# Communication constraints and latency in Networked Control Systems

João P. Hespanha

Center for Control Engineering and Computation

University of California Santa Barbara

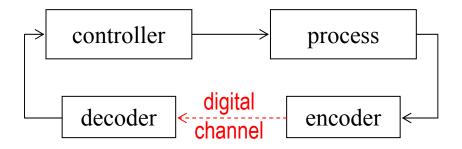


In collaboration with Antonio Ortega (USC) and Yonggang Xu (UCSB)

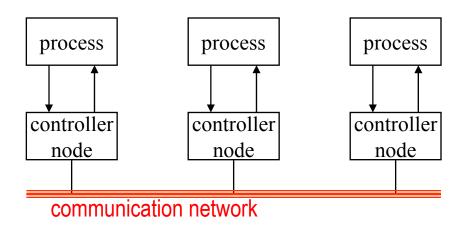
#### **Outline**



1. Feedback control over a digital channel with limited bit-rate:

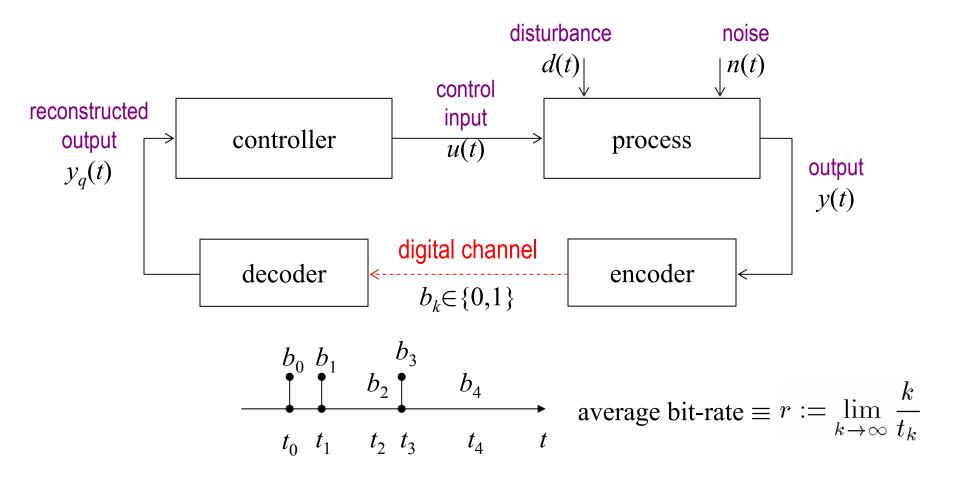


2. Decentralized cooperative control with limited message-rate and delays



#### **Control with finite bit-rate**



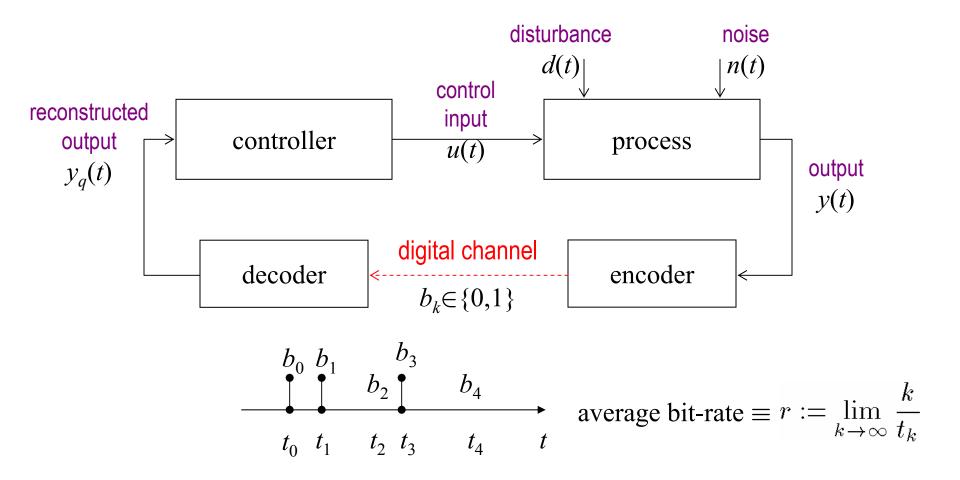


Motivation: Control of systems with sensors and actuators far from each other, connected by a digital network.

E.g., control of an autonomous flying vehicle using measurements from a camera on the ground.

#### **Control with finite bit-rate**





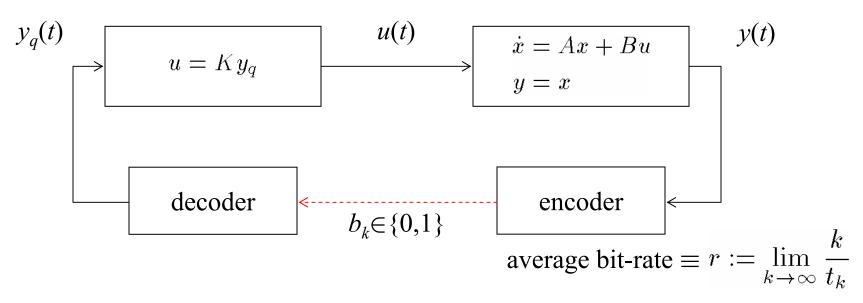
#### Questions:

- 1. What is the minimum bit-rate for which stabilization (boundedness) is possible?
- 2. How to divide the bits among the distinct components of the output?
- 3. How to choose quantization intervals?

#### Minimum bit-rate



no noise/disturbance



**Theorem:** Stabilization is *not* possible with average bit-rate smaller than

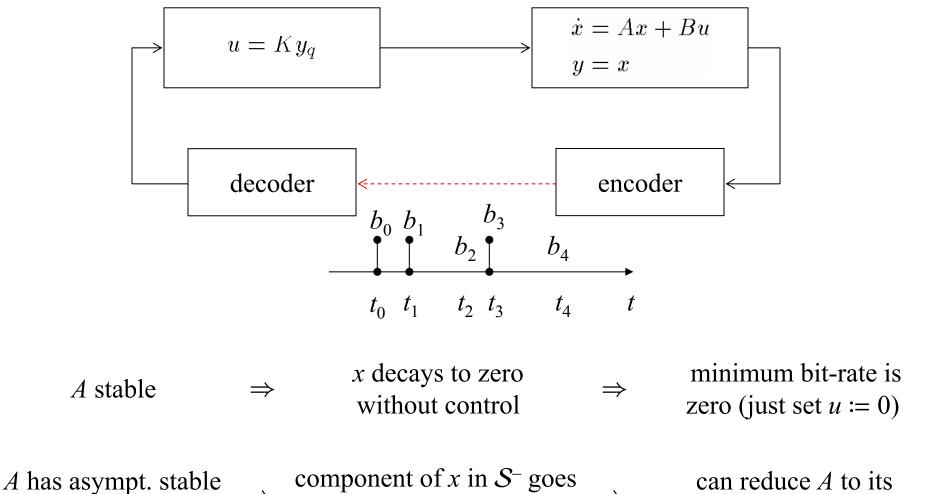
$$r_{\min} := rac{1}{\log 2} \sum_{\Re \lambda_i > 0} \lambda_i$$
 continuous-time process

