

The Consensus algorithm in distributed multi-agent systems



University of Padova

- Founded 1222: 2nd oldest university
- 60K students out of 200K citizens
- First graduate woman in 1678
- Alumni: Galileo, Copernicus, Riccati, Bernoulli
- Department of Information Engineering (EE&CS) 3K students



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Gianluigi Pillonetto



Luca Schenato



Sandro Zampieri

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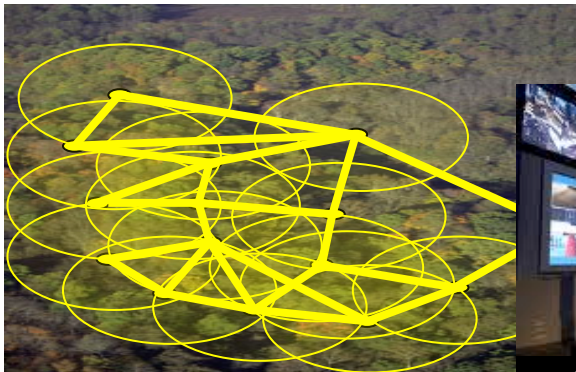
Enrico Lovisari



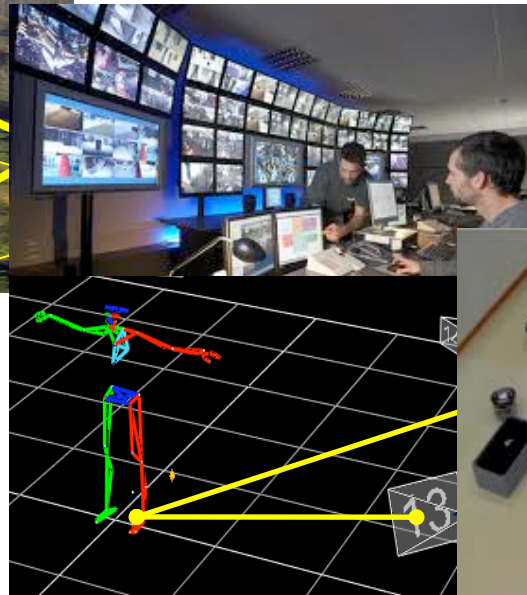
Filippo Zanella

NCS applications at Padova: MAgIC Lab

Wireless Sensor Actuator Networks



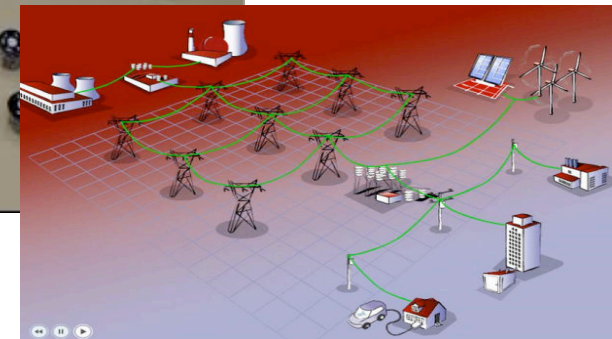
Smart Camera Networks



Robotic Networks



Smart Energy Grids



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

Outline

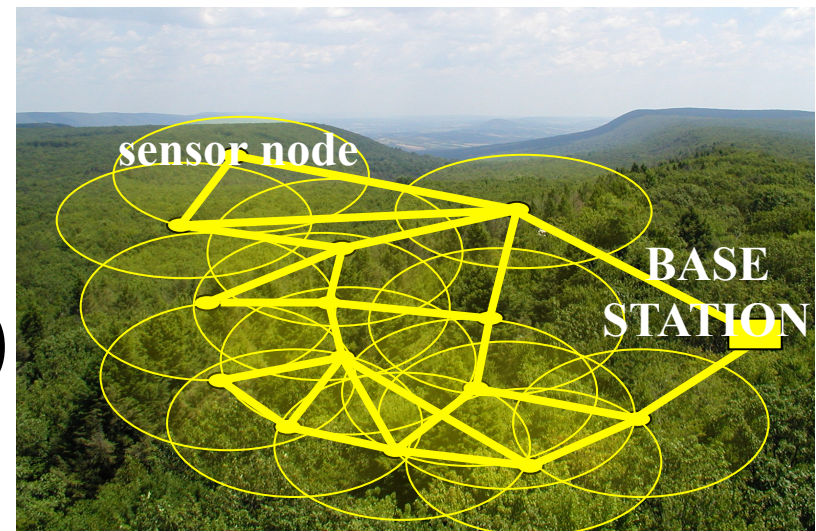
- Motivations and target applications
- Overview of consensus algorithms
- Application of consensus:
 - Sensor calibration in WSN
 - Clock-synchronization in WSN
 - Cooperative map-building in Robotic Networks
 - Perimeter patrolling in camera networks
- Open vistas and conclusions

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- Motivations and target applications
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Wireless Sensor Actuator Networks (WSANs)

