrival sequence necessary:

i.i.d. arrival with stationary distribution

τ_k : delay of packet y_k , $\tau_k = \infty$ if y_k never arrives

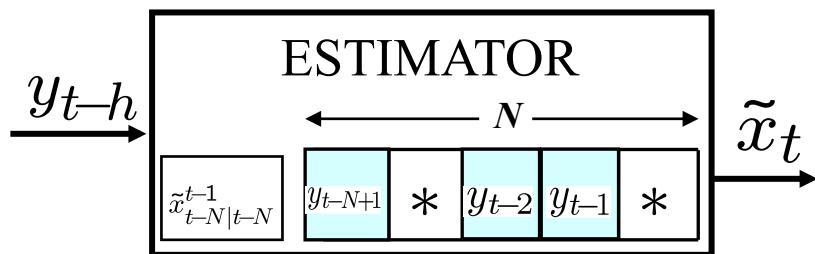


$$\begin{aligned}\lambda_h &\triangleq \mathbb{P}[\tau_k \leq h], \\ \lambda_{loss} &\triangleq \mathbb{P}[\tau_k = \infty]\end{aligned}$$

Optimal estimation with constant gains and buffer finite memory

$\{K_h\}_{h=0}^{N-1}$, N static gains

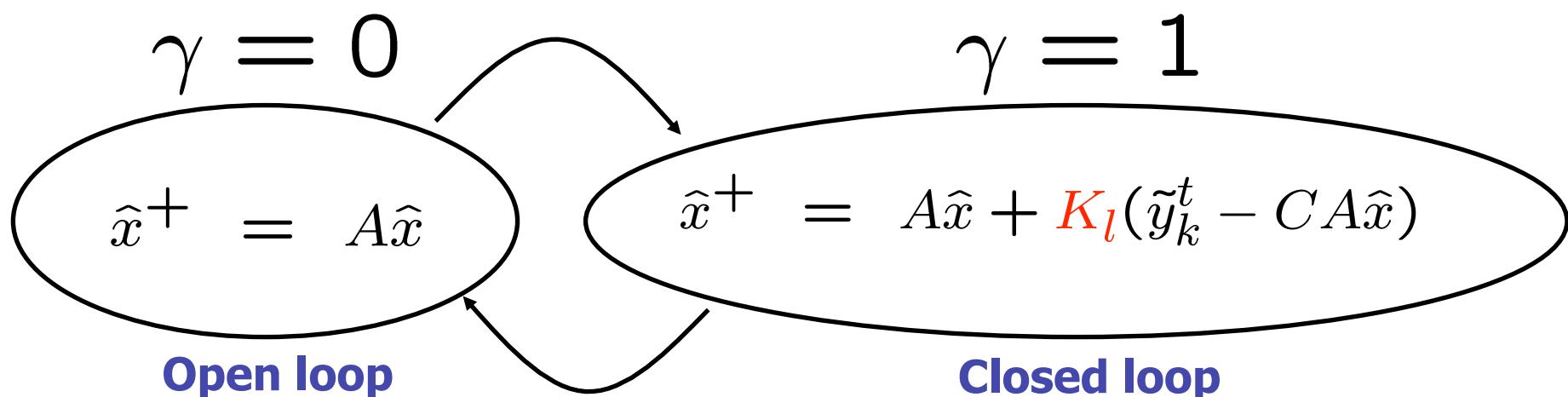
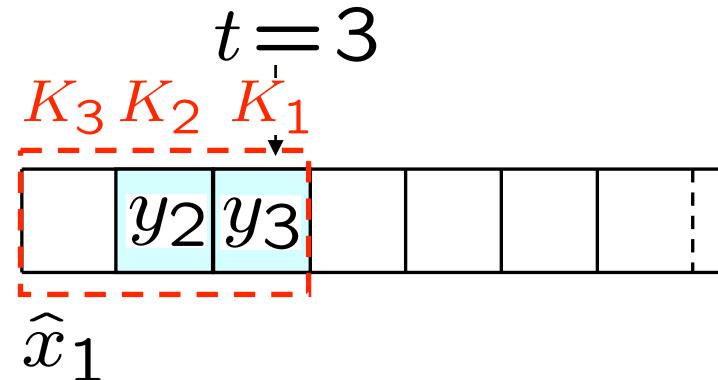
$$\tilde{x}^+ = A\tilde{x} + \gamma_{t-h}^t K_h (\tilde{y}_{t-h}^t - CA\tilde{x}), \quad h = N-1, \dots, 0$$



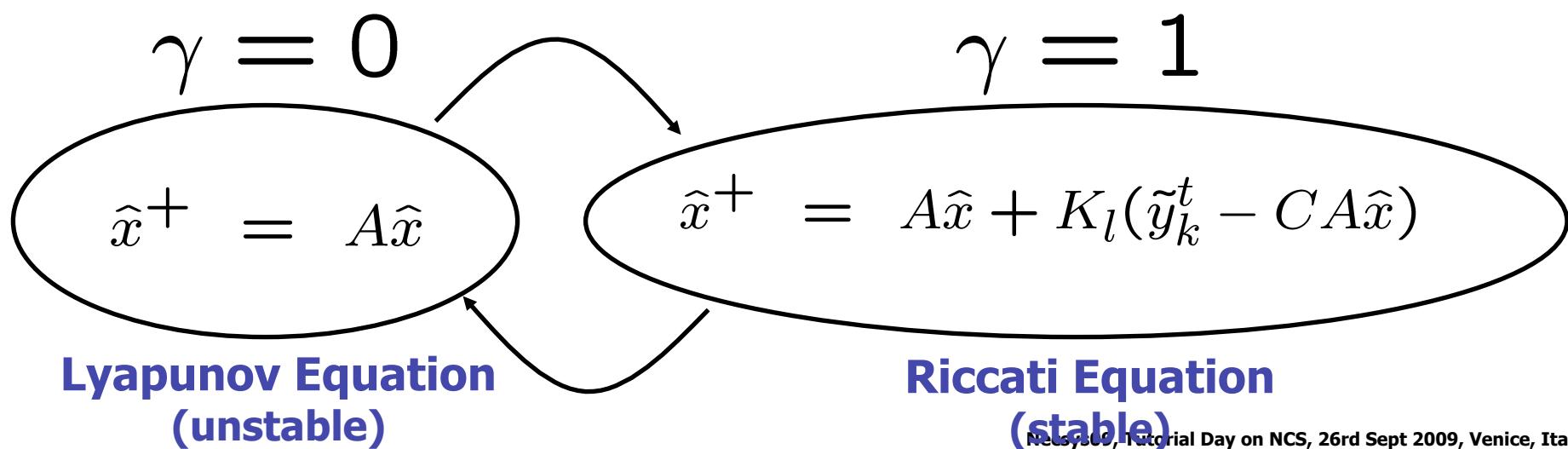
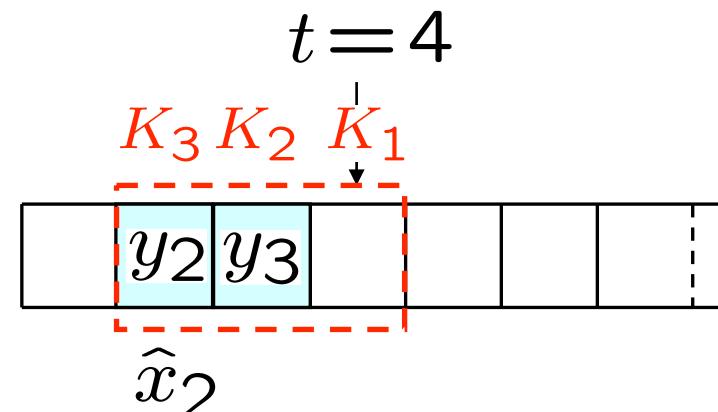
- Does not require any matrix inversion
- Simple to implement
- Upper bound for optimal estimator: $P_t \leq \tilde{P}_{t|t} \implies \mathbb{E}_\gamma[P_{t|t}] \leq \mathbb{E}_\gamma[\tilde{P}_{t|t}] = \bar{P}_{t|t}$
- N is design parameter

GOAL: compute $\bar{P}_{t|t}$

Suboptimal minimum variance estimation



Suboptimal minimum variance estimation



Steady state estimation error

Fixed gains:

$$\mathcal{L}_\lambda(K, P) = \lambda A(I - KC)P(I - KC)^T A^T + (1 - \lambda)APA^T + Q + \lambda AKRK^T A^T$$

$$\begin{aligned}\overline{P} &= \mathcal{L}_{\lambda_{N-1}}(K_{N-1}, \overline{P}) \\ \overline{P}^+ &= \mathcal{L}_{\lambda_k}(K_k, \overline{P}), \quad k = N-2, \dots, 0\end{aligned}$$

$$\lim_{t \rightarrow \infty} \overline{P}_{t|t} = \overline{P}$$

Optimal fixed gains:

$$\Phi_\lambda(P) = APA^T + Q - \lambda APC^T(CPC^T + R)^{-1}CPA^T$$

Modified Algebraic
Riccati Equation (MARE)
($\Phi_1(P)$ =ARE)

$$\min_{K_0, \dots, K_{N-1}} \overline{P} \quad \xrightarrow{\hspace{1cm}}$$

$$\begin{aligned}\overline{P}_{N-1} &= \Phi_{\lambda_{N-1}}(\overline{P}_{N-1}) \\ \overline{P}_k &= \Phi_{\lambda_k}(\overline{P}_{k+1}), \quad k = N-2, \dots, 0 \\ K_k &= \overline{P}_k C^T (C \overline{P}_k C^T + R)^{-1}\end{aligned}$$

(off-line computation)

Stability issues

Static estimator is stable iff there exists $P \geq 0$ such that:

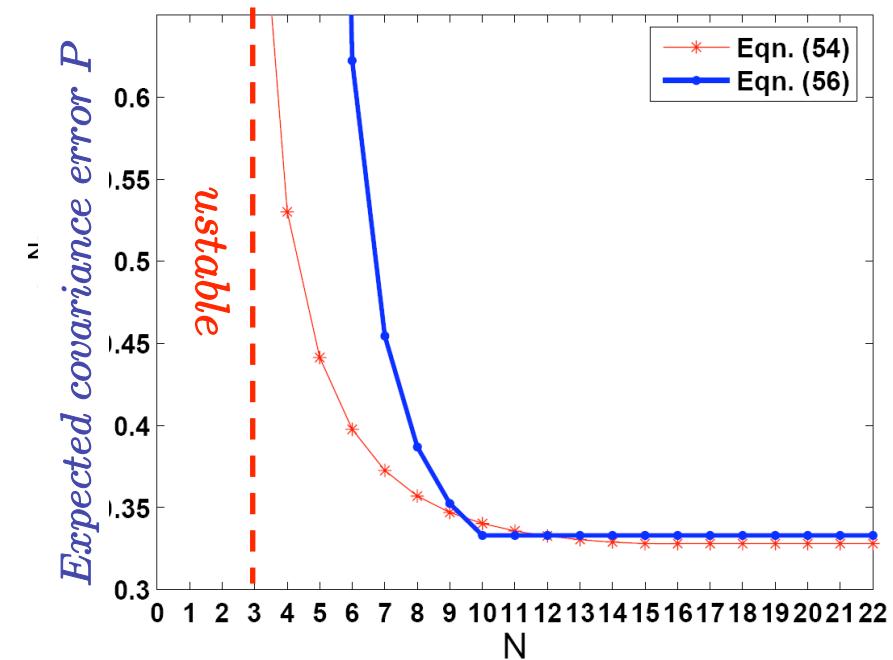
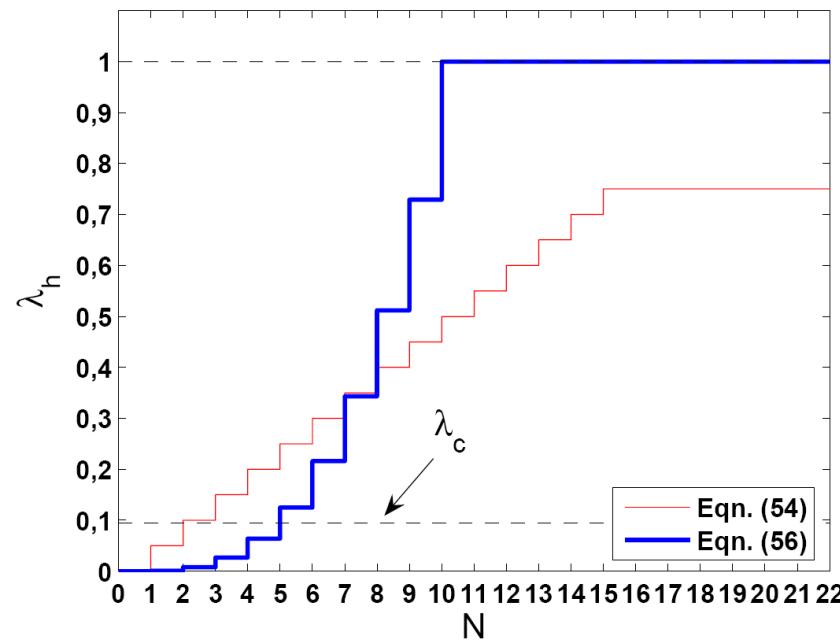
$$P = APA^T + Q - (1 - \lambda) APC^T(CPC^T + R)^{-1}CPA^T$$