$$r_{\min} := rac{1}{\log 2} \sum_{|\lambda_i| > 1} \log \lambda_i$$
 discrete-time process [Tatikonda & Mitter]

$$\lambda_i \equiv \text{eigenvalues of A}$$



unstable inv. subspace

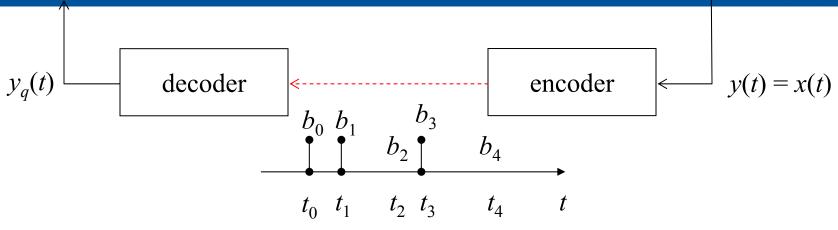


$$\therefore$$
 we will assume that all eigenvalues of A have real part  $\geq 0$ 

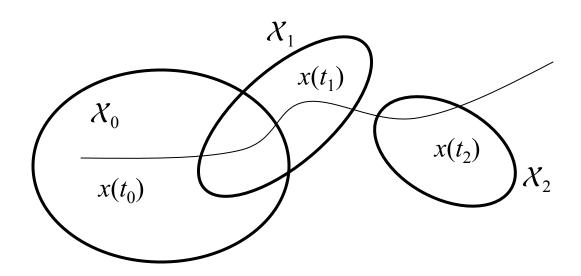
to zero without control

inv. subspace  $S^-$ 

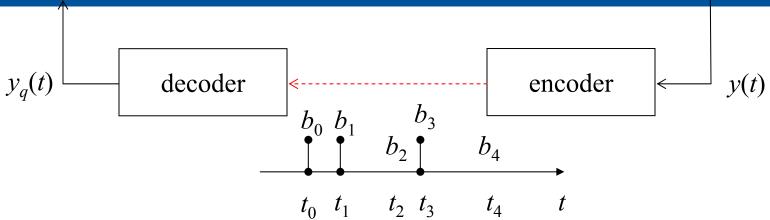




 $X_0 \equiv \text{set to which } x(t_0) \text{ is known to belong after bit } b_0 \text{ is received}$  $X_1 \equiv \text{set to which } x(t_1) \text{ is known to belong after bit } b_1 \text{ is received} \dots$ 





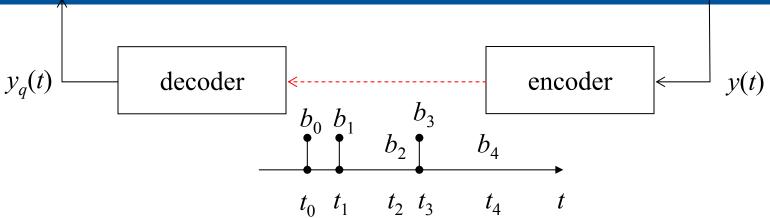


 $X_0 \equiv \text{set to which } x(t_0) \text{ is known to belong after bit } b_0 \text{ is received}$  $X_1 \equiv \text{set to which } x(t_1) \text{ is known to belong after bit } b_1 \text{ is received} \dots$ 

Case 1: For some k,  $X_k$  has a single element  $\Rightarrow$  could take x to zero (even in finite time) after  $t_k$  diameter of  $X_k$  Case 2: As  $k \to \infty$ ,  $\rho(X_k) \to 0$   $\Rightarrow$  could take x to zero as  $k \to \infty$ 

Case 3: As  $k \to \infty$ ,  $\rho(X_k)$  unbounded  $\Rightarrow$  no matter what control we use,  $x(t_k)$  is unbounded





 $X_0 \equiv \text{set to which } x(t_0) \text{ is known to belong after bit } b_0 \text{ is received}$  $X_1 \equiv \text{set to which } x(t_1) \text{ is known to belong after bit } b_1 \text{ is received} \dots$ 

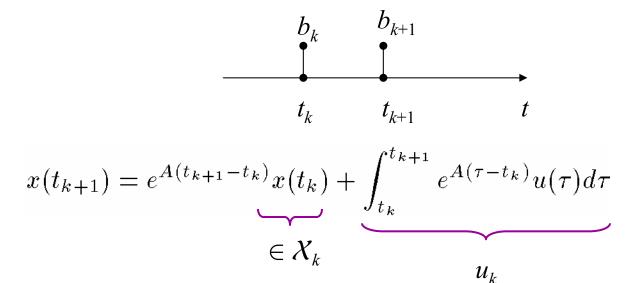
Case 1: For some k,  $X_k$  has a single element  $\Rightarrow$  could take x to zero (even in finite time) after  $t_k$ 

Case 2: As  $k \to \infty$ ,  $\rho(X_k) \to 0$  $\Rightarrow$  could take x to zero as  $k \to \infty$ 

Case 3: As  $k \to \infty$ ,  $\rho(X_k)$  unbounded  $\Rightarrow$  no matter what control we use,  $x(t_k)$  is unbounded

#### Main idea:

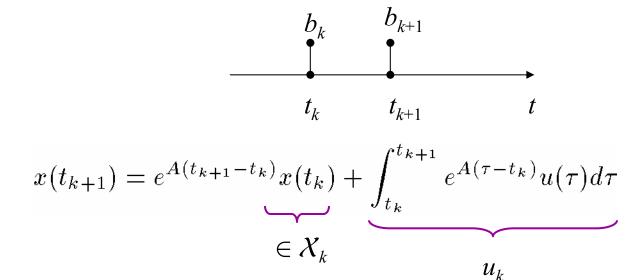




before  $b_{k+1}$  is received, it is only known that

$$x(t_{k+1}) \in \mathcal{X}_{k+1}^- := e^{A(t_{k+1}-t_k)}\mathcal{X}_k + u_k$$
 
$$\mu(\mathcal{X}_{k+1}^-) = |\det e^{A(t_{k+1}-t_k)}| \ \mu(\mathcal{X}_k)$$
 volume of  $\mathcal{X}_k^-$ 





before  $b_{k+1}$  is received, it is only known that

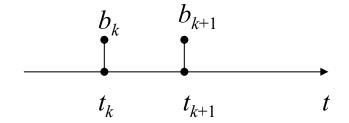
$$x(t_{k+1}) \in \mathcal{X}_{k+1}^- := e^{A(t_{k+1}-t_k)}\mathcal{X}_k + u_k$$
 
$$\mu(\mathcal{X}_{k+1}^-) = |\det e^{A(t_{k+1}-t_k)}| \ \mu(\mathcal{X}_k)$$
 volume of  $\mathcal{X}_{k+1}^-$ 

- Q: Which coding would make  $\mu(X_{k+1})$  as small as possible?
- A: Divide  $X_{k+1}^-$  into two sets of equal volume & use bit  $b_{k+1}$  to locate  $x(t_{k+1})$  in one of them

coding that minimizes volume

$$\mu(\mathcal{X}_{k+1}) = \frac{\mu(\mathcal{X}_{k+1}^-)}{2}$$





At best...

$$\mu(\mathcal{X}_{k+1}) \ge \frac{\mu(\mathcal{X}_{k+1}^-)}{2} = \frac{|\det e^{A(t_{k+1}-t_k)}|}{2} \,\mu(\mathcal{X}_k) = e^{(t_{k+1}-t_k)\sum_{k}\lambda_i} \,\mu(\mathcal{X}_k)$$

with = only for coding that minimizes volume

iterating...