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



WSAN applications: Smart Buildings & greenhouses

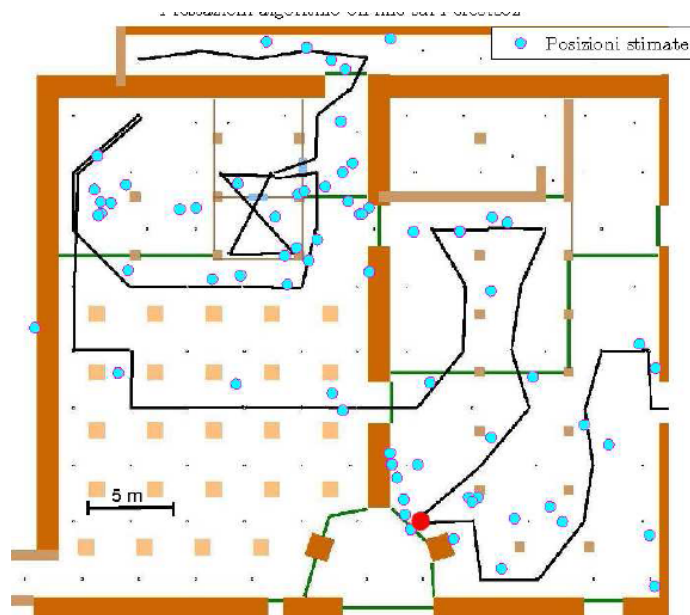
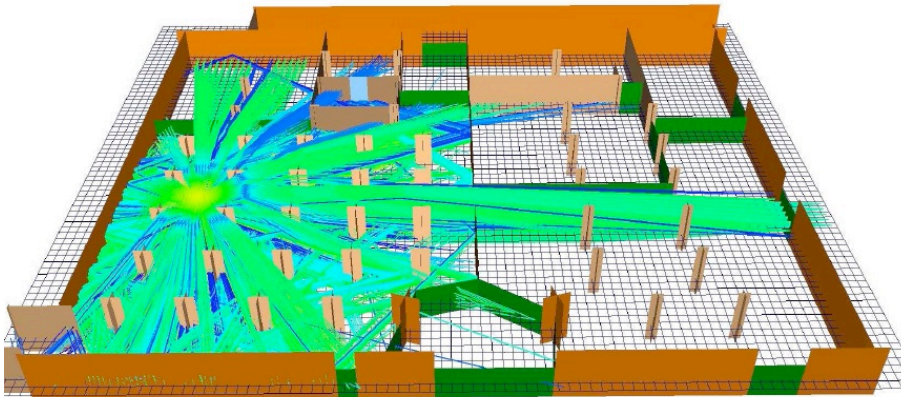
Energy	
Manufacturer Model	Fridge-Freezer
More efficient	A
A	
B	
C	
D	
E	
F	
G	
Less efficient	
Energy consumption kWh/year (Based on standard test results for 24h)	325
Actual consumption will depend on how the appliance is used and where it is located	
Fresh food volume l	190
Frozen food volume l	126
Noise (dB(A) re 1 pW)	
Further information is contained in product brochures	
Norm EN 153 May 1990 Refrigerator Label Directive 94/2/EC	



- Building thermodynamics model identification
- Sensor selection for identification
- Optimal sensor placement
- Optimal control
- Energy efficiency certification



WSAN applications: RF Localization & Tracking



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 Berkeley engineers
- Monitors occupancy, smoke, light and fire
- Tracks emergency crew inside the building and displays the details inside the firefighter's mask



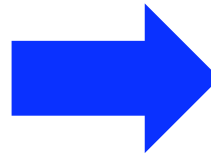
Technology for Innovators™

TEXAS INSTRUMENTS

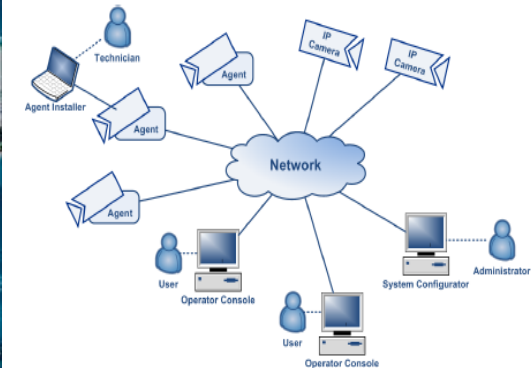
- Indoor radio signal modeling
- Real-time localization
- Distributed tracking
- Coordination

Smart camera networks apps: surveillance systems

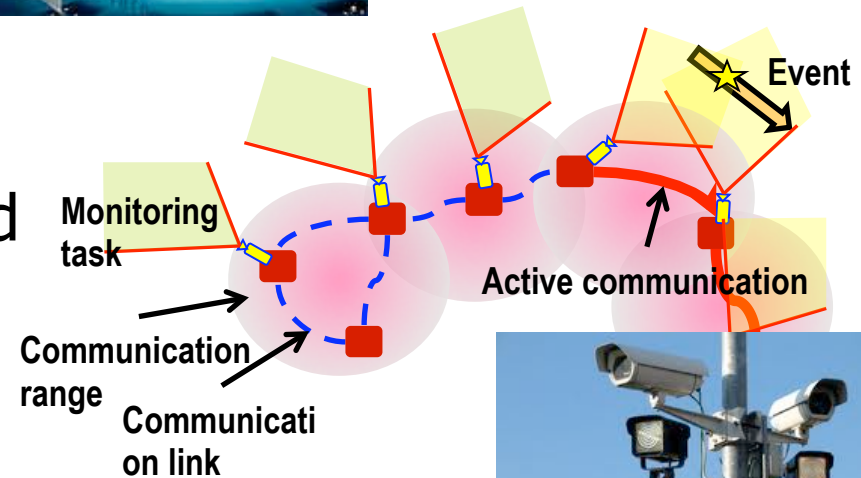
today



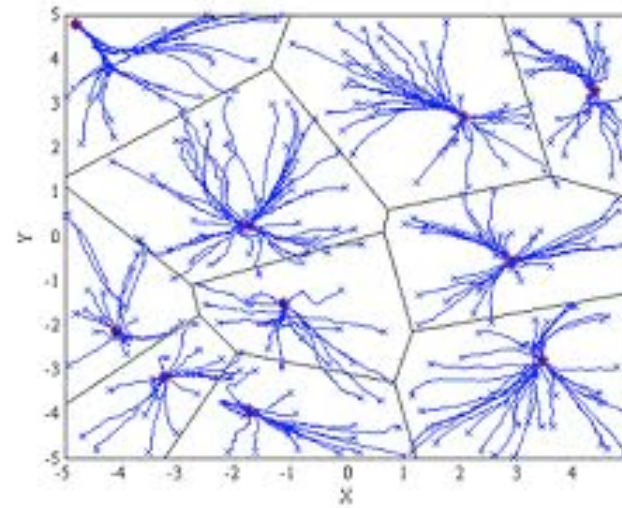
tomorrow



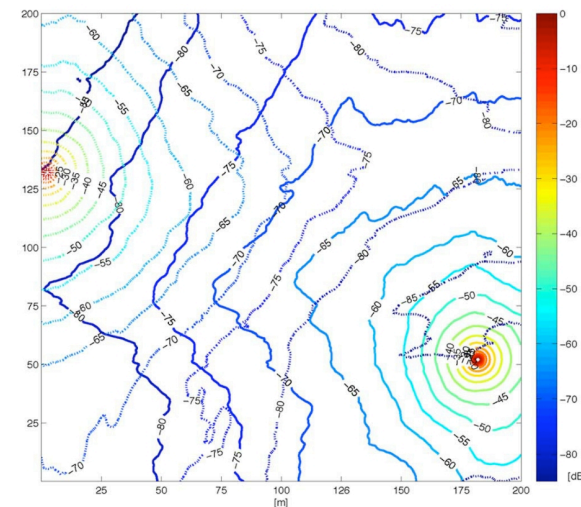
- Distributed camera calibration
- Real-time adaptive patrolling
- Cooperative event detection and tracking
- Distributed fault detection and compensation
- Virtual world navigation