- If $\lambda = 0$ then standard ARE
- Modified Riccati Algebraic Equation known since [Nahi TIF'69]
- If A is unstable then there exist critical probability: if $\lambda < \lambda_c$ stable, if $\lambda > \lambda_c$ unstable
- Upper bound $\lambda_c \leq \frac{1}{\max |\text{eig}(A)|^2}$. Equality if C invertible [Katayama TAC"76]
- Lower bound $\lambda_c \geq \frac{1}{\prod_{unstable} |\text{eig}(A)|^2}$. Equality if $\text{rank}(C) = 1$ [Elia TAC'01, SCL'05]
- Closed form expression for λ_c not known for general (A, C)

Numerical example (I)

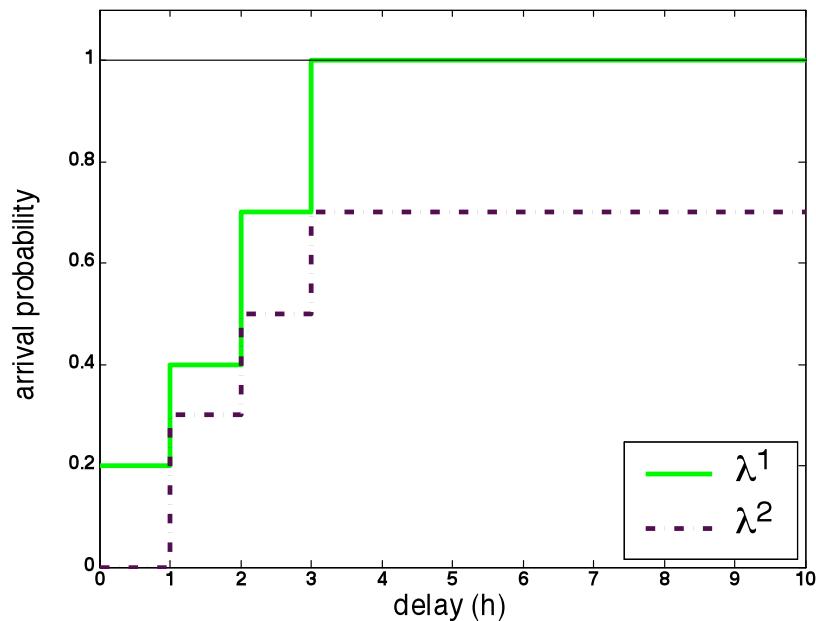
Discrete time linearized inverted pendulum:

$$A = \begin{bmatrix} 1.01 & 0.05 \\ 0.05 & 1.01 \end{bmatrix}, \quad C = [1 \ 0], \quad R = 1, \quad Q = \begin{bmatrix} 0.01 & 0.01 \\ 0.01 & 1 \end{bmatrix}$$

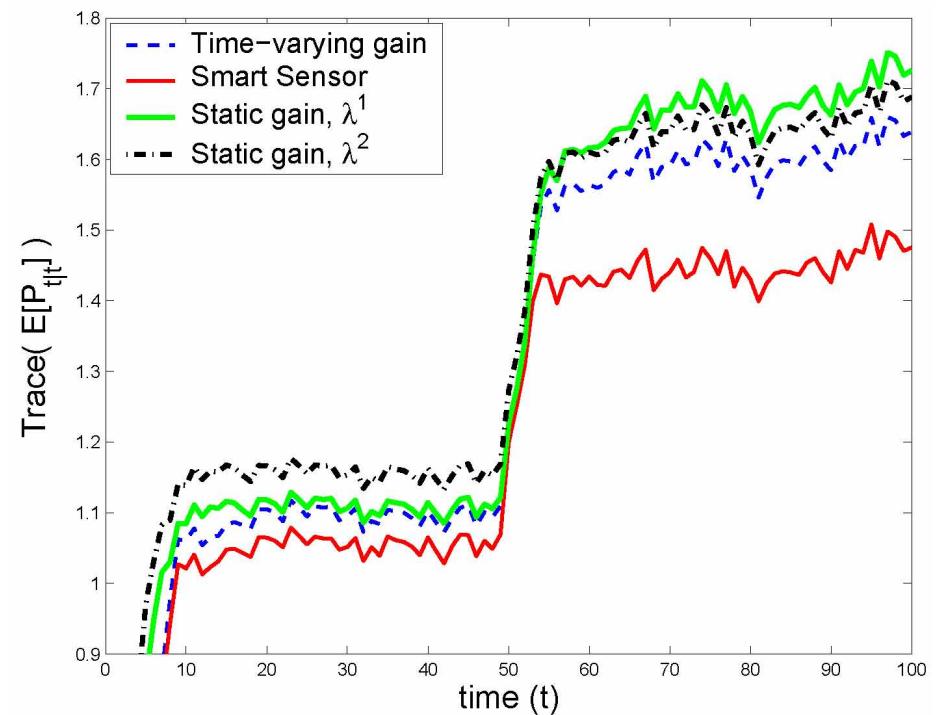


Numerical example (II)

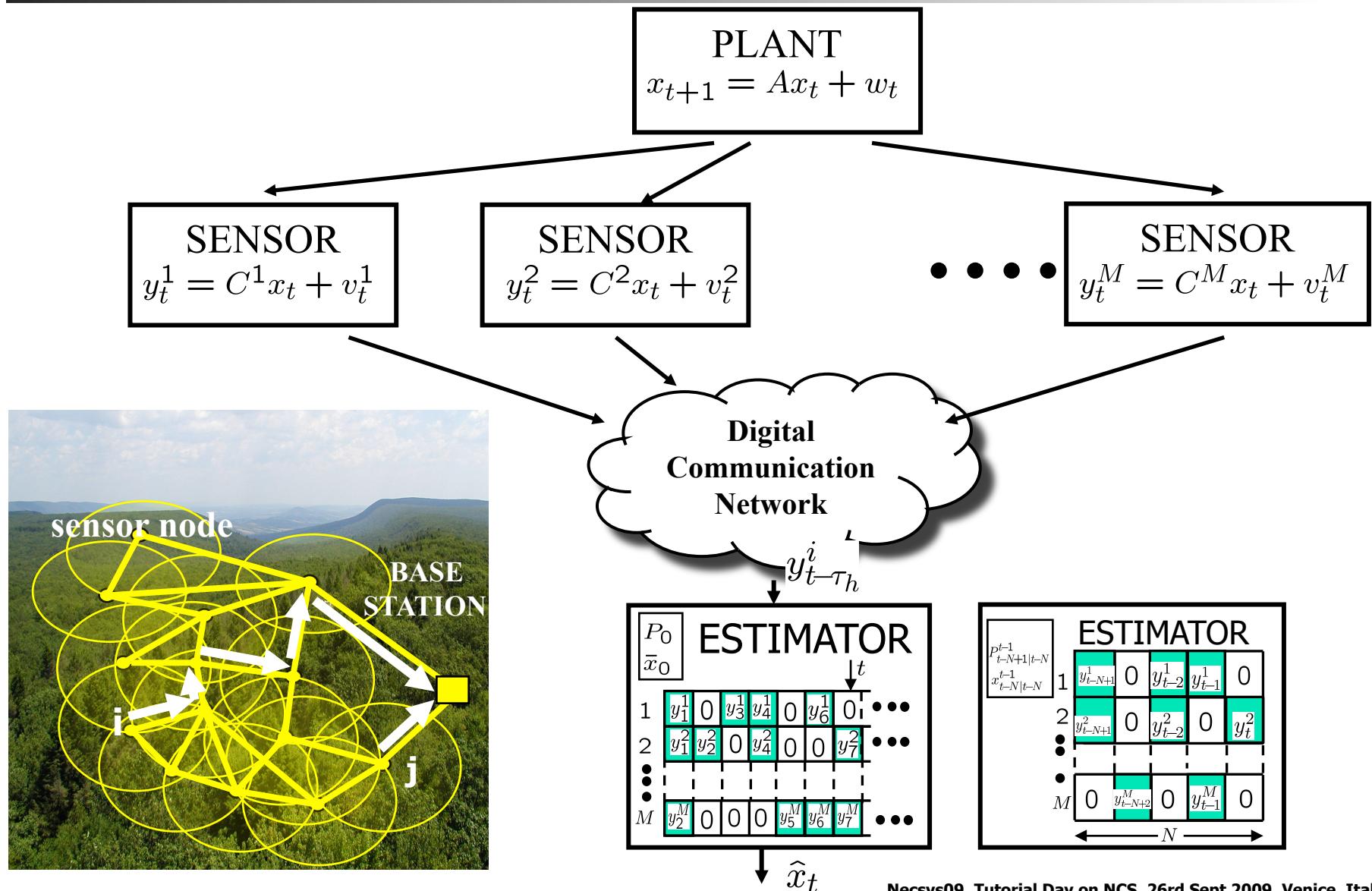
Time-varying arrival probability distribution



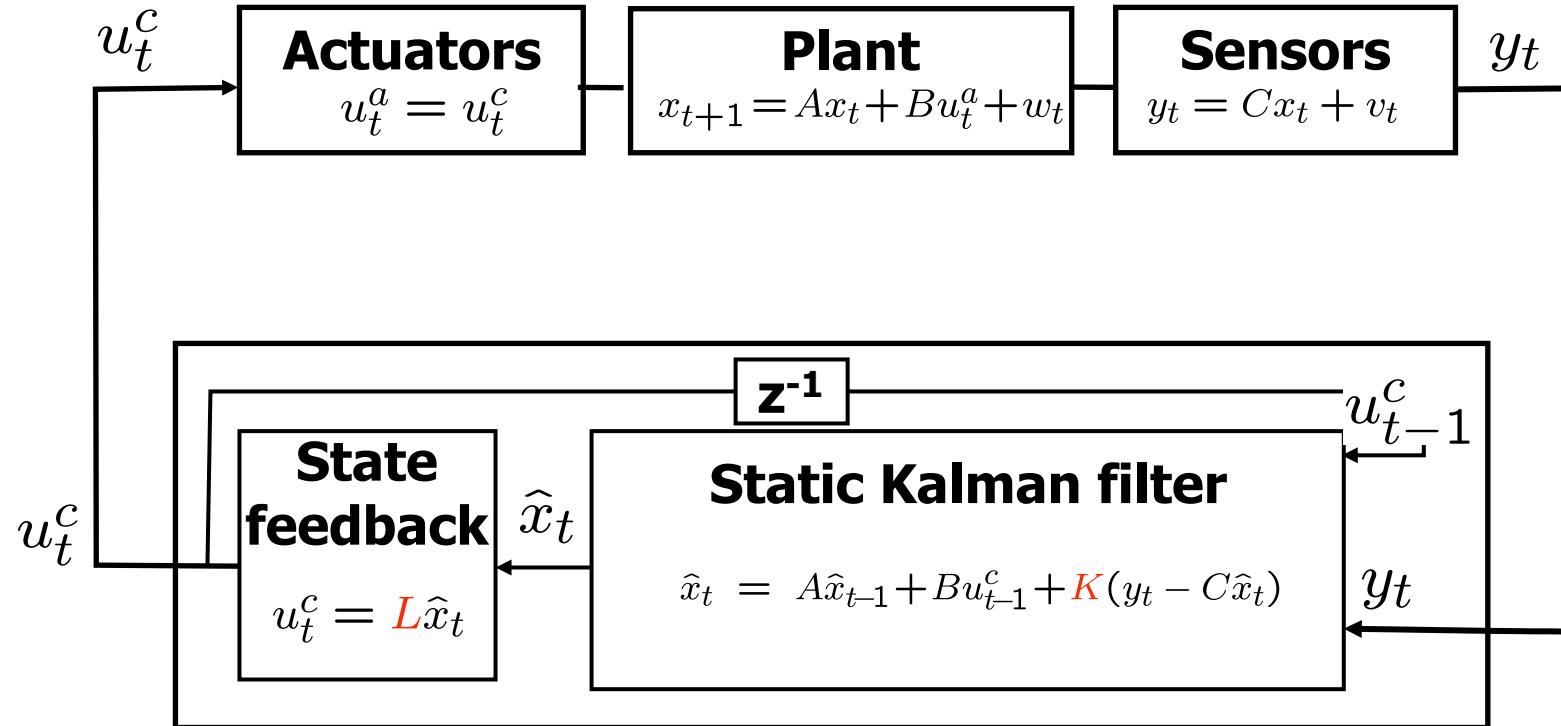
$$\begin{aligned} \lambda^1 & \quad 0 \leq t \leq 50 \\ \lambda^2 & \quad t > 50 \end{aligned}$$