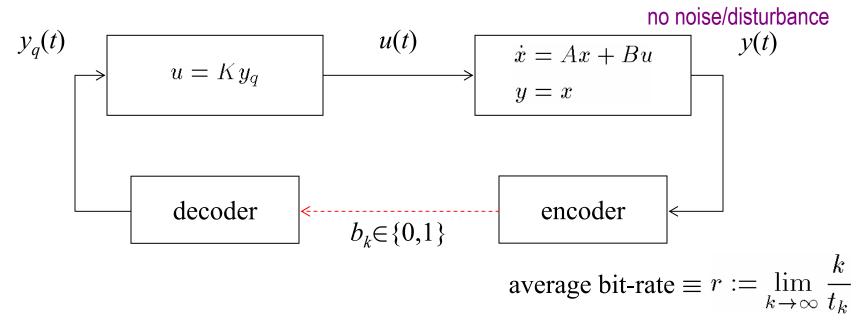
$$\mu(\mathcal{X}_{k+1}) \ge e^{t_k(\sum \lambda_i) - k \log 2} \mu(\mathcal{X}_k)$$

explodes if average bit-rate is smaller than

$$r_{\min} := \frac{1}{\log 2} \sum \lambda_i$$

#### Minimum bit-rate





**Theorem:** Stabilization is *not* possible with average bit-rate smaller than

$$r_{\min} := rac{1}{\log 2} \sum_{\Re \lambda_i > 0} \lambda_i$$
 continuous-time process

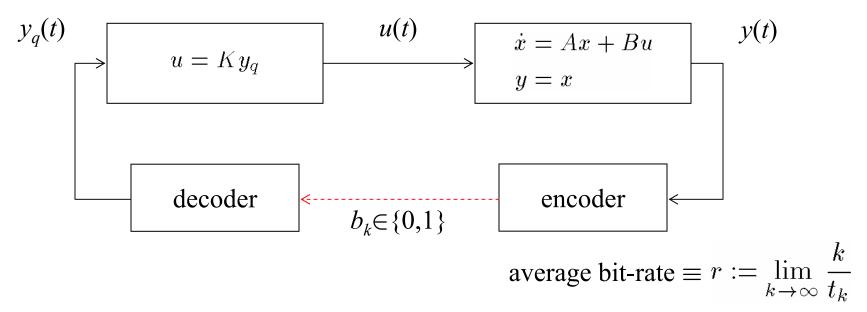
$$r_{\min} := rac{1}{\log 2} \sum_{|\lambda_i| > 1} \log \lambda_i$$
 discrete-time process [Tatikonda & Mitter]

$$\lambda_i \equiv \text{eigenvalues of A}$$

#### Minimum bit-rate



no noise/disturbance



**Theorem:** Assume *A* is diagonalizable

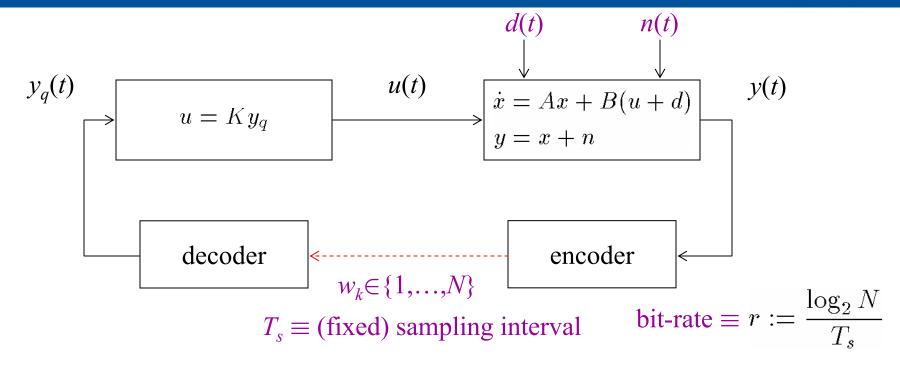
- 1. It is possible to keep the state bounded with any average bit rate larger or equal to  $r_{\min}$
- 2. It is possible to make the state converge to zero with any average bit rate strictly larger than  $r_{\min}$

previous bound is tight

But ... minimum volume coding may not work because unbounded volume ⇒ unbounded diameter bounded volume ⇒ bounded diameter

## Encoding/decoding schemes



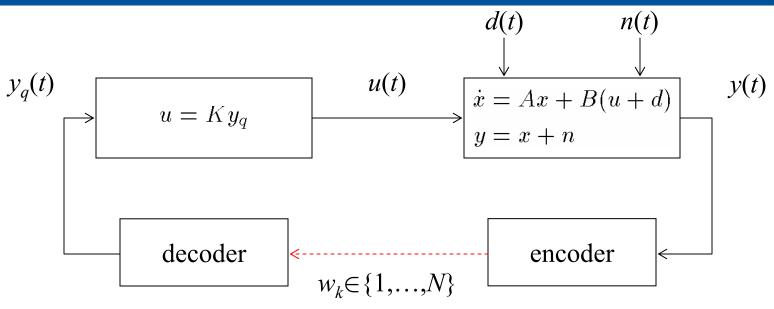


Assume: closed-loop is stable for "transparent" encoding/decoding, i.e., A + B K asymptotically stable

#### Questions:

- 1. How to design the encoder/decoder pair to make the closed-loop stable?
- 2. How much larger than  $r_{min}$  does the bit-rate need to be for stability?

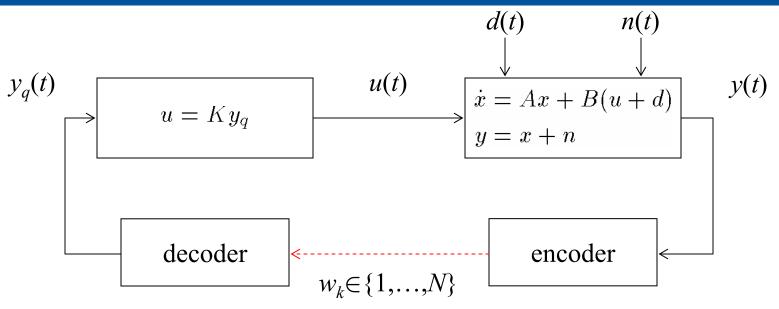




Inspired by Differential Pulse Code Modulation (DPCM)...