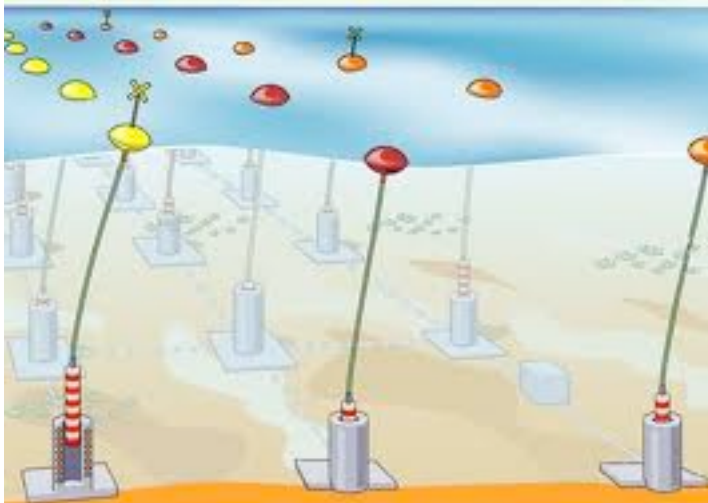
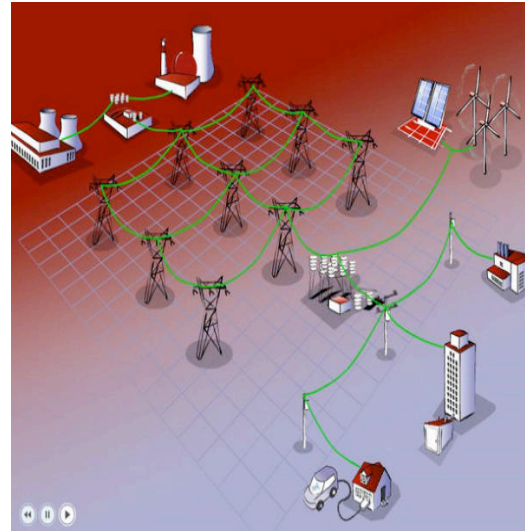
Robotic networks apps: exploration & map-building



- Optimal patrolling
- Optimal coverage
- Distributed sensing
- Collaborative map-building
- Adaptive navigation