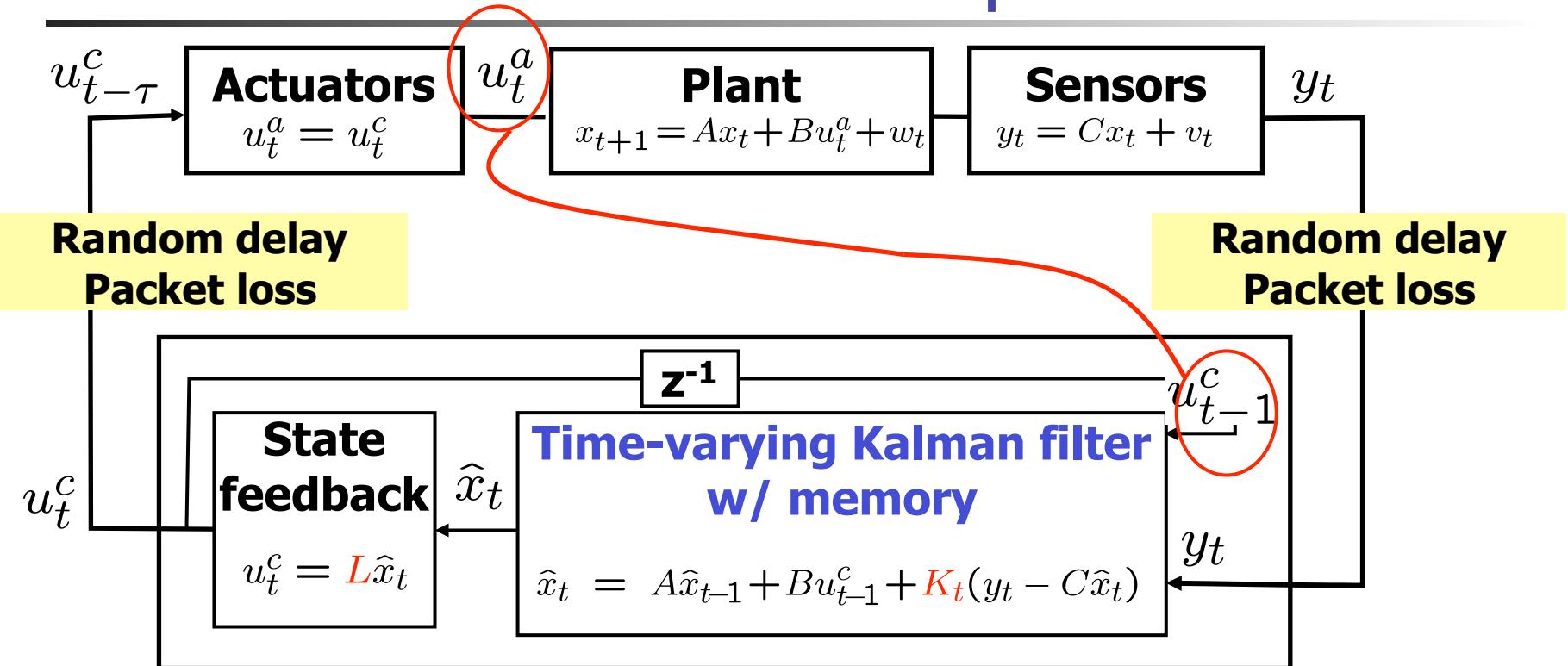
Multiple sensors



Back to the control problem



Back to the control problem



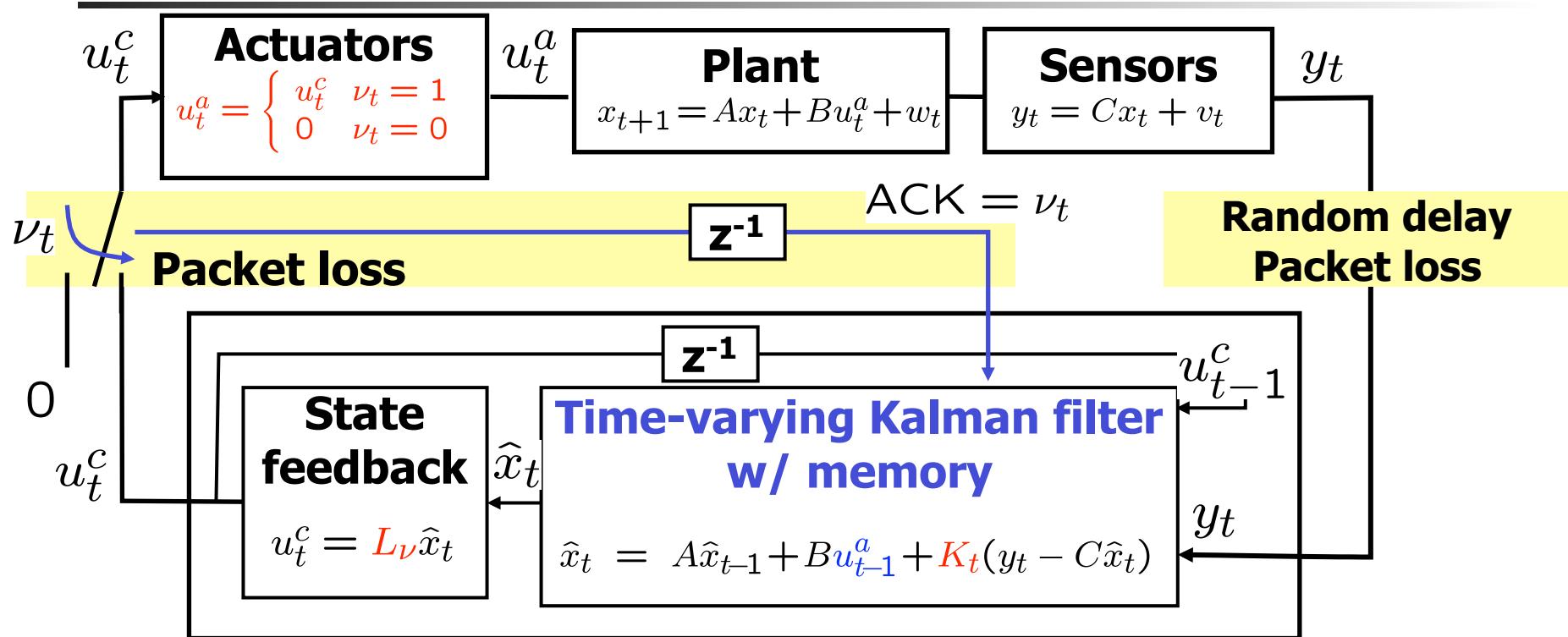
$$\hat{x}_t = E[x_t | y_t, y_{t-1}, \dots, y_0, u_{t-1}^a, \dots, u_1^a]$$

$$\text{if } u_{t-1}^c \neq u_{t-1}^a \implies e_t = x_t - \hat{x}_t = f(y_t, \dots, y_0, u_t^c, \dots, u_0^c, u_t^a, \dots, u_0^a)$$

$$P_{t|t-1} = AP_{t-1|t-1}A^T + Q + B(u_{t-1}^a - u_{t-1}^c)(u_{t-1}^a - u_{t-1}^c)^T B^T$$

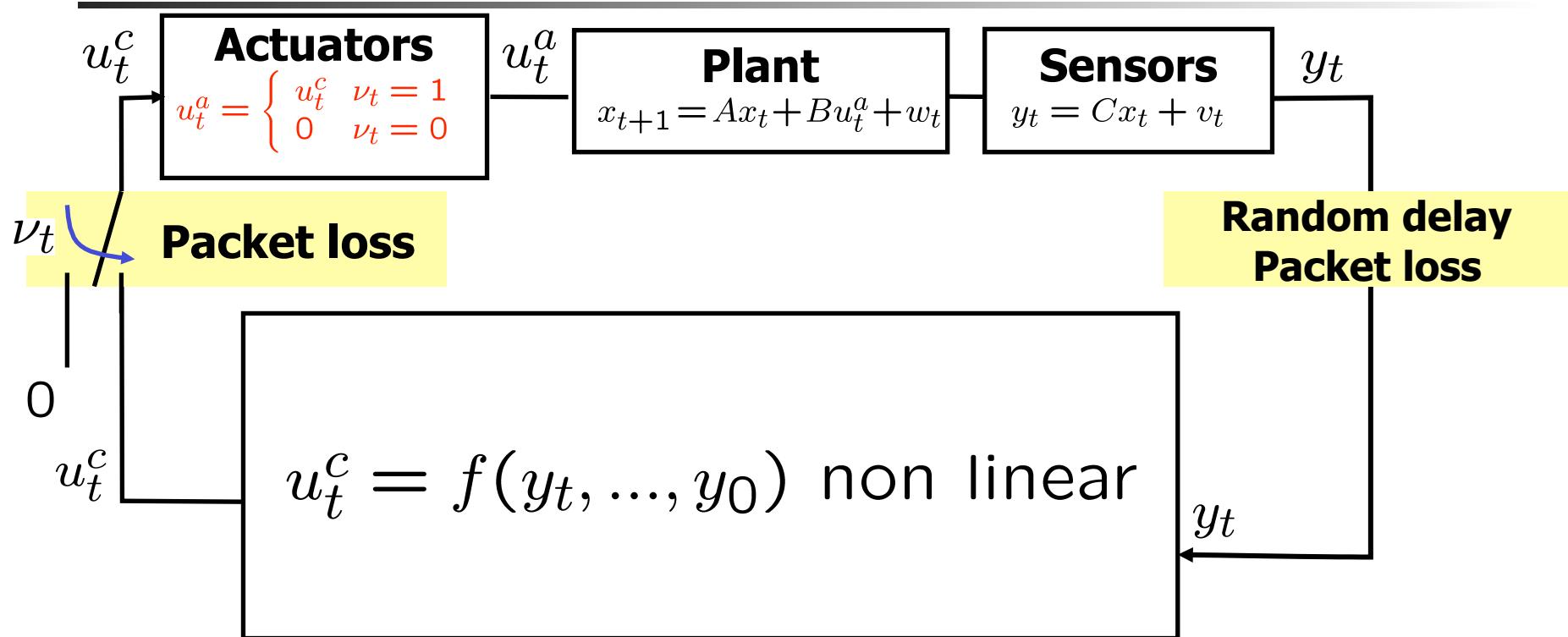
Estimation error coupled with control action → no separation principle

LQG over TCP-like (ACK-based) protocols



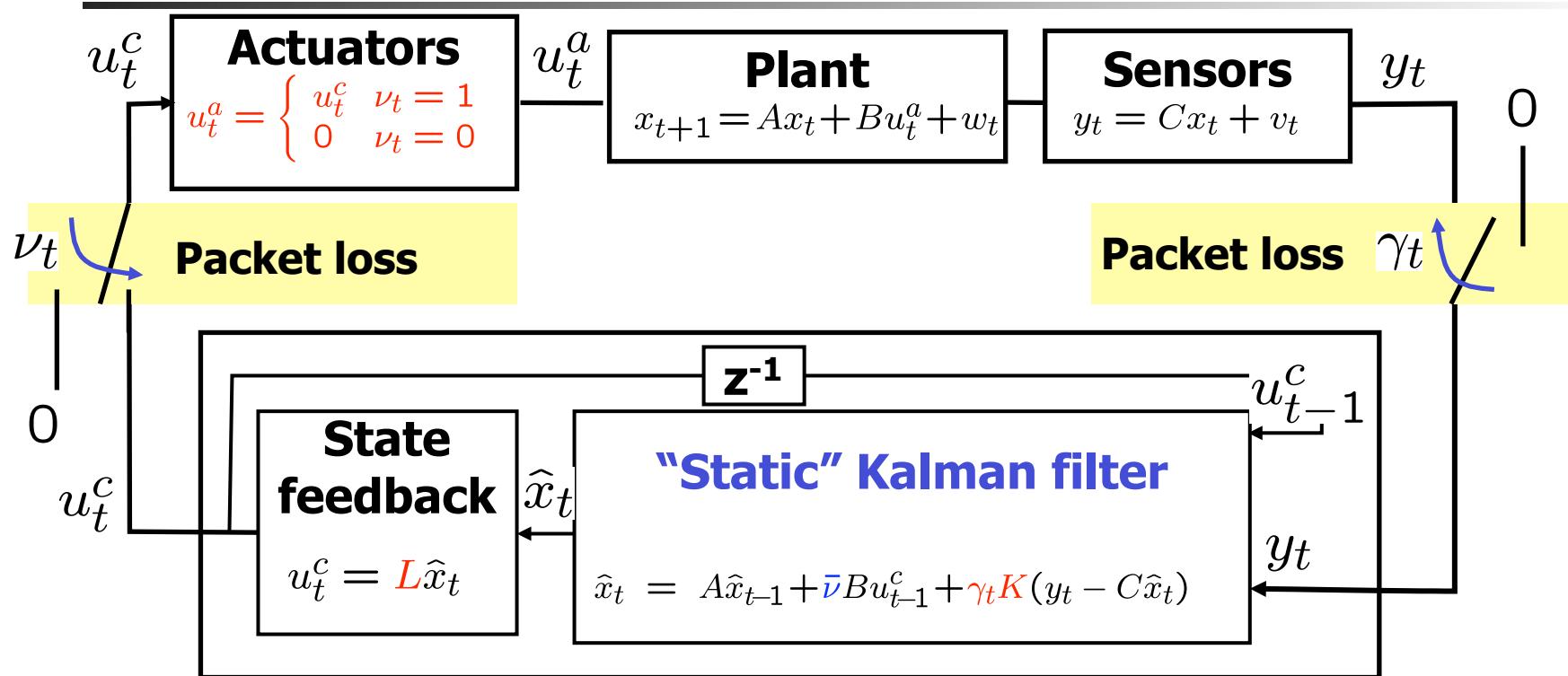
- Separation principle hold (I know exactly u_{t-1}^a)
- ν_t Bernoulli rand. var and independent of observation arrival process
- Static state feedback, L_ν solution of dual MARE