- 1. Encoder and decoder maintain consistent estimates of the state, based only on the quantized information sent to the decoder.
- 2. At sampling times, the difference between the measured state and its estimate (based on previously transmitted data) is quantized and transmitted digitally. (hopefully state estimation error has smaller dynamic range than state itself)
- 3. Upon transmission, the state-estimates are corrected using the quantized error.

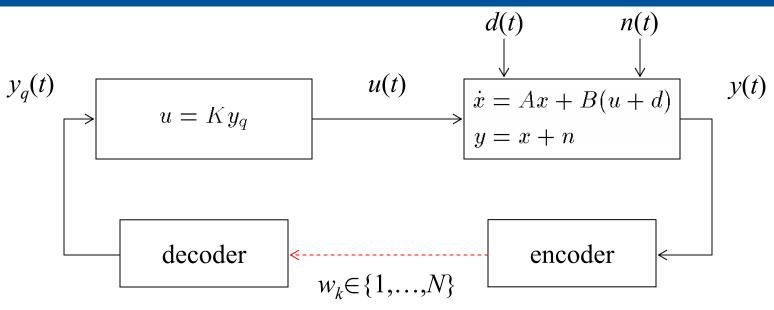




1. Encoder and decoder maintain consistent estimates of the state, based only on the quantized information sent to the decoder.

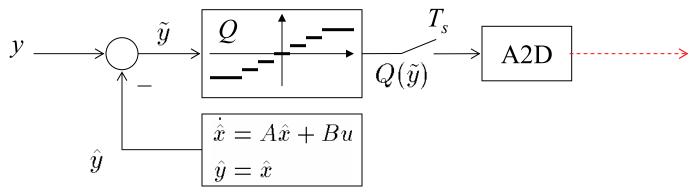
process estimate 
$$\dot{x} = Ax + B(u+d) \qquad \qquad \dot{\hat{x}} = A\hat{x} + Bu$$
 
$$y = x+n \qquad \qquad \hat{y} = \hat{x}$$



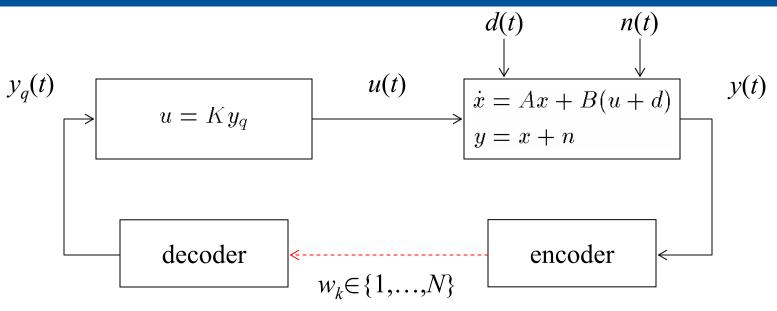


- 1. Encoder and decoder maintain consistent estimates of the state, based only on the quantized information sent to the decoder.

  smaller dynamic range
- 2. At sampling times, the difference between the measured state and its estimate is quantized and transmitted digitally.





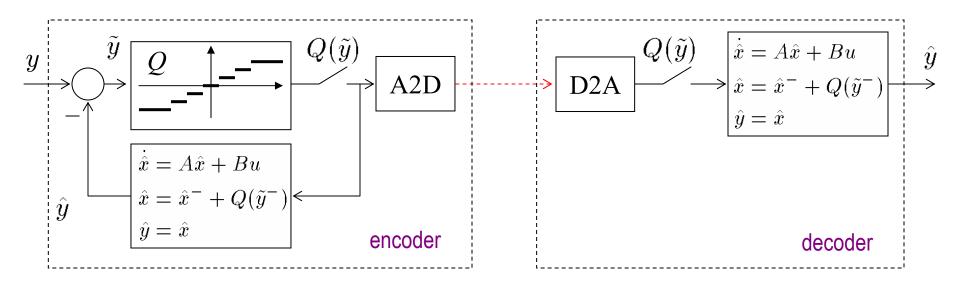


- 1. Encoder and decoder maintain consistent estimates of the state, based only on the quantized information sent to the decoder.
- 2. At sampling times, the difference between the measured state and its estimate is quantized and transmitted digitally.
- 3. Upon transmission, the state-estimates are corrected using the quantized error:

$$\hat{x}(t_k) = \hat{x}(t_k^-) + Q\big(\tilde{y}(t_k^-)\big) = \hat{x}(t_k^-) + Q\Big(y(t_k) - \hat{x}(t_k^-)\big)$$
 without quantization ( $Q$  = identity) and noise, we would have 
$$\hat{x}(t_k) = y(t_k) = x(t_k)$$

## Encoder/decoder pair





- 1. Encoder and decoder maintain consistent estimates of the state, based only on the quantized information sent to the decoder.
- 2. At sampling times, the difference between the measured state and its estimate is quantized and transmitted digitally
- 3. Upon transmission, the state-estimates are corrected using the quantized error.

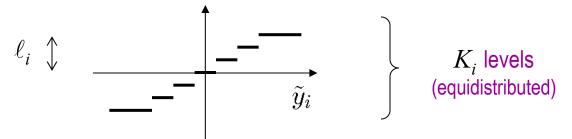
## **Fixed-step quantization**



#### For simplicity...

- assume A diagonal with real eigenvalues
- quantize the vector by using a scalar quantizer on each of its components

If A was not diagonal one would precede the componentwise quantization by a diagonalizing linear transformation (see [JH, Ortega, Vasudevan, 02] for case of A with complex eigenvalues)



 $\ell_i \equiv \text{saturation level for the } i \text{th component quantizer}$ 

 $K_i \equiv \#$  of quantization levels used for the *i*th component of  $\tilde{y}$ 

# of words needed 
$$\equiv N = \prod_{i=1}^{n} K_i$$
 bit-rate  $\equiv \frac{\log_2 N}{T_s} = \frac{\sum_i \log K_i}{T_s \log 2}$ 

## **Fixed-step quantization**



quantizer saturation level

Theorem: The state of the closed-loop system will remain bounded provided that

$$K_i \ge \frac{\ell_i e^{\lambda_i T_s}}{\ell_i - \eta_i - \delta_i} \qquad \& \qquad |x_i(0)| \le \ell_i - \eta_i$$

# of quant. levels

 $\eta_i, \, \delta_i \equiv \text{constants that depend on } upper \\
bounds on the noise/disturbance$ 

bit allocation...

 $\lambda_i \text{ large} \Rightarrow e^{\lambda i T_S} \text{ large} \Rightarrow K_i \text{ large} \Rightarrow \text{many bits needed for } i\text{th eigenspace}$ 

## Fixed-step quantization



quantizer saturation level

Theorem: The state of the closed-loop system will remain bounded provided that

$$K_i \ge \frac{\ell_i e^{\lambda_i T_s}}{\ell_i - \eta_i - \delta_i} \qquad \& \qquad |x_i(0)| \le \ell_i - \eta_i$$

# of quant. levels

 $\eta_i$ ,  $\delta_i \equiv$  constants that depend on *upper* bounds on the noise/disturbance

bit allocation...