Smart Power Grids and Renewable energies

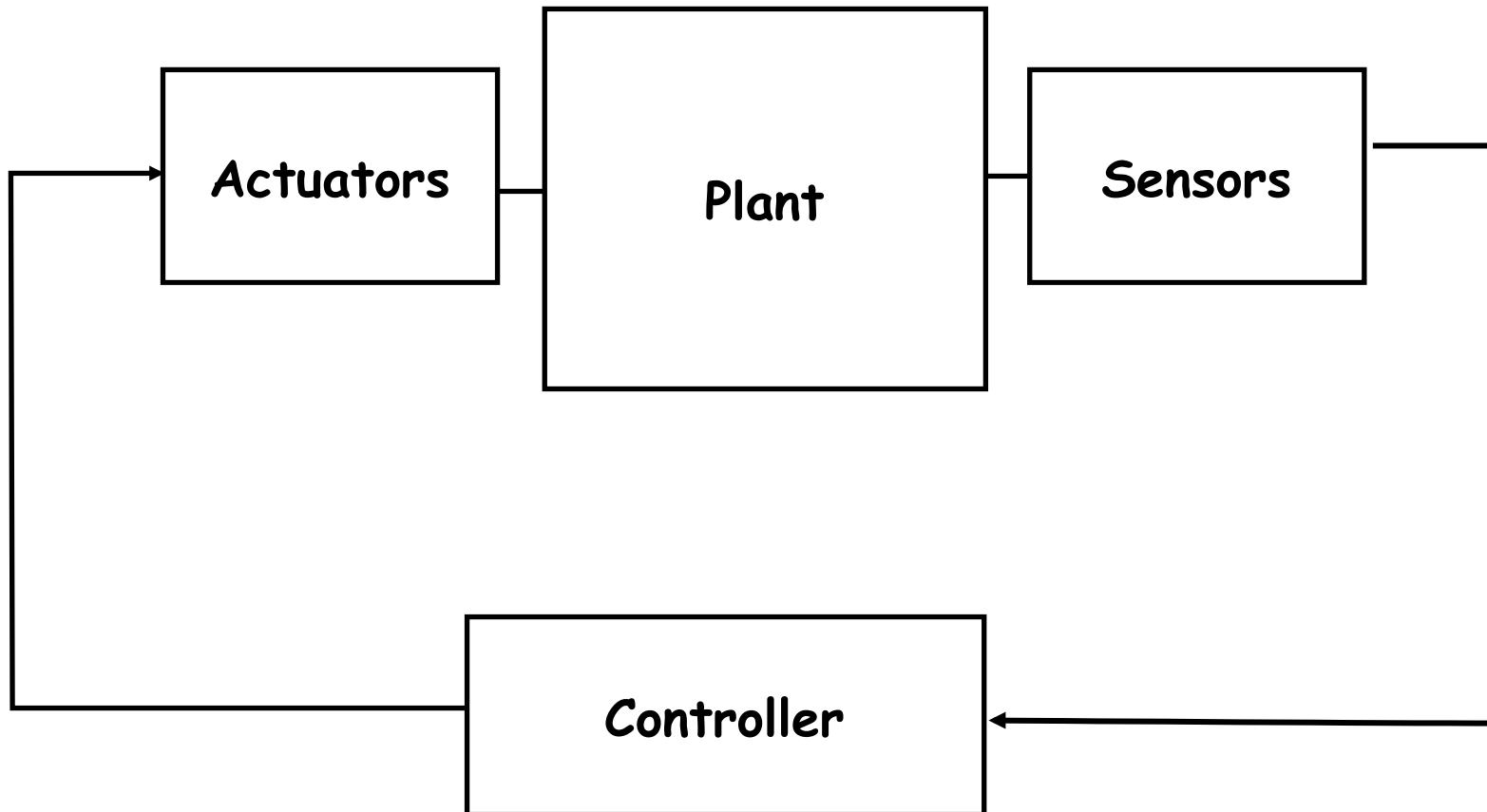


■ Foreseeable future

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

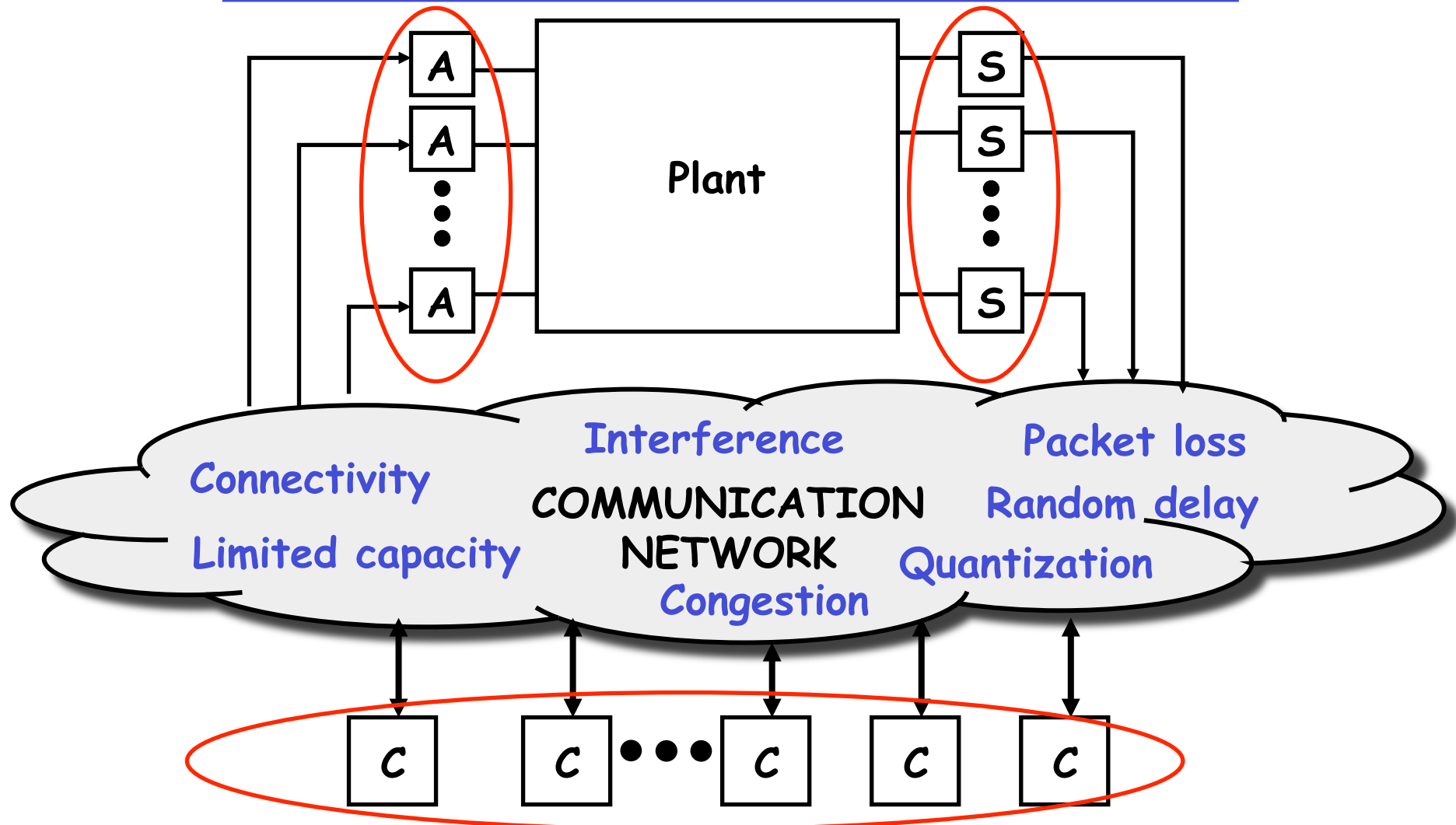
NCSs: what's new for control?

Classical architecture: Centralized structure



NCSs: what's new for control?

NCSs: Large scale distributed structure



Outline

- Motivations and target applications
- Overview of consensus algorithms
- Application of consensus to WSN:
 - Sensor calibration
 - Least-square parameter identification
 - Time-synchronization
 - Distributed Kalman filtering
- Open vistas and conclusions

The consensus problem

■ Main idea

- Having a set of agents to agree upon a certain value (usually **global function**) using only local information exchange (**local interaction**)

■ Also known as:

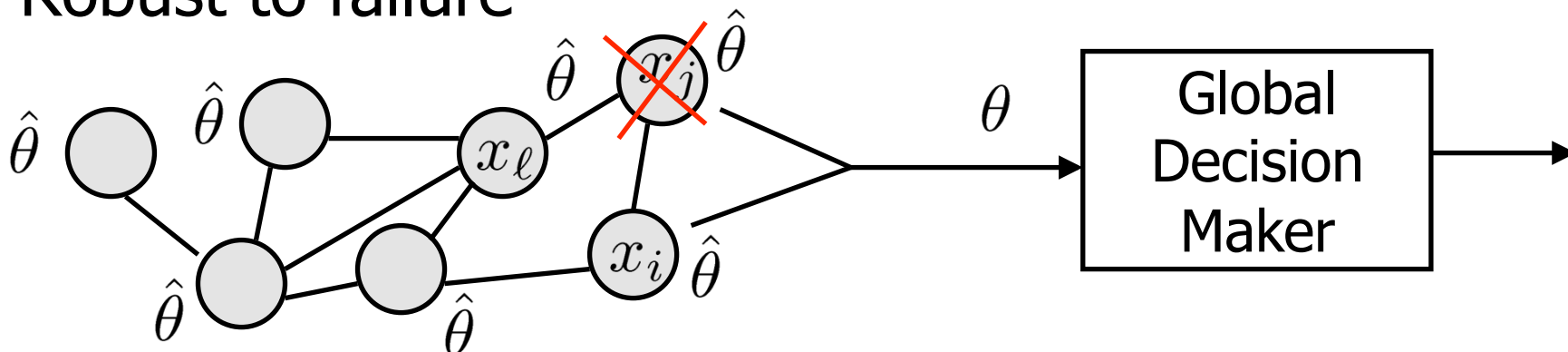
- Agreement problem (economics, signal processing, social networks)
- Gossip algorithms (CS & communications)
- Synchronization (statistical mechanics)
- Rendezvous and flocking (robotics)

Main features

- Distributed computation of general functions

$$\theta = f(x_1, \dots, x_N) = f\left(\frac{1}{N} \sum_{i=1}^N g_i(x_i)\right) \quad \left(\text{ex. } \theta = \frac{1}{N} \sum_{i=1}^N x_i \text{ for } f = g = \text{ident}\right)$$