LQG over UDP-like (no-ACK) protocols



- LQG problem still well defined: $\min_{u_t^c, \dots, u_1^c} E[\sum_{h=1}^t x_t^T W x_t + (u_t^a)^T U u_t^a]$
- No separation principle hold (u_{t-1}^a NOT known exactly)
- ... but still have some statistical information about u_{t-1}^a

LQG over UDP-like (no-ACK) protocols

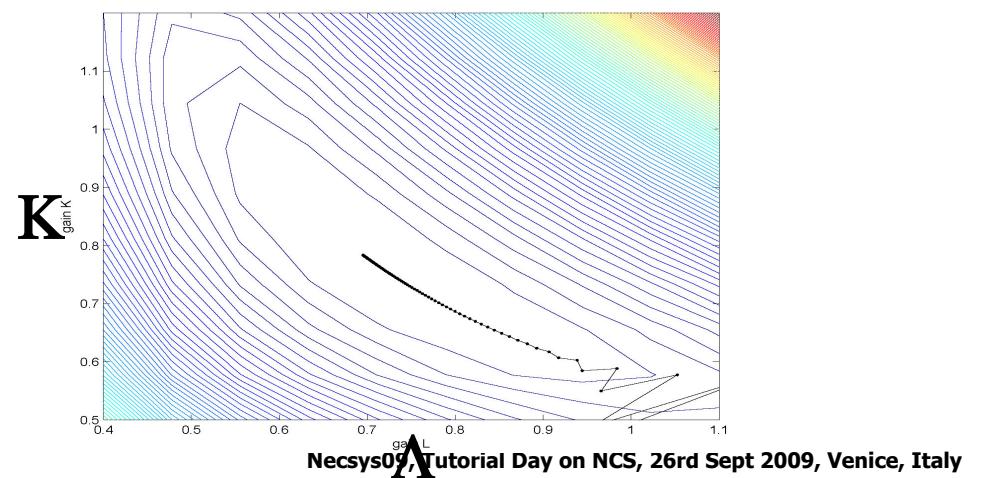
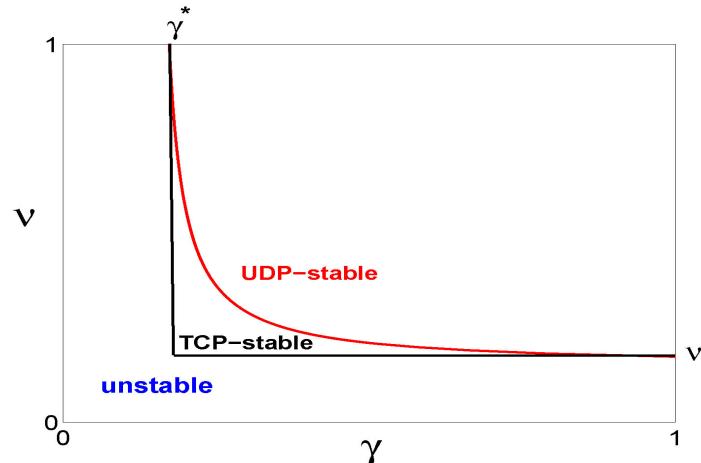


- Bernoulli arrival process $P[\nu_t = 1] = \bar{\nu}, P[\gamma_t = 1] = \bar{\gamma}$
- $\bar{\nu}u_{t-1}^c = E[u_{t-1}^a]$
- Sub-optimal controller forced to be state estimator+state feedback
- Optimal choice of K, L is unique solution of 4 coupled Riccati-like equations

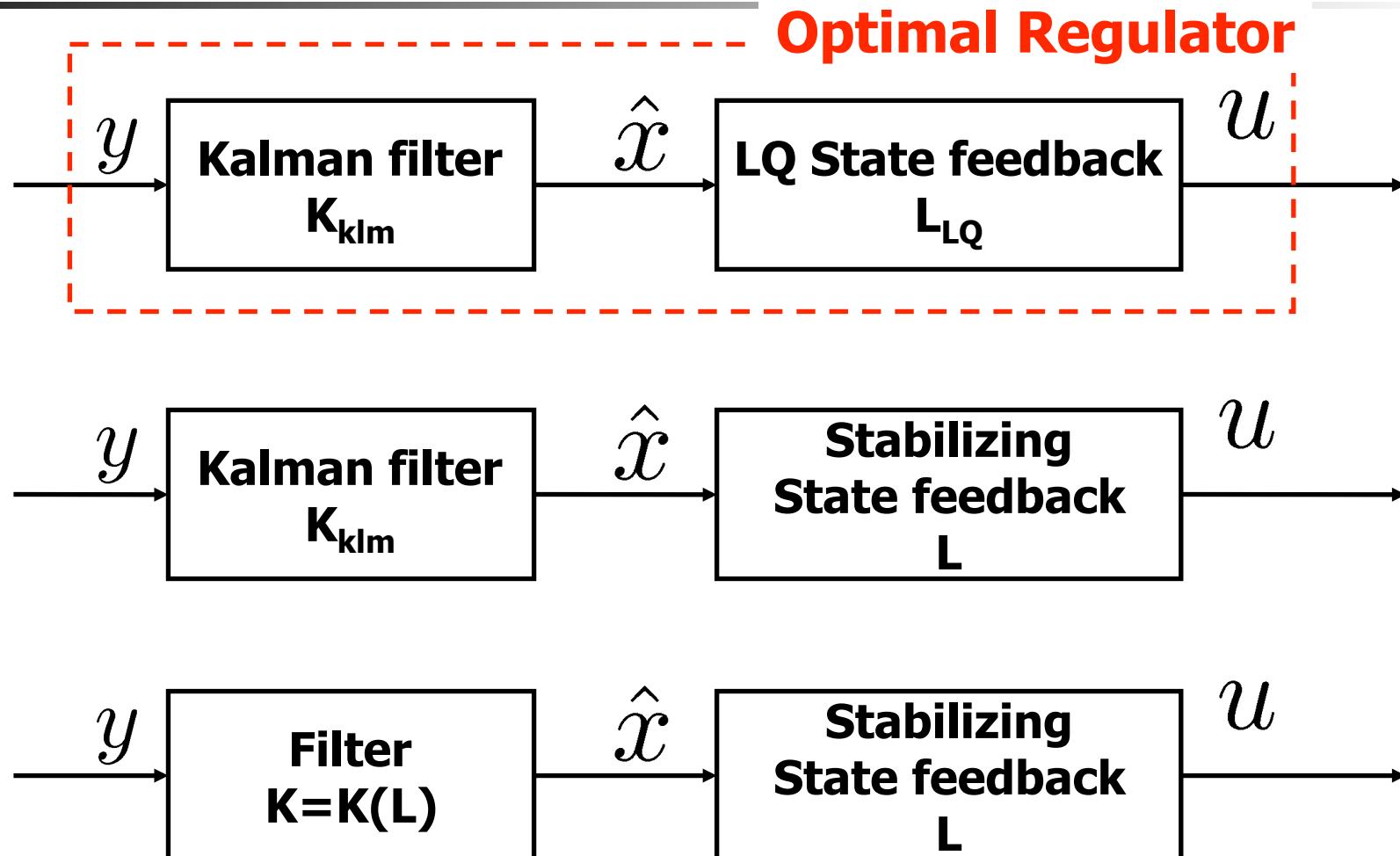
LQG as optimization problem

$$\begin{aligned}
 \text{Min}_{K,L} \quad & \text{Trace} \left(\begin{bmatrix} W & 0 \\ 0 & \bar{\nu} L^T U L \end{bmatrix} P \right) \quad P \triangleq \mathbb{E} \left[\begin{bmatrix} x \\ \hat{x} \end{bmatrix} [x^T \ \hat{x}^T] \right] = \begin{bmatrix} P_{11} & P_{12} \\ P_{12}^T & P_{22} \end{bmatrix} \\
 \text{s.t.} \quad & P = \mathbb{E} \left[\begin{bmatrix} A & -\nu_k BL \\ \gamma_k KC & A - \bar{\nu} BL - \gamma_k KC \end{bmatrix} P \begin{bmatrix} A & -\nu_k BL \\ \gamma_k KC & A - \bar{\nu} BL - \gamma_k KC \end{bmatrix}^T \right] + \begin{bmatrix} Q & 0 \\ 0 & \bar{\gamma} K R K^T \end{bmatrix} \\
 & P \geq 0
 \end{aligned}$$

- Non convex problem even for $\nu=\gamma=1$, i.e. classic LQG
- Classic and TCP-based LQG become convex when exploiting optimality conditions like uncorrelation between estimate and error estimate $\mathbb{E}[x(x - \hat{x})^T] = 0$
- For UDP-like problem non convex but unique solution using Homotopy and Degree Theory (DeKoning,Athans,Bernstain) (maybe using Sum-of-Squares?)
- Stability on ν and γ is coupled



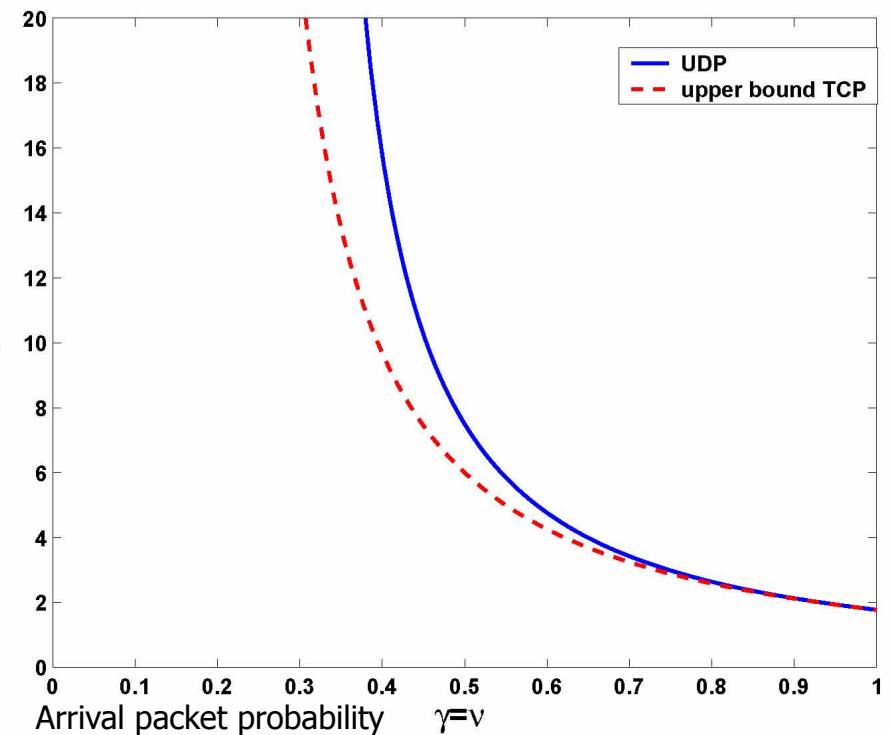
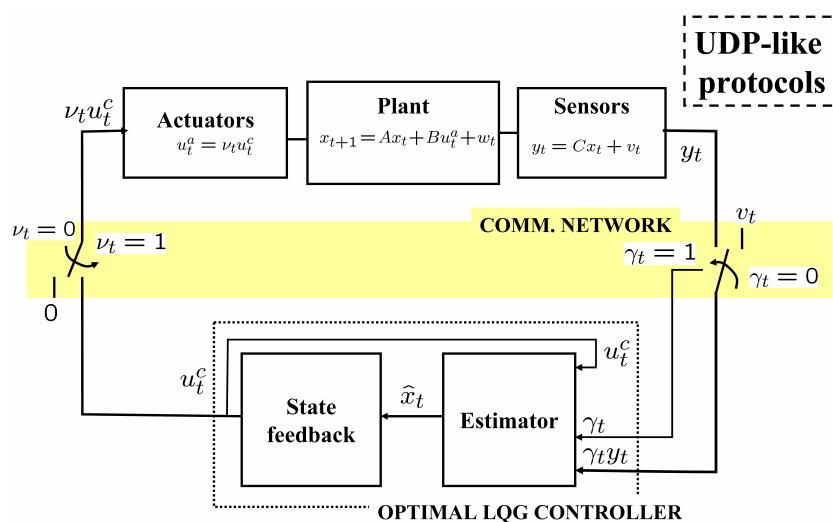
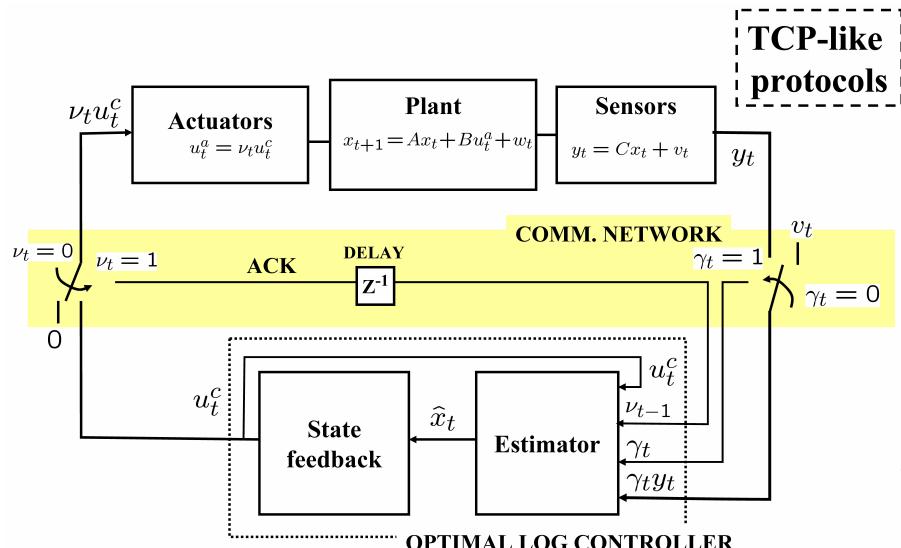
Paradox: Kalman filter is not always optimal !