 $\lambda_i \text{ large} \Rightarrow e^{\lambda i T_S} \text{ large} \Rightarrow K_i \text{ large} \Rightarrow \text{many bits needed for } i\text{th eigenspace}$ 

required bit-rate...

$$\text{bit-rate} \dots \\ \text{bit-rate} \dots \\ N = \prod_{i=1}^{n} K_i \ge \prod_{i=1}^{n} \max \left\{ 1, \frac{\ell_i e^{\lambda_i T_s}}{\ell_i - \eta_i - \delta_i} \right\}$$

$$\text{bit-rate } \geq \sum_{K_i > 1} \left( \frac{\lambda_i}{\log 2} + \frac{1}{T_s} \log_2 \frac{\ell_i}{\ell_i - \eta_i - \delta_i} \right) \quad \begin{cases} \text{approximately } r_{\min} \\ \text{when } \ell_i \gg \eta_i + \delta_i \end{cases}$$
 (but course quantization

leads to large x even without noise/disturbance)

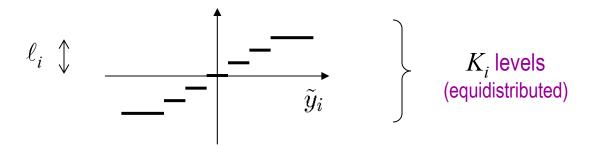
# Variable-step quantization



#### For simplicity...

- assume A diagonal with real eigenvalues
- quantize the vector by using a scalar quantizer on each of its components

If A was not diagonal one would precede the componentwise quantization by a diagonalizing linear transformation (see paper for case of A with complex eigenvalues)



 $\ell_i(k) \equiv$  saturation level for the *i*th component quantizer at sampling time  $t_k$ 

 $K_i \equiv \#$  of quantization levels used for the *i*th component of  $\tilde{y}$ 

# of words needed 
$$\equiv N = \prod_{i=1}^{n} K_i$$
 bit-rate  $\equiv \frac{\log_2 N}{T_s} = \frac{\sum_i \log K_i}{T_s \log 2}$ 

## Variable-step quantization



**Theorem:** The state of the closed-loop system will remain bounded provided that

$$K_i \geq e^{\lambda_i T_s}$$
  $\eta_i$ ,  $\delta_i \equiv \text{constants that depend on } upper bounds \text{ on the noise/disturbance}$   $\ell_i(k+1) = \frac{e^{\lambda_i T_s}}{K_i} \ell_i(k) + \eta_i + \delta_i$   $|x_i(0)| \leq \ell_i(0) - \eta_i$ 

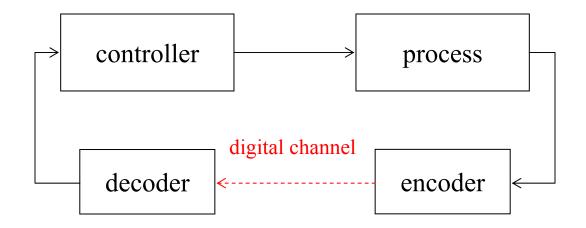
bit allocation...

$$\lambda_i \text{ large} \Rightarrow e^{\lambda i Ts} \text{ large} \Rightarrow K_i \text{ large} \Rightarrow \text{many bits needed for } i\text{th eigenspace}$$

$$\text{bit-rate} \ldots \frac{1}{\log 2} \sum_{\lambda_i > 0} =: r_{\min} \quad \Big\} \qquad \text{minimum rate can be achieved } !!!$$

#### **Conclusions**





There exists a minimum rate below which stabilization is not possible

We proposed encoder/decoder pairs (inspired by DPCM) that can achieve rates arbitrarily close to the minimal

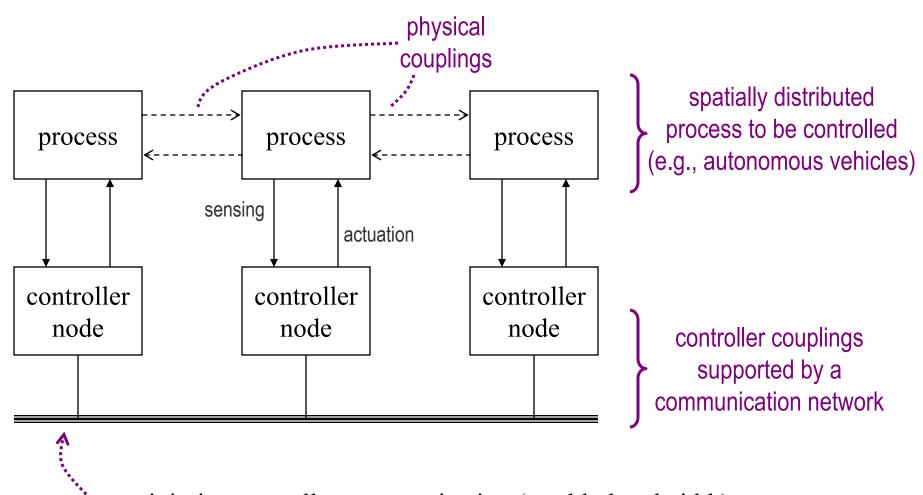
Variable-step quantization allows one to achieve the minimum bit rate

Performance/robustness vs. bit-rate tradeoffs are still poorly understood

Need to investigate problem in stochastic setting (Will entropy-like coding work with lower rates?)

## **Distributed Control**

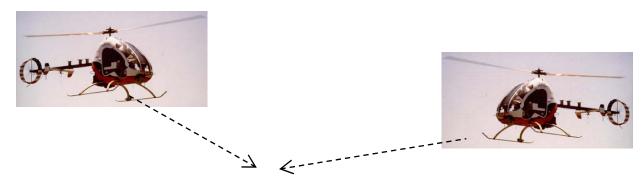




- minimize controller communication (stealth, bandwidth)
- study the effect of nonideal communication (delays, drops, blackouts)

## **Scenarios**





Rendezvous in minimum-time or using minimum-energy (in spite of disturbances)





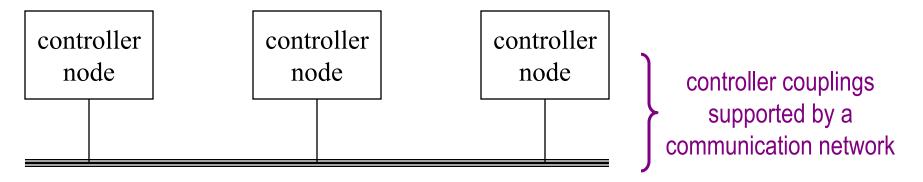




Group of autonomous agents cooperate in searching for a target (perhaps mobile—search & pursuit)

### Communication minimization





The "every bit-counts" paradigm...

**Goal**: Design each controller to minimize the number of *bits/second* that

need to be exchanged between nodes (quantization, compression, ...)