- Computational efficient (linear & asynchronous)
- Independent of graph topology
- Incremental (i.e. anytime)
- Robust to failure



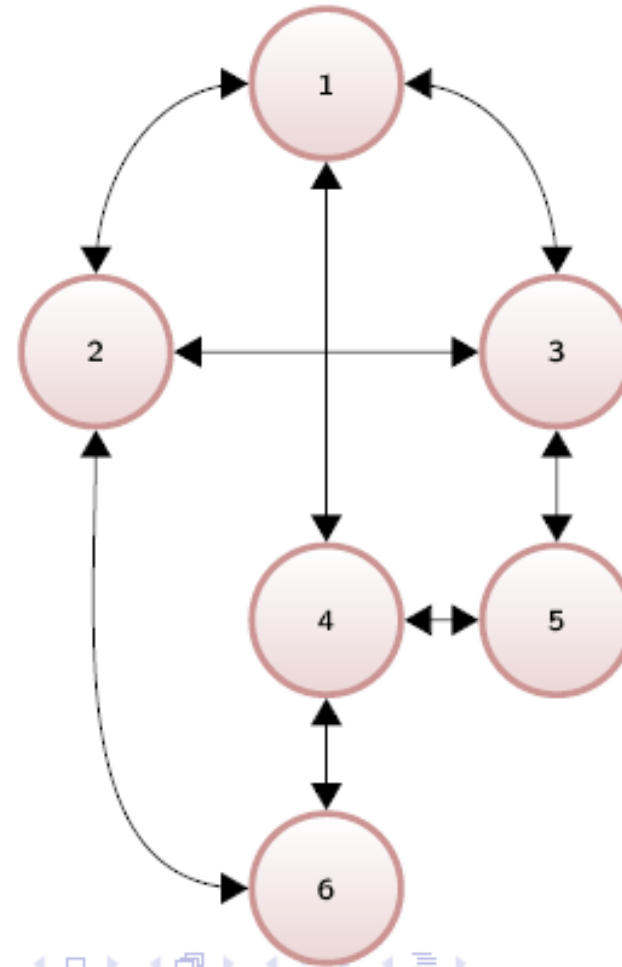
Some history (in control)

- Convergence of Markov Chains (60' s) and Parallel Computation (70' s)
- John Tsitsiklis “*Problems in Decentralized Decision Making and Computation*”, Ph.D thesis, MIT 1984
- A. Jadbabaie, J. Lin, and A. S. Morse “*Coordination of groups of mobile autonomous agents using nearest neighbor rules*”, CDC' 02 (Axelby Best Paper Award TAC)
- Time-varying topologies (worst-case)
 - **L. Moreau**, “*Consensus seeking in multi-agent systems using dynamically changing interaction topologies*,” IEEE, Transactions on Automatic Control, vol 50, No. 2, 2005
 - **M. Cao, A. S. Morse, and B. D. O. Anderson**. “*Reaching a Consensus in a Dynamically Changing Environment: A Graphical Approach*.” SIAM Journal on Control and Optimization, Feb 2008
- Randomized topologies
 - **S. Boyd, A. Ghosh, B. Prabhakar, D. Shah** “*Randomized Gossip Algorithms*”, TIT 2006
 - **F. Fagnani, S. Zampieri**, “*Randomized consensus algorithms over large scale networks*”, JSAC 08
- Applications:
 - Vehicle coordination: Jadbabaie, Francis' s group, Tanner, ...
 - Kalman Filtering: Olfati Saber-Murray, Alighanbari-How, Carli-Chiuso-Schenato-Zampieri
 - Generalized means: Giarre' ,Cortes
 - Time-synchronization: Solis-P.R. Kumar,Osvaldo-Spagnolini, Carli-Chiuso-Schenato-Zampieri
 - WSN sensor calibration and parameter identification: Bolognani-DelFavero-Schenato-Varagnolo

Consensus formulation (1/2)

Network of

- N agents
- Communication graph
 $\mathcal{G} = (\mathcal{N}, \mathcal{E})$
- i-th node neighbors: $\mathcal{N}(i)$
- Every node stores a variable:
node i stores x_i .



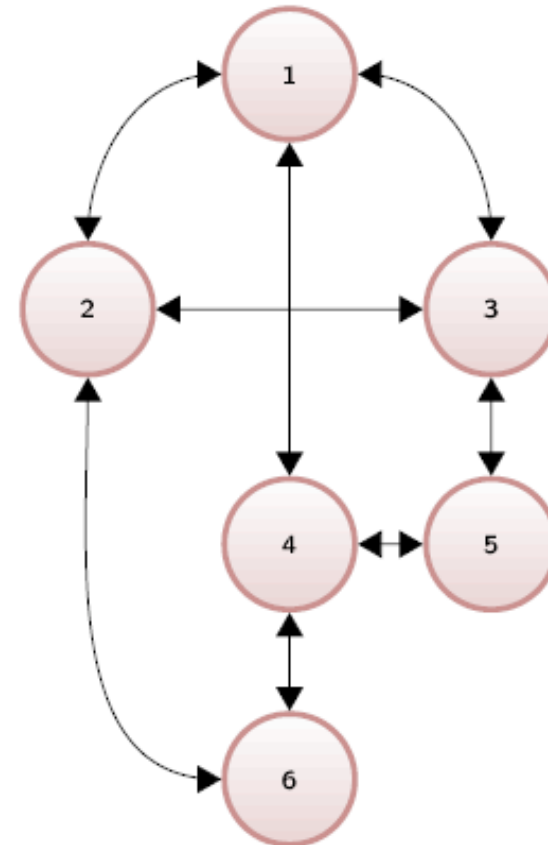
Consensus formulation (2/2)

Definition (Recursive Distributed Algorithm adapted to the graph \mathcal{G})