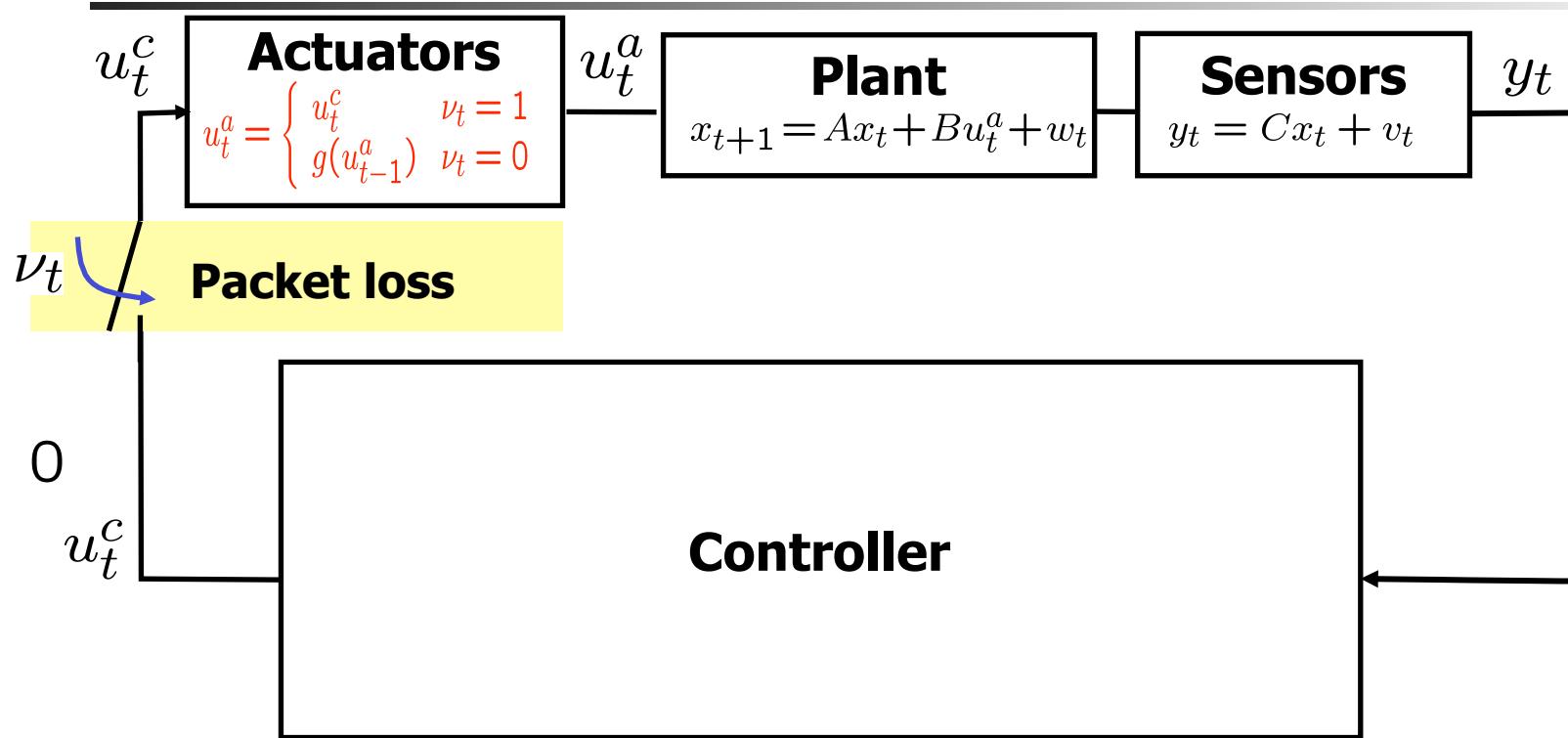
- Kalman filter always gives smallest estimate error **regardless** of controller L
- If controller $L \neq L_{LQ}$, then performance improves if my estimate is “bad” !



Numerical example: TCP vs UDP



To hold or to zero control input?



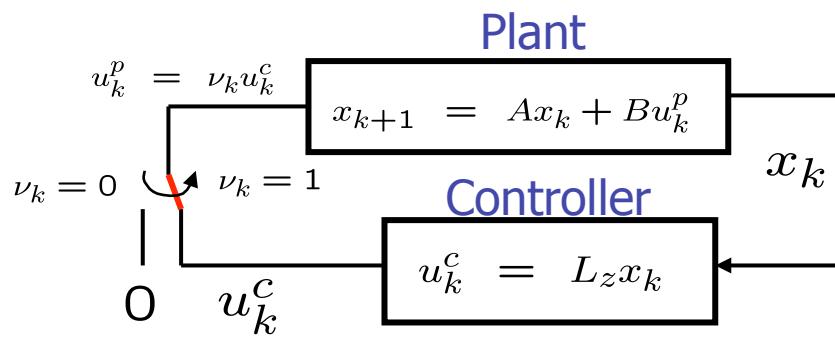
Most common strategy:

$g(u_{t-1}^a) = 0$ zero-input strategy **(mathematically appealing)**

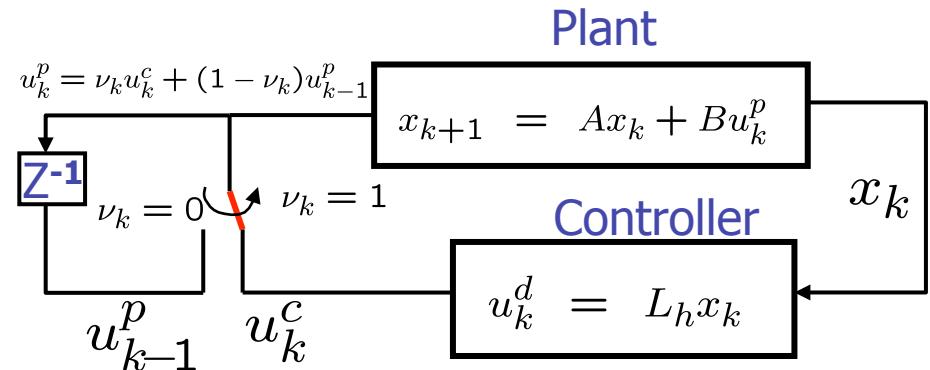
$g(u_{t-1}^a) = u_{t-1}^a$ hold-input strategy **(most natural)**

To hold or to zero control input: no noise (jump linear systems)

Zero-input Strategy



Hold-input Strategy



$$J_z^* = \min_{L_z} E\left[\sum_{t=1}^{\infty} x_t^T W x_t + (u_t^a)^T U u_t^a\right]$$

$$J_h^* = \min_{L_h} E\left[\sum_{t=1}^{\infty} x_t^T W x_t + (u_t^a)^T U u_t^a\right]$$

Using cost-to-go function (dynamic programming)

$$J_z^* = E[x_0^T S_z x_0]$$

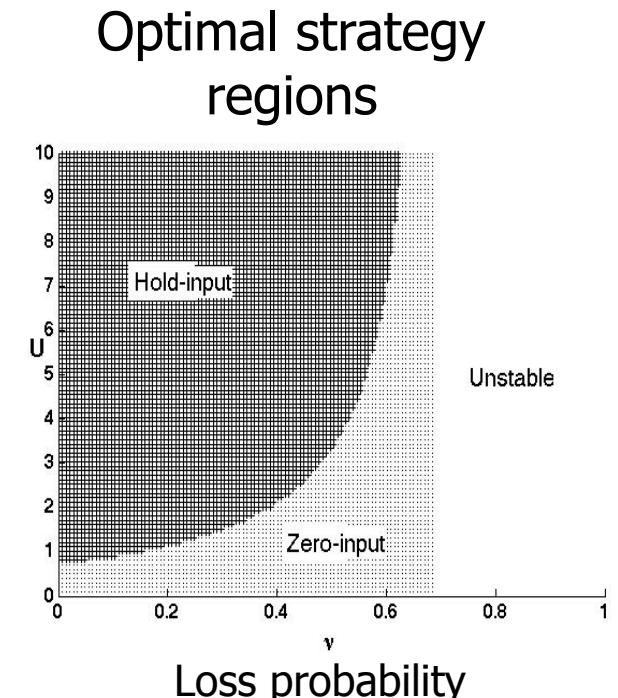
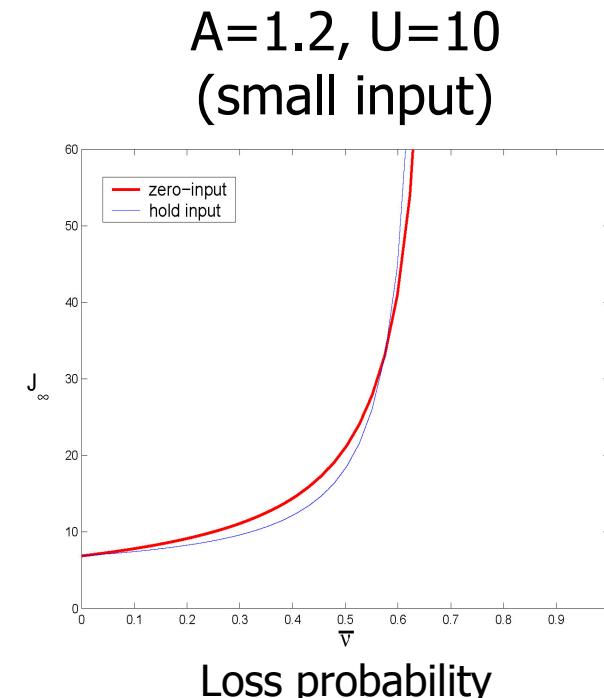
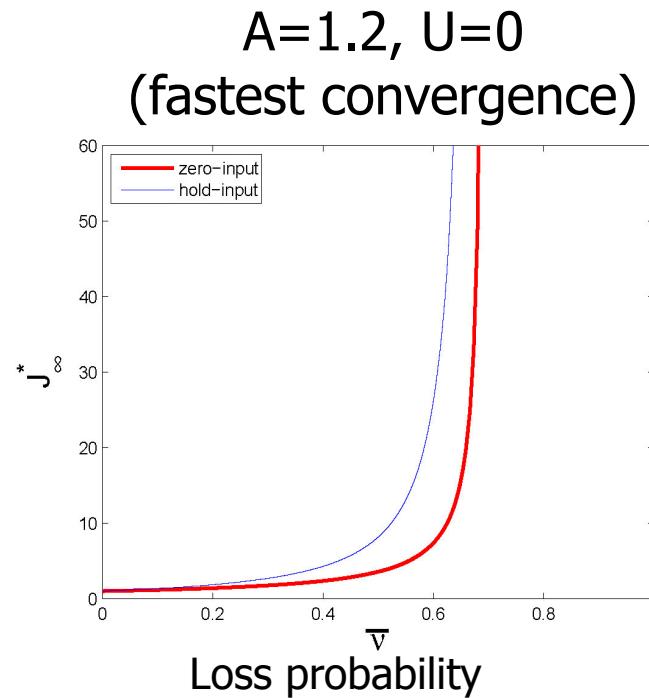
$$J_h^* = E[x_0^T S_h x_0]$$

$$S_z = \Phi_z(S_z) \xleftarrow{\text{Riccati-like equation}} S_h = \Phi_h(S_h)$$