**Domain:** Media with little capacity and low-overhead protocols (bit at-a-time)

E.g., underwater acoustic comm. between a small number of nodes.

The "cost-per-message" paradigm...

**Goal**: Design each controller to minimize the number of *message exchanges* 

between nodes (scheduling, estimation, ...)

**Domain:** Media shared by a large number of nodes with nontrivial media

access control (MAC) protocol (packet at-a-time)

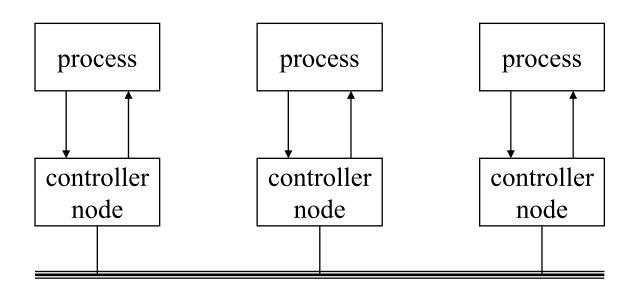
E.g., 802.11 wireless comm. between a large number of nodes.

current focus

previous case

## Prototype problem





In this talk:

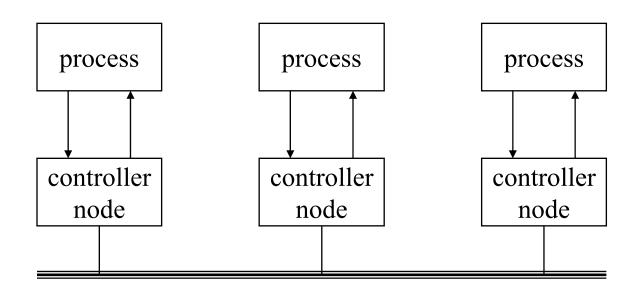
★ decoupled linear processes(with stochastic disturbance d)

$$x^{+} = \begin{bmatrix} \star & 0 & 0 \\ 0 & \star & 0 \\ 0 & 0 & \star \end{bmatrix} x + \begin{bmatrix} \star & 0 & 0 \\ 0 & \star & 0 \\ 0 & 0 & \star \end{bmatrix} u + d$$

$$\sum_{k=0}^{\infty} x' \begin{bmatrix} \star & * & 0 \\ * & \star & * \\ 0 & * & \star \end{bmatrix} x + \|u\|^2$$

## Prototype problem





In this talk:

★ decoupled linear processes(with stochastic disturbance d)

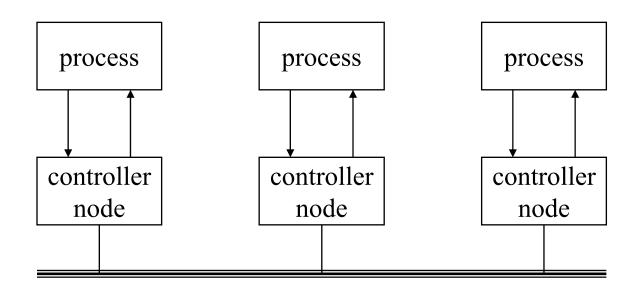
★ coupled quadratic control objective

$$x^{+} = \begin{bmatrix} A_{1} & 0 \\ 0 & A_{2} \end{bmatrix} x + \begin{bmatrix} B_{1} & 0 \\ 0 & B_{2} \end{bmatrix} u + d \qquad \sum_{k=0}^{\infty} x' \begin{bmatrix} C'_{1}C_{1} & -C'_{1}C_{2} \\ -C'_{2}C_{1} & C'_{2}C_{2} \end{bmatrix} x + \|u\|^{2}$$

E.g., rendez-vous of two vehicles

## Prototype problem





#### In this talk:

★ decoupled linear processes(with stochastic disturbance d)

$$x^{+} = \begin{bmatrix} \star & 0 & 0 \\ 0 & \star & 0 \\ 0 & 0 & \star \end{bmatrix} x + \begin{bmatrix} \star & 0 & 0 \\ 0 & \star & 0 \\ 0 & 0 & \star \end{bmatrix} u + d$$

#### **Minimum-cost solution (centralized)**

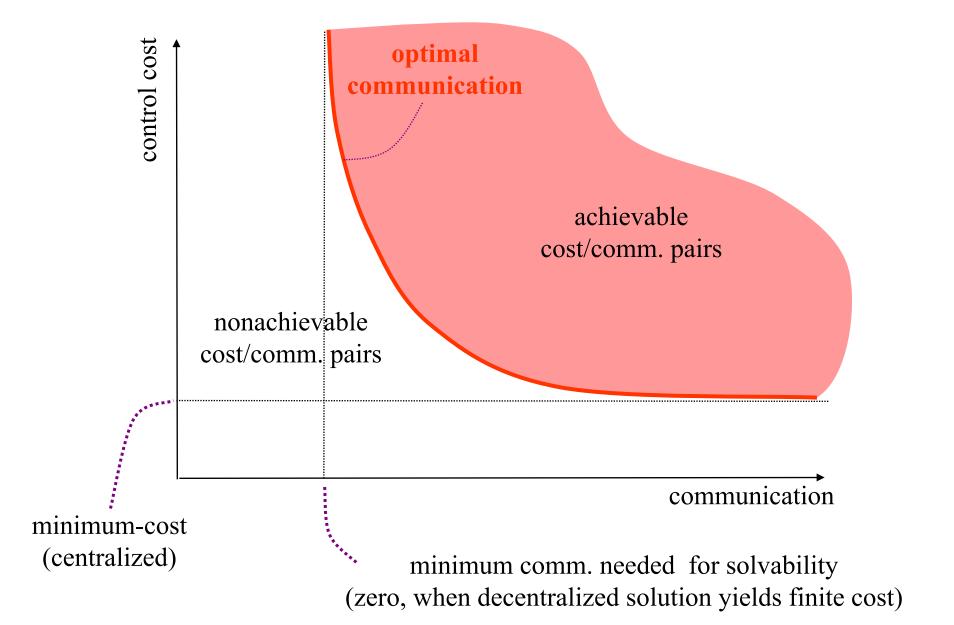
$$u = \begin{bmatrix} \star & * & * \\ * & \star & * \\ * & * & \star \end{bmatrix} x$$

#### **Completely decentralized solution**

$$u = \begin{bmatrix} \star & 0 & 0 \\ 0 & \star & 0 \\ 0 & 0 & \star \end{bmatrix} x$$