Any recursive algorithm where the i node's update law depends only on the state of i and in its neighbors $j \in \mathcal{N}(i)$

$$x_i(t+1) = f(x_i(t), x_{j_1}(t), \dots, x_{j_{N_i}}(t))$$

with $j_1, \dots, j_{N_i} \in \mathcal{N}(i)$

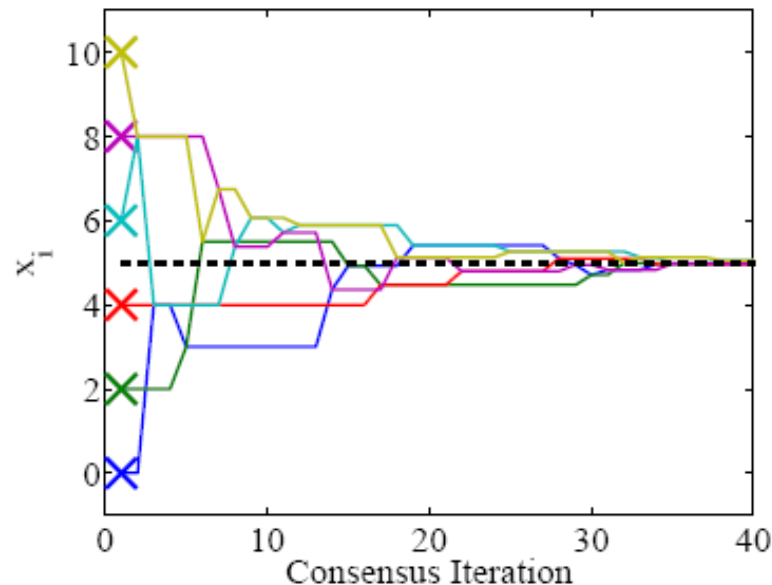
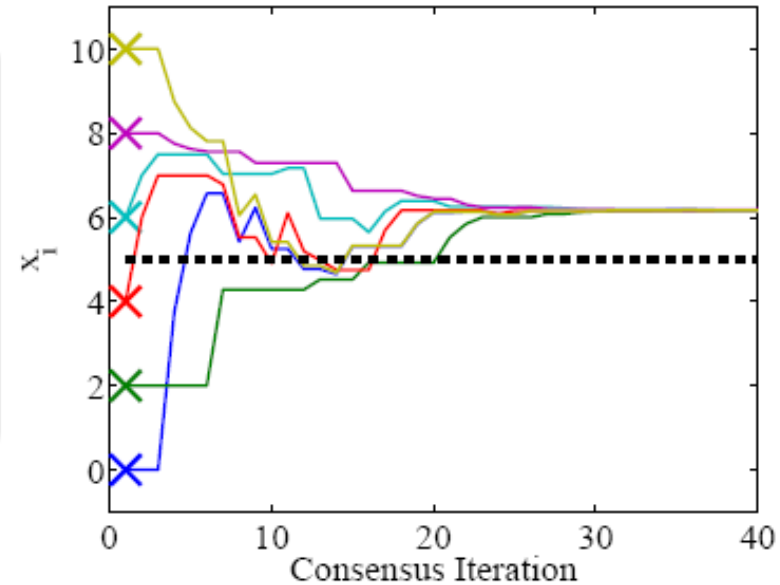


Consensus definitions

Definition

A Recursive Distributed Algorithm adapted to the graph \mathcal{G} is said to **asymptotically achieve consensus** if

$$x_i(t) \rightarrow \alpha \quad \forall i \in \mathcal{N}$$



Definition

A Recursive Distributed Algorithm adapted to the graph \mathcal{G} is said to **asymptotically achieve average consensus** if

$$x_i(t) \rightarrow \frac{1}{N} \sum_{i \in \mathcal{N}} x_i(0) \quad \forall i \in \mathcal{N}$$

Linear consensus

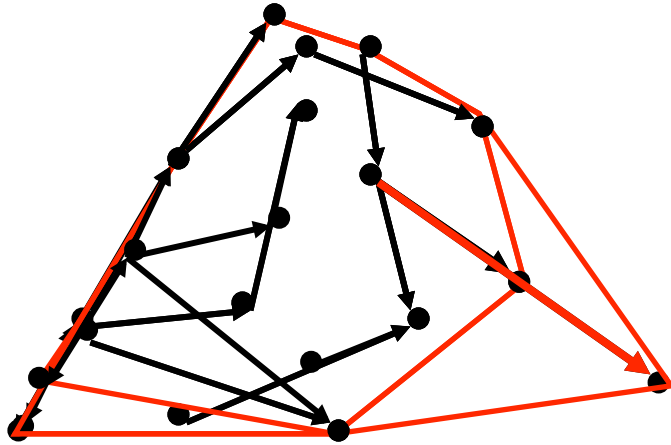
$$x_i(t+1) = p_{ii}x_i(t) + \sum_{j \in \mathcal{N}(i)} p_{ij}x_j(t)$$

$$x(t) = \begin{bmatrix} x_1(t) \\ \vdots \\ x_N(t) \end{bmatrix} \quad x(t+1) = P(t)x(t)$$

Say \mathcal{G}_P Graph associated to P , $P_{ij} \neq 0 \iff (i, j) \in \mathcal{E}_P$,

$$\mathcal{G}_P \subseteq \mathcal{G} \quad (\mathcal{N} \equiv \mathcal{N}_P, \quad \mathcal{E} \subseteq \mathcal{E}_P)$$

A robotics example: the rendezvous problem



$$x_i(t + 1) = x_i(t) + u_i(t)$$
$$x_i(t + 1) = p_{ii}x_i(t) + \sum_{j \in N(i)} p_{ij}x_j$$

Convex hull always shrinks.

If communication graph sufficiently connected, then shrinks to a point

Stochastic matrix

Definition (Stochastic Matrix)

If $P_{ij} \geq 0$ and $\sum_j P_{ij} = 1 \forall i$, then P is said to be **stochastic**

$$P\mathbb{1} = \mathbb{1} \quad \mathbb{1} = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}$$

Remark

If P is stochastic the linear algorithm can be written in both forms:

$$x_i(t+1) = p_{ii}x_i(t) + \sum_{j \in \mathcal{N}(i)} p_{ij}x_j(t)$$

$$x_i(t+1) = x_i(t) + \sum_{j \in \mathcal{N}(i)} p_{ij}(x_j(t) - x_i(t))$$

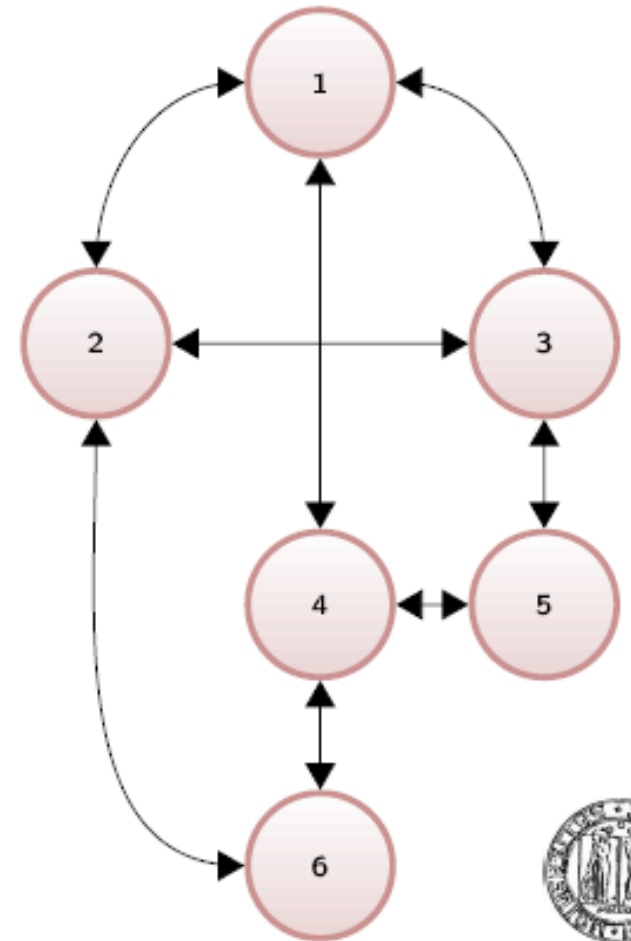
Constant matrix P

Synchronous Communication:

At each time all nodes communicate according to the communication graph

$P(t)=P$:

$$P = \begin{bmatrix} 3/6 & 1/6 & 1/6 & 1/6 & 0 & 0 \\ 1/6 & 3/6 & 1/6 & 0 & 0 & 1/6 \\ 1/6 & 1/6 & 3/6 & 0 & 1/6 & 0 \\ 1/6 & 0 & 0 & 3/6 & 1/6 & 1/6 \\ 0 & 0 & 1/6 & 1/6 & 4/6 & 0 \\ 0 & 1/6 & 0 & 1/6 & 0 & 4/6 \end{bmatrix}$$



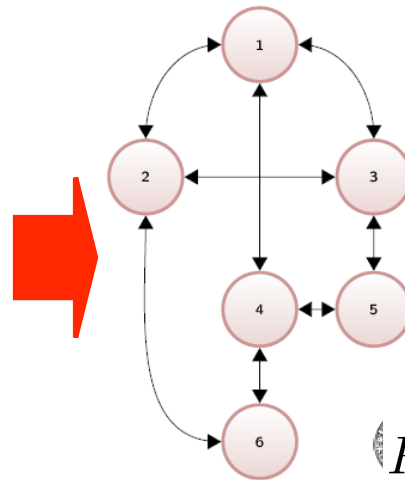
Convergence results

Theorem

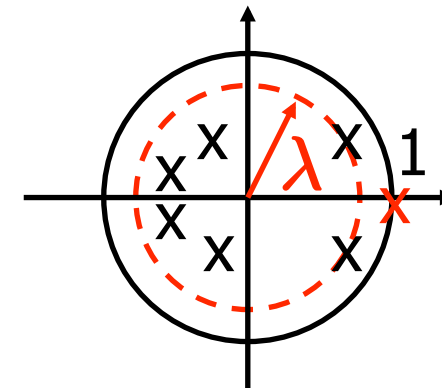
$P(t) = P$ stochastic.

- If P such that $\mathcal{G}_P \subseteq \mathcal{G}$ is rooted then the algorithm achieves consensus
- If also P^T is stochastic (P doubly stochastic), then *average* consensus is achieved

$$P = \begin{bmatrix} p_{1,1} & p_{1,2} & p_{1,3} & p_{1,4} & 0 & 0 \\ p_{2,1} & p_{2,2} & p_{2,3} & 0 & 0 & p_{2,6} \\ p_{3,1} & p_{3,2} & p_{3,3} & 0 & p_{3,5} & 0 \\ p_{4,1} & 0 & 0 & p_{4,4} & p_{4,5} & p_{4,6} \\ 0 & 0 & p_{5,4} & p_{5,3} & p_{5,5} & 0 \\ 0 & p_{6,2} & 0 & p_{6,4} & 0 & p_{6,6} \end{bmatrix}$$



eigenvalues of P :



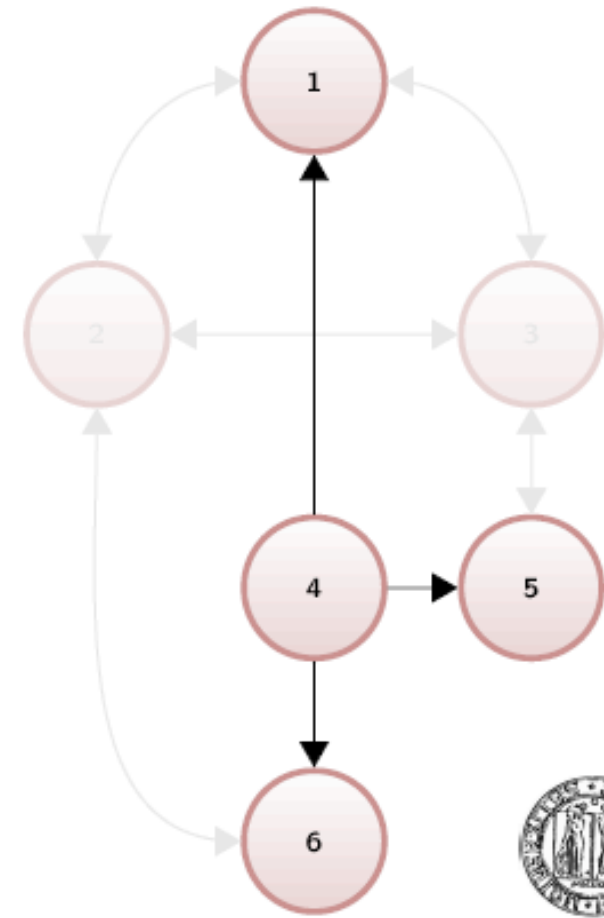
$P^t \xrightarrow{\lambda^t} \mathbf{1}\rho^T$, ρ is left eigenvector of 1
 $\sum_i \rho_i = 1, \rho_i \geq 0$, ($\rho_i > 0$ if strong. conn.)
 $\rho = \frac{1}{N}\mathbf{1}$ if P doubly stochastic

Time varying $P(t)$: broadcast

Broadcast:

At each time one node randomly wakes up and broadcasts its information to all its neighbors.

$$P(t) = \begin{bmatrix} 3/4 & 0 & 0 & 1/4 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1/4 & 3/4 & 0 \\ 0 & 0 & 0 & 1/4 & 0 & 3/4 \end{bmatrix}$$