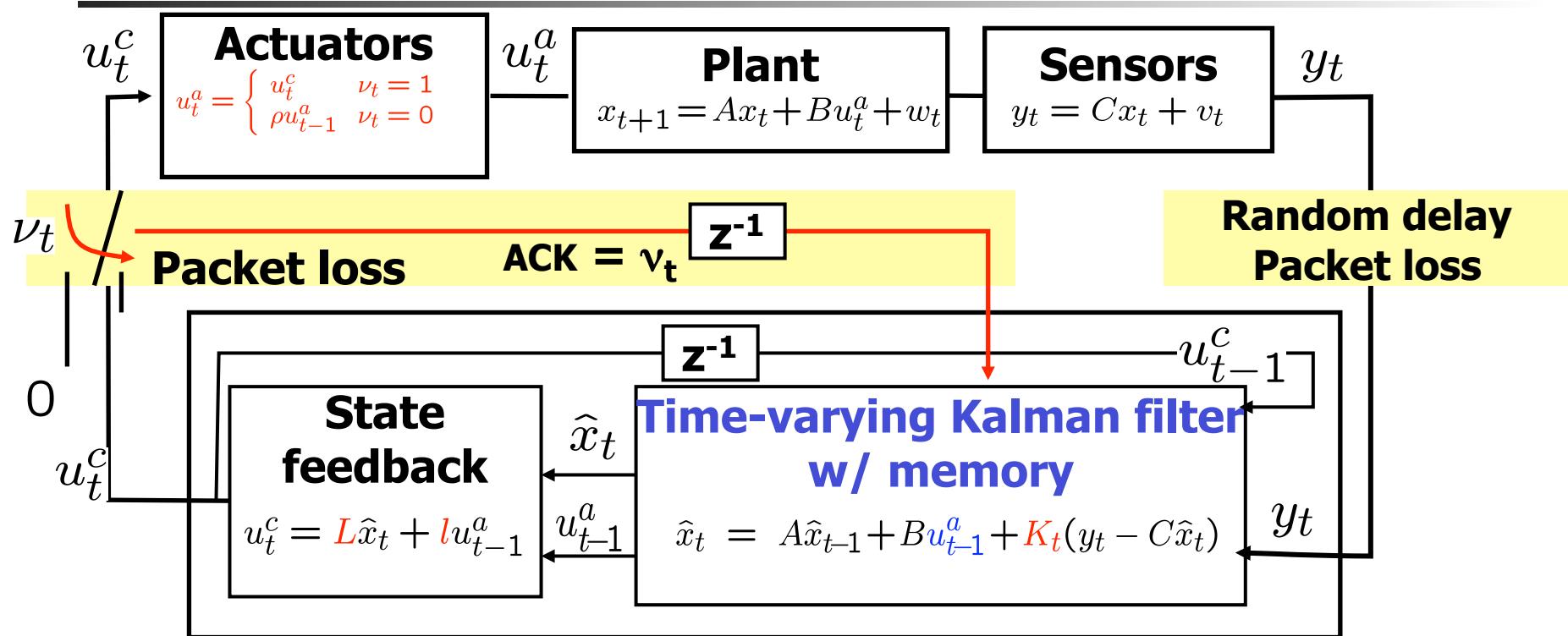
$$L_z^* = f_z(S_z)$$

$$L_h^* = f_h(S_h)$$

Example: unstable scalar system



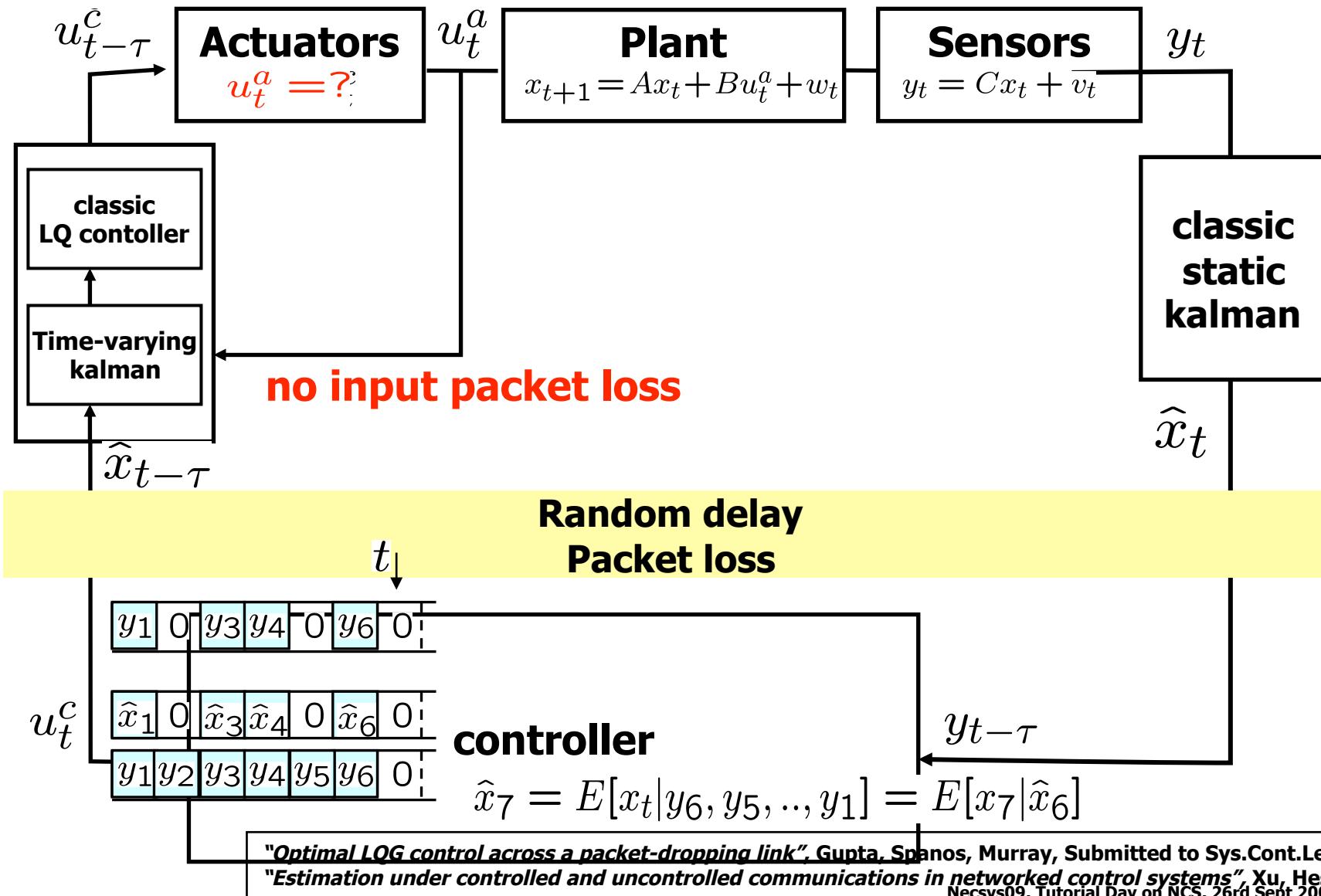
LQG over TCP-like protocols revised



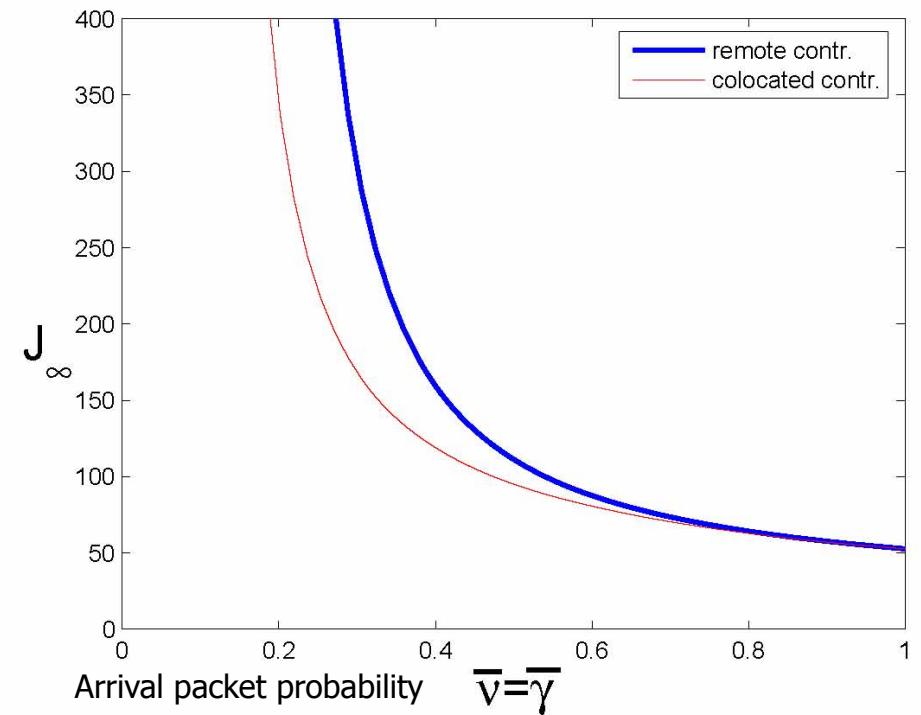
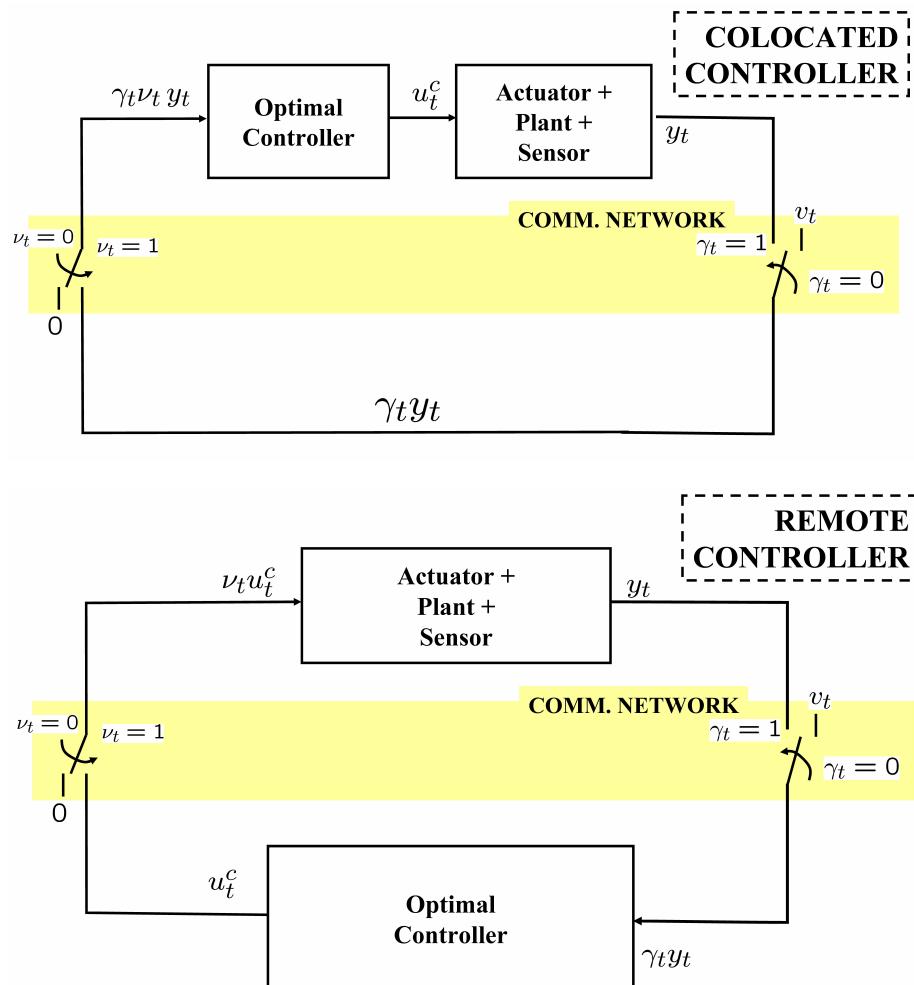
Conjecture:

- Separation principle hold
- Optimal function $g(u_{t-1}^a) = \rho u_{t-1}$
- Design parameter L, l, ρ obtained via LQ-like optimal state feedback