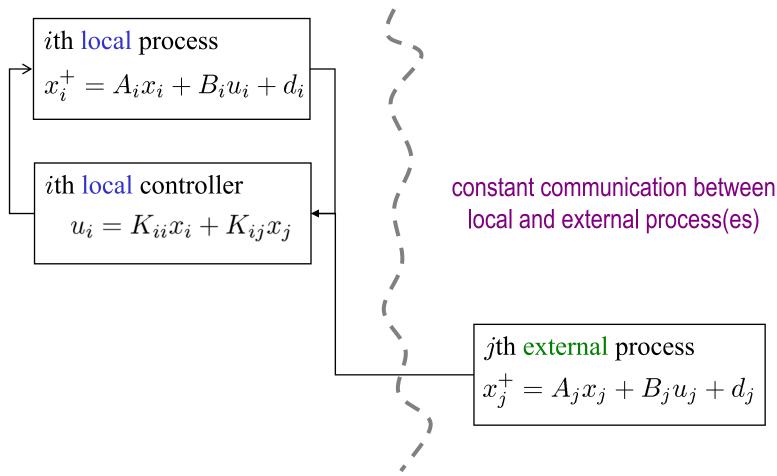
# Communication performance trade-off





#### Centralized architecture





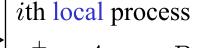
Closed-loop system

$$x_i^+ = (A_i + B_i K_{ii}) x_i + B_i K_{ij} x_j + d_i$$
  
$$x_j^+ = (A_j + B_j K_{jj}) x_j + B_j K_{ji} x_i + d_j$$

for simplicity here we assume only *two* processes

#### Estimator-based distributed architecture





$$x_i^+ = A_i x_i + B_i u_i + d_i$$

ith local controller

$$u_i = K_{ii} x_i + K_{ij} \hat{\mathbf{x}}_j$$

[Yook & Tilbury, Montestruque & Antsaklis, Xu & JH]

continuous open-loop estimator with discrete "updates" from the network

jth local estimator for jth external process  $\hat{x}_{j}^{+} = A_{j}\hat{x}_{j} + B_{j}\hat{u}_{j}$ 

$$\hat{u}_j = K_{jj}\hat{x}_i + K_{ji}\hat{x}_i$$

jth external process

$$x_j^+ = A_j x_j + B_j u_j + d_j$$

#### Closed-loop system

$$x_i^+ = (A_i + B_i K_{ii}) x_i + B_i K_{ij} x_j + d_i - B_i K_{ij} e_j$$

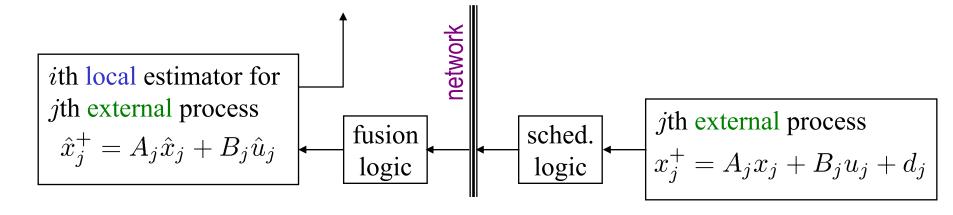
$$e_i := x_i - \hat{x}_i$$

$$x_j^+ = (A_j + B_j K_{jj}) x_j + B_j K_{ji} x_i + d_j - B_j K_{ji} e_i$$

$$e_j := x_j - \hat{x}_j$$

## **Communication logic**





How to fuse data?

When to send data?

With no noise & delay (for now...)

 $x_j(k)$  received from network at time k



$$\hat{x}_j(k+1) = A_j x_j(k) + B_j u_j(k)$$

"best-estimate" based on data received

$$\psi$$

$$e_{i}(k+1) = -d_{i}(k)$$

Scheduling logic action

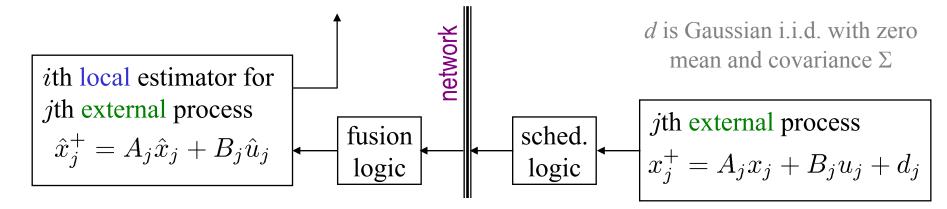
$$a_j(k) = \begin{cases} 1 & x_j(k) \text{ sent at time } k \\ 0 & \text{no transmission at } k \end{cases}$$

Options...

- periodically  $a_j(k) = \{k \text{ divisible by } T?\}, \quad T \in \mathbb{N}$
- feedback policy  $a_i(k) = F(x_i(k), ...)$
- "optimal" ...

## **Optimal Scheduling Logic**





#### Goals:

minimize the estimation error  $\Rightarrow$  minimize cost-penalty w.r.t. centralized minimize the number of transitions  $\Rightarrow$  minimize communication bandwidth

$$\limsup_{T \to \infty} \mathbf{E} \left[ \frac{1}{T} \sum_{k=0}^{T-1} e_j(k)' Q e_j(k) \right] \qquad \qquad \limsup_{T \to \infty} \mathbf{E} \left[ \frac{1}{T} \sum_{k=0}^{T-1} a_j(k) \right]$$

average L-2 norm

average transmission rate

$$\min_{\boldsymbol{a}(k)} \limsup_{T \to \infty} \mathrm{E} \left[ \frac{1}{T} \sum_{k=0}^{T-1} e_j(k)' Q e_j(k) + \frac{\lambda}{\lambda} a_j(k) \right]$$

relative weight of two criteria (will lead to Pareto-optimal solution)

## **Dynamic Programming solution**



$$\min_{a(k)} \ \limsup_{T \to \infty} \mathbf{E} \left[ \frac{1}{T} \sum_{k=0}^{T-1} e(k)' Q e(k) + \lambda \, a(k) \right]$$
 undiscounted average-cost problem

#### **Theorem**

$$(TV)(e) := \min_{a} \operatorname{E} \left[ e^{+'}Qe^{+} + \lambda a + V(e^{+}) \mid e \right]$$
 dynamic programming (DP) operator

1. There exists  $J^* \in \mathbb{R}$  and bounded  $h^* : \mathbb{R}^n \to \mathbb{R}$  such that

$$h^*(0) = 0, \qquad h^* + J = Th^*$$

2.  $J^*$  is the optimal cost and is achieved by the (deterministic) static policy

$$a(k) = \pi^* (e(k)), \quad \pi^*(e) := \begin{cases} 1 & \mathrm{E}[h^*(Ae+d)] + e'A'QAe \ge \mathrm{E}[h^*(d)] + \lambda \\ 0 & \text{otherwise} \end{cases}$$

3. *h* can be found by *value iteration* 

$$h_{i+1} = Th_i - (Th_i)(0) \xrightarrow[i \to \infty]{exp.} h^*$$

## **Dynamic Programming solution**



#### **Proof outline:**

- 1. e(k) is Markov and its transition distribution satisfies an Ergodic property (requires a mild restriction on the set of admissible policies omitted here)
- 2. T is a span-contraction [Hernandez-Lerma 96]
- 3. Result follows using standard arguments based on Banach's Fixed-Point Theorem for semi-norms.