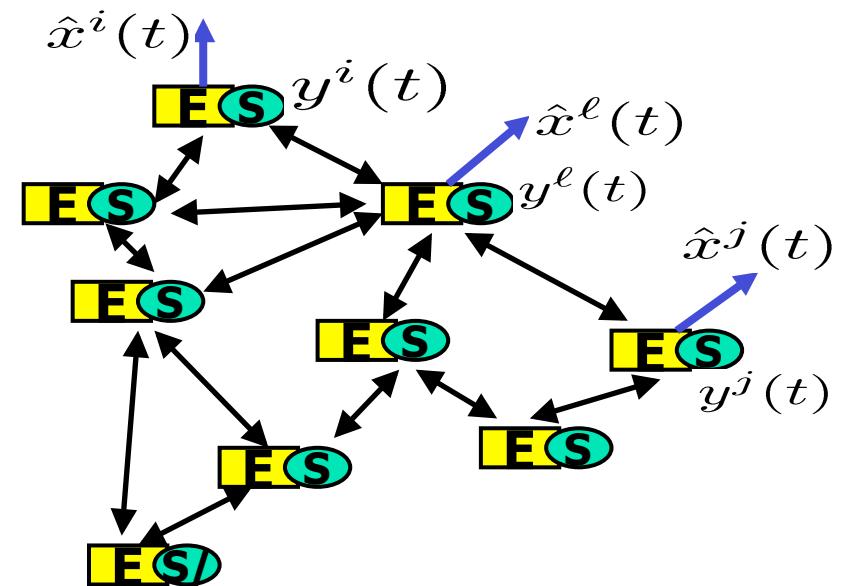
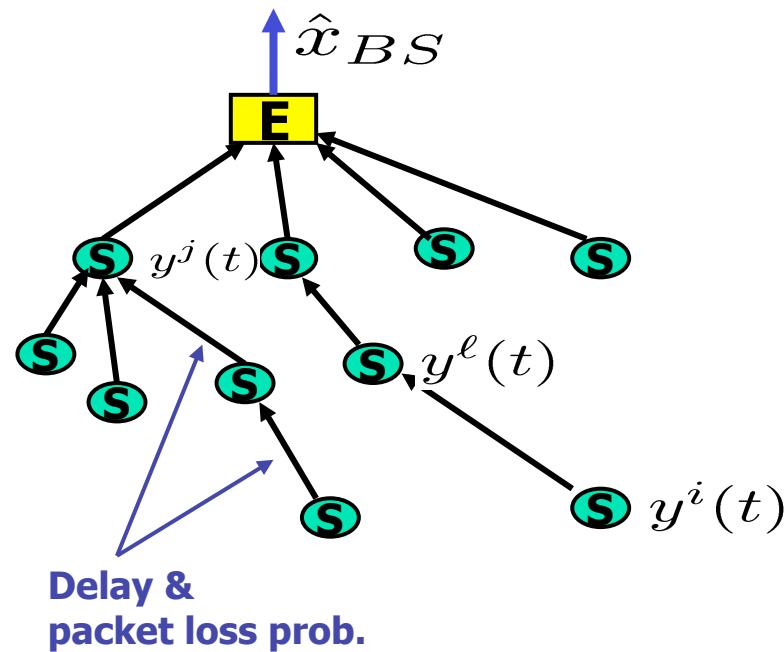
Smart sensors & smart actuators



Numerical example: remote vs co-located controller

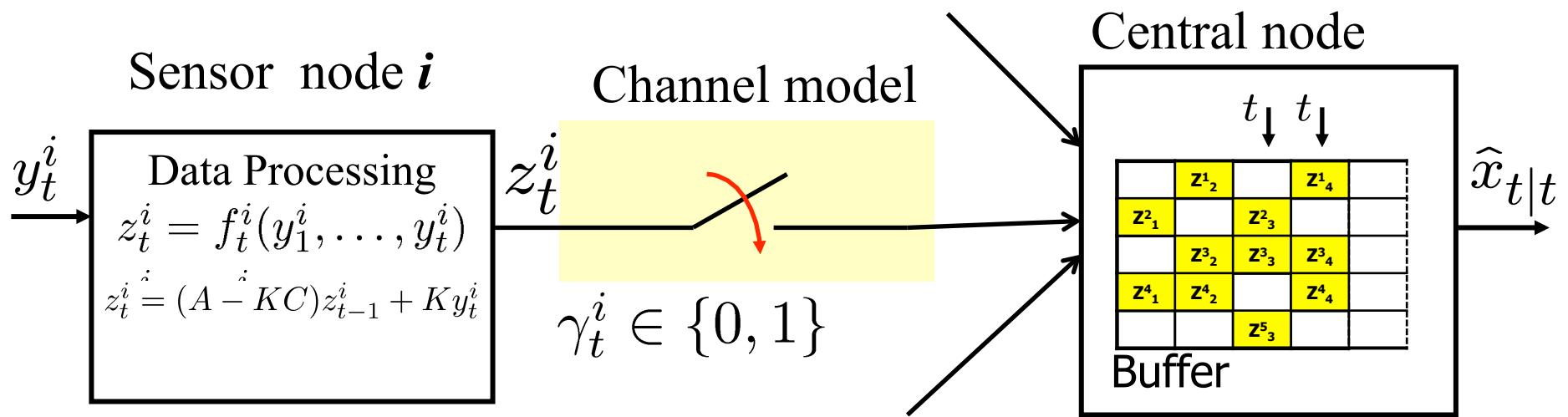


Distributed estimation: previous work



- Distributed estimation is old problem (see Levy, Willsky 80's, Bar-Shalom 90's)
- Consensus-based estimation (Olfati-Saber et al. 07, Carli et al. 08)
- Many results on optimal estimation under perfect communication
- Distributed estimation with packet loss still open problem

Modeling

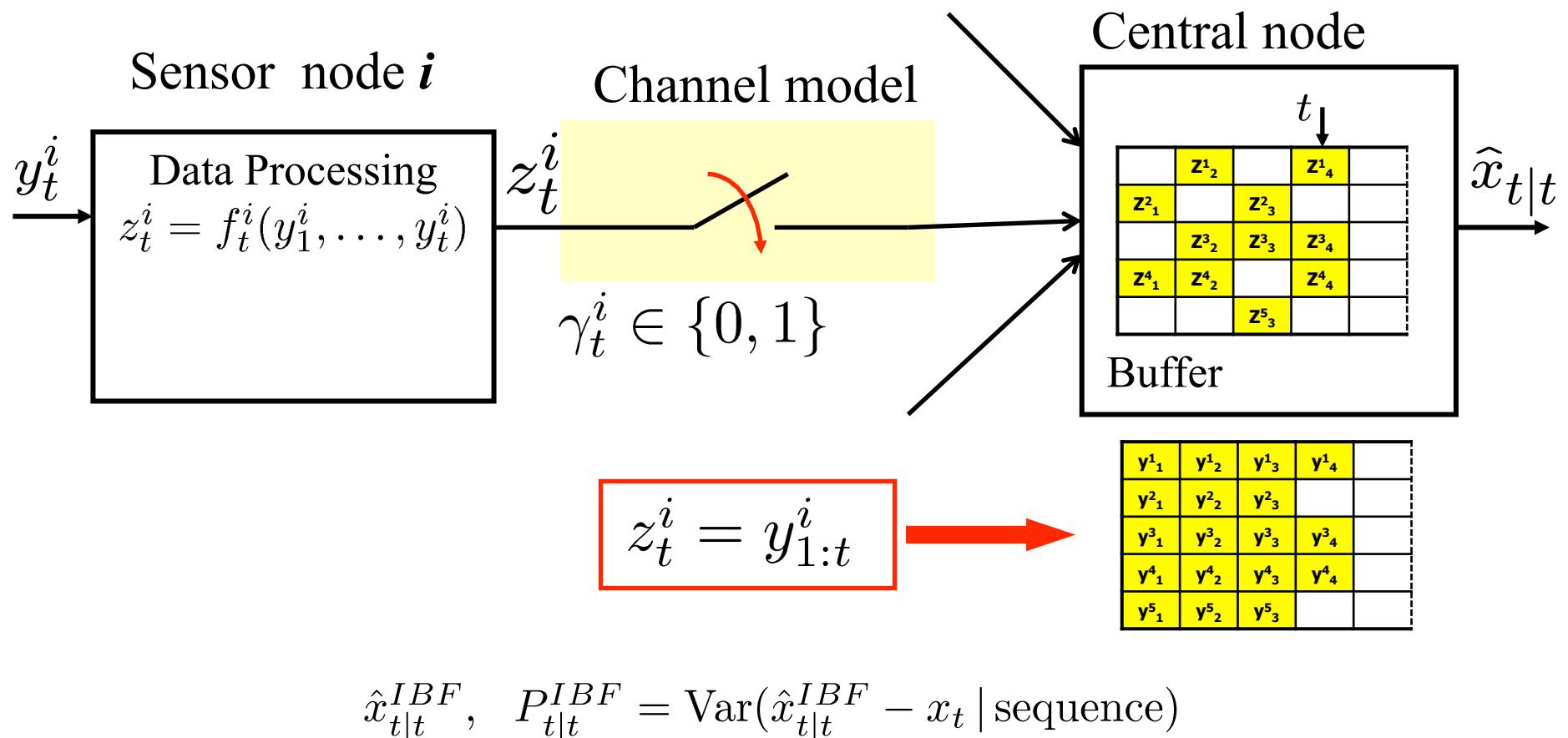


$$\begin{aligned}
 x_{t+1} &= Ax_t + w_t \\
 y_t^i &= C^i x_t + v_t^i \quad i = 1, \dots, M \\
 E[w_t] &= E[v_t^i] = 0, \quad E[w_t w_t^T] = Q, \quad E[v_t^i (v_t^j)^T] = R_{ij} \\
 P[\gamma_t^i] &= \bar{\gamma}
 \end{aligned}$$

Objective:

$$\hat{x}_{t|t}^{BS} = E[x_t | \text{information } z_{1:t}^i \text{ available at base station}]$$

Optimal strategy: Infinite Bandwidth Filter



A negative result

Theorem Let us consider the state estimate $\hat{x}_{t|t}$ and $\hat{x}_{t|t}^{IBF}$ defined as above. Then there do not exist (possibly nonlinear) functions $z_t^i = f_t^i(y_{1:t}^i) \in \mathbb{R}^\ell$ with bounded size $\ell < \infty$ such that $P_{t|t}^{IBF} = P_{t|t}$ for any possible packet loss sequence, i.e.

$$\nexists f_t^i() \mid P_{t|t} = P_{t|t}^{IBF}, \forall \gamma_t^i$$

A negative result

Theorem Let us consider the state estimate $\hat{x}_{t|t}$ and $\hat{x}_{t|t}^{IBF}$ defined as above. Then there do not exist (possibly nonlinear) functions $z_t^i = f_t^i(y_{1:t}^i) \in \mathbb{R}^\ell$ with bounded size $\ell < \infty$ such that $P_{t|t}^{IBF} = P_{t|t}$ for any possible packet loss sequence, i.e.

$$\nexists f_t^i() \mid P_{t|t} = P_{t|t}^{IBF}, \forall \gamma_t^i$$

Sketch of proof:

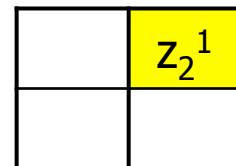
$$\begin{aligned} x_{t+1} &= x_t + w_t \\ y_t^1 &= x_t + v_t^1 \\ y_t^2 &= x_t + v_t^2 \end{aligned}$$

$$\ell \in \mathbb{R} \text{ and } f_t^i() \text{ linear, } \mathbb{E}[x_0] = 0 \quad z_2^1 = f_2^1(y_1^1, y_2^1) = \bar{\alpha}_1^1 y_1^1 + \bar{\alpha}_2^1 y_2^1 \quad z_2^1 = \bar{\alpha}_1^1 y_1^1 + \bar{\alpha}_2^1 y_2^1$$

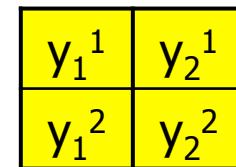
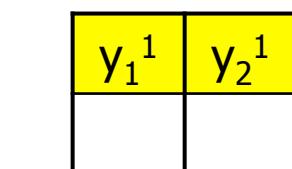
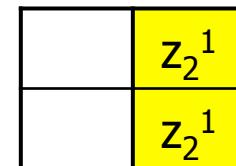
$$\sigma_x = \sigma_w = \sigma_{v_1} = \sigma_{v_2}$$

$$\begin{bmatrix} \alpha_1^{1,a} \\ \alpha_2^{1,a} \end{bmatrix} \neq \beta \begin{bmatrix} \alpha_1^{1,b} \\ \alpha_2^{1,b} \end{bmatrix}$$

Scenario a



Scenario b



$$\hat{x}^{IBF,a} = \alpha_1^{1,a} y_1^1 + \alpha_2^{1,a} y_2^1$$

$$\begin{aligned} \hat{x}^{IBF,b} = & \alpha_1^{1,b} y_1^1 + \alpha_2^{1,b} y_2^1 \\ & + \alpha_1^{2,b} y_1^2 + \alpha_2^{2,b} y_2^2 \end{aligned}$$

Suboptimal strategies

■ Measurement fusion:

- $z_t^i = y_t^i$ at sensor
- $\hat{x}_{t|t}^{MF} = E[x_t | \text{all } z_t^i \text{ arrived}]$: base station

■ Optimal Kalman Filter Fusion

- $z_t^i = \hat{x}_t^i = (A - C^i K^{i,loc}) \hat{x}_{t-1}^i + K^{i,loc} y_t^i$
- $\hat{x}_{t|t}^{OKFF} = E[x_t | \text{latest } z_t^i \text{ arrived } \forall i] = \sum_i \Psi_t^i z_{t-\tau_t^i}^i$

■ Optimal Partial Estimate Fusion

- $z_t^i = \hat{x}_t^i = (A - \sum_i C^i K^{i,cent}) \hat{x}_{t-1}^i + K^{i,cent} y_t^i$
- $\hat{x}_{t|t}^{OPEF} = E[x_t | \text{latest } z_t^i \text{ arrived } \forall i] = \sum_i \Phi_t^i z_{t-\tau_t^i}^i$

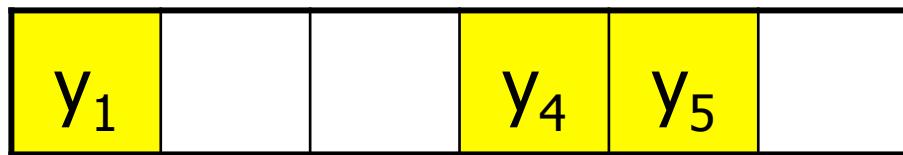
■ Open Loop Partial Estimate Fusion

- $z_t^i = \hat{x}_t^i = (A - C^i K^{i,cent}) \hat{x}_{t-1}^i + K^{i,cent} y_t^i$
- $\hat{x}_{t|t}^{OLPEF} = \sum_i A^{\tau_t^i} z_{t-\tau_t^i}^i$

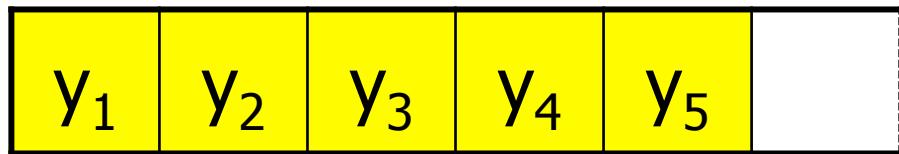


Single sensor & packet loss

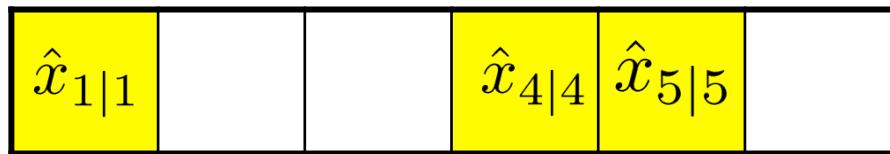
↓ $t = 6$



$$\hat{x}_{6|6}^{MF} = E[x_6|y_1, y_4, y_5]$$



$$\hat{x}_{6|6}^{IBF} = E[x_6|y_{1:5}] = E[x_6|\hat{x}_{5|5}] = A\hat{x}_{5|5}$$



$$\hat{x}_{6|6}^{OKFF} = E[x_6|\hat{x}_{5|5}] = A\hat{x}_{5|5}$$

$$P_{t|t}^{IBF} = P_{t|t}^{OKFF} = P_{t|t}^{OLPEF} = P_{t|t}^{OPEF} < P_{t|t}^{MF}$$

Multi sensor & no packet loss

$\downarrow t = 3$

y_1^1	y_2^1	y_3^1
y_1^2	y_2^2	y_3^2
y_1^3	y_2^3	y_3^3

$$\hat{x}_{t|t}^{MF} = E[x_t | y_{1:t}^i \forall i] = \hat{x}_{t|t}^{IBF} = \hat{x}_{t|t}^{cent}$$

$\downarrow t = 3$

$\hat{x}_{3 3}^{1,loc}$
$\hat{x}_{3 3}^{2,loc}$
$\hat{x}_{3 3}^{3,loc}$

$$\hat{x}_t^{i,loc} = (A - K^{i,loc}C^i)\hat{x}_{t-1}^{i,loc} + K^{i,loc}y_t^i$$

$$\hat{x}_{t|t}^{OKFF} = E[x_t | \hat{x}_{t|t}^{i,loc} \forall i] \neq \hat{x}_{t|t}^{IBF} = \hat{x}_{t|t}^{cent}$$

Centralized Kalman Filter

$$\begin{array}{l} x_{t+1} = Ax_t + w_t \\ y_t^i = C^i x_t + v_t^i \end{array} \quad C = \begin{bmatrix} C^1 \\ C^2 \\ \vdots \\ C^M \end{bmatrix}, \quad y_t = \begin{bmatrix} y_t^1 \\ y_t^2 \\ \vdots \\ y_t^M \end{bmatrix}, \quad v_t = \begin{bmatrix} v_t^1 \\ v_t^2 \\ \vdots \\ v_t^M \end{bmatrix}, \quad E[v_t v_t^T] = R$$

$$K^{cent} = [K^{1,cent} \ K^{2,cent} \ \dots \ K^{M,cent}]$$

$$\begin{aligned} \hat{x}_t^{cent} &= (A - K^{cent}C)\hat{x}_{t-1}^{cent} + K^{cent}y_t \\ &= \underbrace{(A - \sum_i K^{i,cent}C^i)}_{\hat{x}_t^{i,cent}} \hat{x}_{t-1}^{cent} + \sum_i K^{i,cent}y_t^i \\ \hat{x}_t^{i,cent} &= F\hat{x}_{t-1}^{i,cent} + K^{i,cent}y_t^i, \quad \text{local filter} \end{aligned}$$

$$\hat{x}_{t|t}^{cent} = \sum_i \hat{x}_{t|t}^{i,cent}$$

Multi sensor & no packet loss

$\downarrow t = 3$

y_1^1	y_2^1	y_3^1
y_1^2	y_2^2	y_3^2
y_1^3	y_2^3	y_3^3

$$\hat{x}_{t|t}^{MF} = E[x_t | y_{1:t}^i \forall i] = \hat{x}_{t|t}^{IBF} = \hat{x}_{t|t}^{cent}$$

$\downarrow t = 3$

$\hat{x}_{3 3}^{1,cent}$
$\hat{x}_{3 3}^{2,cent}$
$\hat{x}_{3 3}^{3,cent}$

$$\hat{x}_{t|t}^{OKFF} = E[x_t | \hat{x}_{t|t}^{i,loc} \forall i] \neq \hat{x}_{t|t}^{IBF} = \hat{x}_{t|t}^{cent}$$

$$\hat{x}_t^{i,loc} = (A - K^{i,loc} C^i) \hat{x}_{t-1}^{i,loc} + K^{i,loc} y_t^i$$

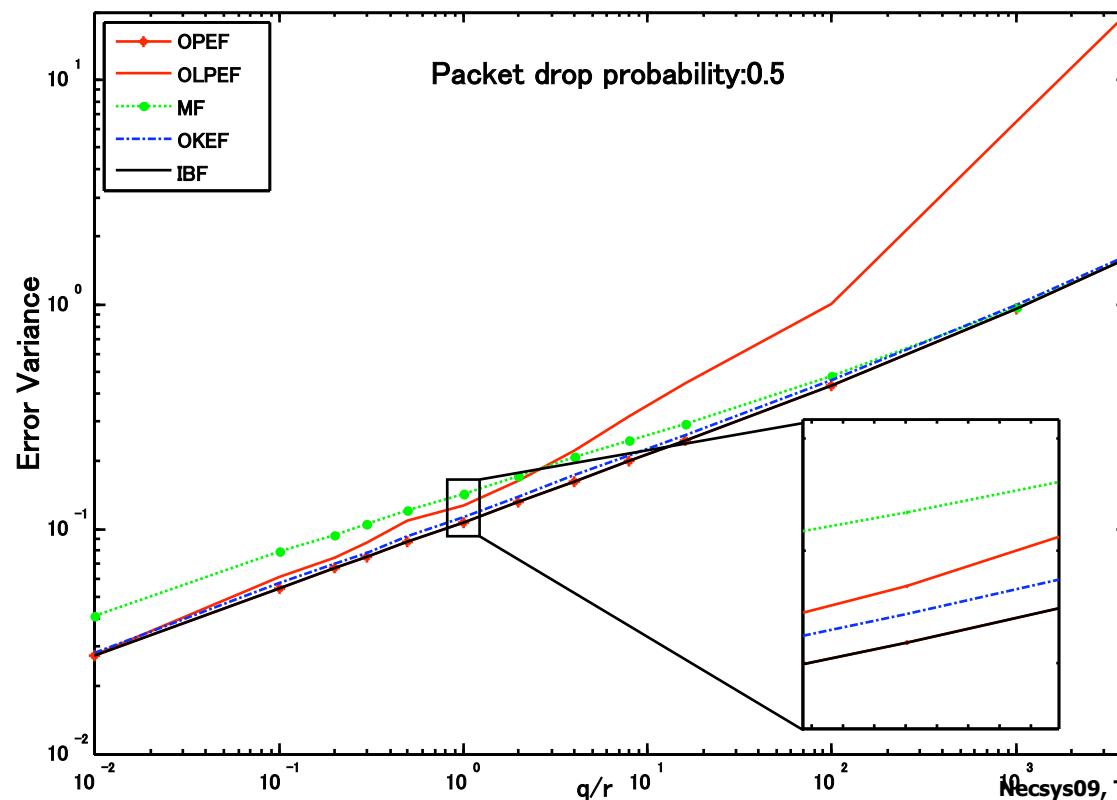
$$\hat{x}_t^{i,cent} = (A - \sum_i C^i K^{i,cent}) \hat{x}_{t-1}^{i,cent} + K^{i,cent} y_t^i$$

$$P_{t|t}^{IBF} = P_{t|t}^{MF} = P_{t|t}^{OLPEF} = P_{t|t}^{OPEF} < P_{t|t}^{OKFF}$$

Multi sensor & packet loss

$$Q = 0 \implies P_{t|t}^{IBF} = P_{t|t}^{OLPEF} = P_{t|t}^{OPEF} < P_{t|t}^{OKFF}, P_{t|t}^{MF}$$

6 sensors, double integrator dynamics, uncorrelated noise



Strategy summary

	Estimation error	Sensor complex.	Base station complex
Measurement fusion	Almost optimal for R/Q small, Acceptable for R/Q large	none	Medium (inversion of n-dimensional matrix)
Optimal Kalman filter Fusion	Almost optimal always	Medium (local Kalman filter)	High (inversion of many matrices)
Optimal Partial Estimate Fusion	Optimal for Q/R small, almost optimal elsewhere	Medium (local Kalman-like filter)	High (inversion of many matrices)
Open loop partial estimate fusion	Optimal for Q/R small, very poor for R/Q small	Medium (local Kalman-like filter)	None

Strategy summary (con'd)

- Distributed estimation is old problem (Willsky, Bar-Shalom)
- Packet loss makes distributed estimation hard: optimal sensor preprocessing depends on future loss sequence
- No optimal strategy for all scenarios
- Some results based on simulations only: no theoretical proofs

- A.S. Willsky, D. Castanon, B. Levy, and G. Verghese, "Combining and updating of local estimates and regional maps along sets of one-dimensional tracks," IEEE Trans. on Aut. Cont., 1982
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- Alessandro Agnoli, Alessandro Chiuso, Pierdomenico D'Errico, Andrea Pegoraro, L. Schenato "Sensor fusion and estimation strategies for data traffic reduction in rooted wireless sensor networks", ISCCSP08,
- A. Chiuso, L. Schenato, "Information fusion strategies from distributed filters in packet-drop networks," CDC'08
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Takeaway points

- Input packet loss more dangerous than measurement packet loss
- TCP-like protocols help controller design as compared to UDP-like (but harder for communication designer)
- If you can, place controller near actuator
- If you can, send estimate rather than raw measurement
- Zero-input control seems to give smaller closed loop state error ($\|x_t\|$) than hold-input (but higher input)
- Trade-off in terms of performance, buffer length, computational resources (matrix inversion) when random delay
- Can help comparing different communication protocols from a real-time application performance
- Packet loss makes problem extremely hard
- No good-for-all-scenarios strategy when packet loss

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■ Related workshops and slides

- WIDE'09 Ph.D. School: http://ist-wide.dii.unisi.it/school09/school_program.htm
- Frontiers in Distributed Communication, Sensing and Control in <http://www.eng.yale.edu/dcsc/schedule.html>

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