#### **Theorem**

$$(TV)(e) := \min_{a} \operatorname{E} \left[ e^{+\prime} Q e^{+} + \lambda \, a + V(e^{+}) \mid e \right]$$
 dynamic programming (DP) operator

1. There exists  $J^* \in \mathbb{R}$  and bounded  $h^* : \mathbb{R}^n \to \mathbb{R}$  such that

$$h^*(0) = 0, \qquad h^* + J = Th^*$$

2.  $J^*$  is the optimal cost and is achieved by the (deterministic) static policy

$$a(k) = \pi^* (e(k)), \quad \pi^*(e) := \begin{cases} 1 & \operatorname{E}[h^*(Ae + d)] + e'A'QAe \ge \operatorname{E}[h^*(d)] + \lambda \\ 0 & \text{otherwise} \end{cases}$$

3. *h* can be found by *value iteration* 

$$h_{i+1} = Th_i - (Th_i)(0) \xrightarrow[i \to \infty]{exp.} h^*$$

## Example (2-dim)

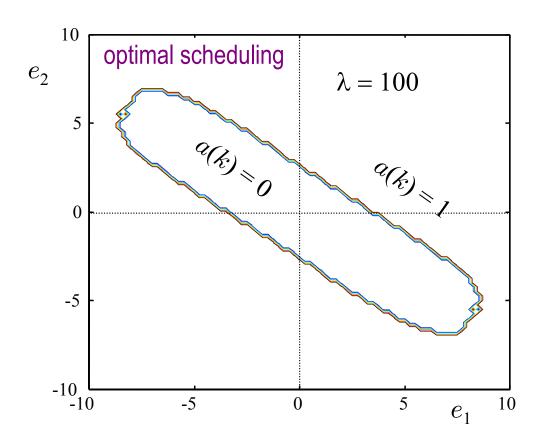


$$\limsup_{T \to \infty} \mathbf{E} \left[ \frac{1}{T} \sum_{k=0}^{T-1} e(k)' \begin{bmatrix} 4 & 0 \\ 0 & 1 \end{bmatrix} e(k) + \lambda a(k) \right]$$

local process

$$A := A_j + B_j K_j = \begin{bmatrix} 1 & 1 \\ .1 & .9 \end{bmatrix}$$

$$\mathrm{E}\left[d(k)d(k)'\right] = \begin{bmatrix} 1 & 0\\ 0 & 1 \end{bmatrix}$$



not ellipses!

# Example (2-dim)

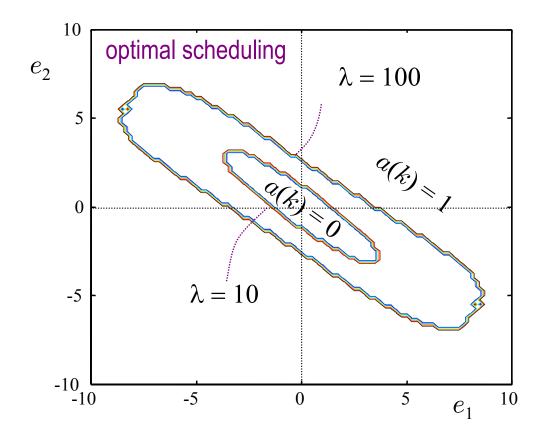


$$\limsup_{T \to \infty} \mathbf{E} \left[ \frac{1}{T} \sum_{k=0}^{T-1} e(k)' \begin{bmatrix} 4 & 0 \\ 0 & 1 \end{bmatrix} e(k) + \lambda a(k) \right]$$

local process

$$A := A_j + B_j K_j = \begin{bmatrix} 1 & 1 \\ .1 & .9 \end{bmatrix}$$

$$\mathrm{E}\left[d(k)d(k)'\right] = \begin{bmatrix} 1 & 0\\ 0 & 1 \end{bmatrix}$$



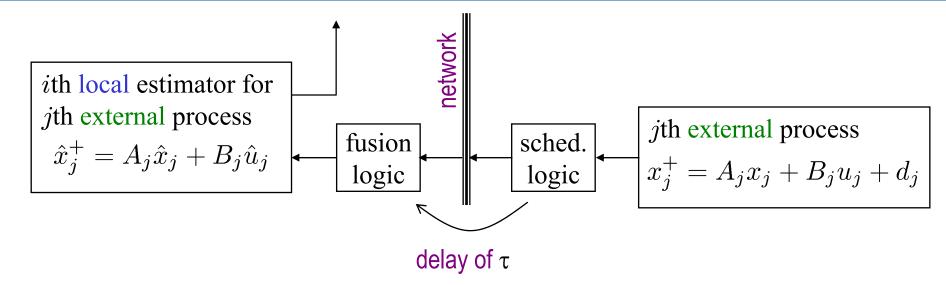
large weight in comm. cost

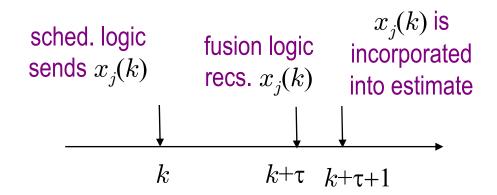
large error threshold

only communicate
when error is very large

# **Communication with latency**



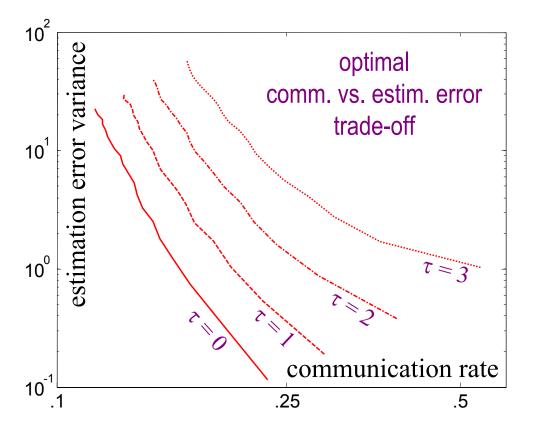




# Example (1-dim)



$$\limsup_{T \to \infty} E\left[\frac{1}{T} \sum_{k=0}^{T-1} e(k)^2 + \lambda a(k)\right]$$



$$A := A_j + B_j K_j = 2$$

$$E[d(k)^2] = .01, \ \forall k$$

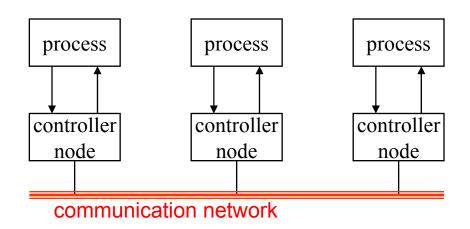
optimal scheduling

$$a(k) = egin{cases} 1 & |ar{e}(k)| \geq e_{\mathrm{threshold}} \\ 0 & \mathrm{otherwise} \\ & \mathrm{estimation\ error,\ given} \\ & \mathrm{all\ information\ enroute} \end{cases}$$

with network latency same error variance requires more bandwidth

#### **Conclusions**





We constructed communications logics that minimize communication (measured in messages sending rate)

We considered networks with (fixed) latency

Study the effect of *packet losses* (especially important in wireless networks)

Coupled control/communication-logic design

Nonlinear processes