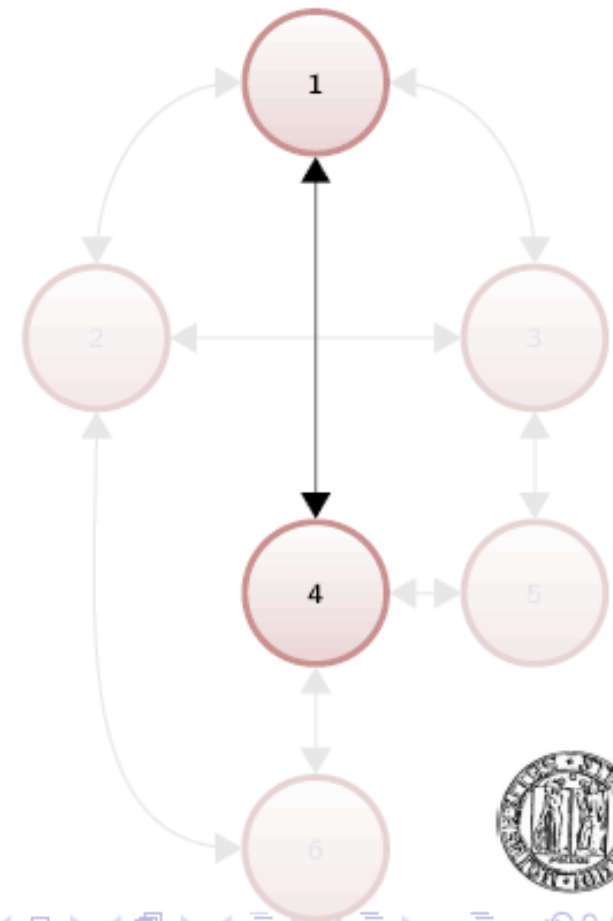


Time varying $P(t)$: symmetric gossip

Symmetric Gossip:

At each time one node randomly wakes up and chose randomly a its neighbor. Those two nodes exchange information

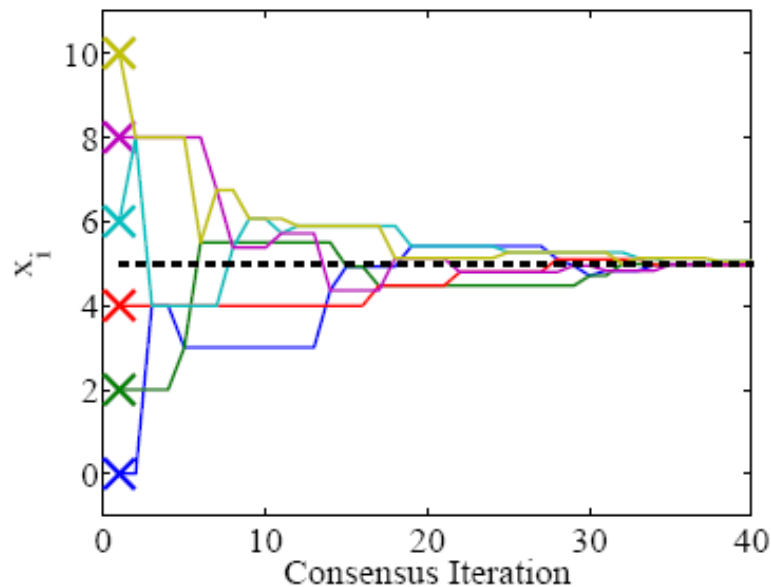
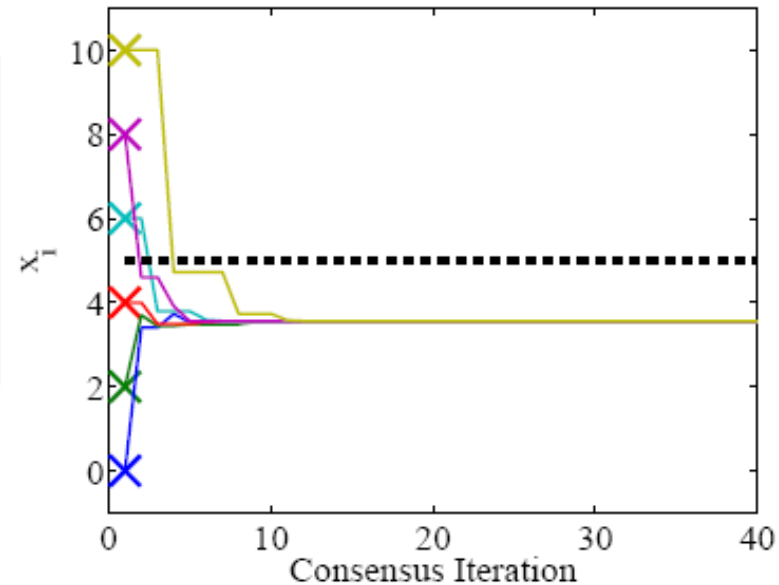
$$P(t) = \begin{bmatrix} 1/2 & 0 & 0 & 1/2 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 1/2 & 0 & 0 & 1/2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$



Consensus strategies for WSA

Broadcast

- 1 message broadcasted, $|\mathcal{N}(i)|$ estimate updated
- Does not guarantee average consensus



Symmetric Gossip

- At least 3 messages exchanged, 2 estimate updated
- Guarantee average consensus



Convergence results: $P=P(t)$ deterministic

Theorem

Suppose that $P_{ii}(t) > 0, \forall i, \forall t$ and that there exists K such that $\mathcal{G}_\ell = \mathcal{G}_{P((\ell+1)K)} \cup \dots \cup \mathcal{G}_{P(\ell K)}$ is rooted at some node j for all ℓ then

- the sequence $\{P(t)\}$ achieves consensus
- if also $P^T(t)$ are stochastic for all t , then the sequence $\{P(t)\}$ achieves *average* consensus

Remark:

Estimates of rate of convergence are very conservative (worst case)

L. Moreau, "Consensus seeking in multi-agent systems using dynamically changing interaction topologies," IEEE, Transactions on Automatic Control, vol 50, No. 2, 2005

M. Cao, A. S. Morse, and B. D. O. Anderson. "Reaching a Consensus in a Dynamically Changing Environment: A Graphical Approach." SIAM Journal on Control and Optimization, Feb 2008

Convergence results: $P=P(t)$ randomized

Theorem

Suppose $\{P(t)\}$ is a sequence of i.i.d. stochastic random matrices. Suppose moreover $\mathcal{G}_{P(t)} \subseteq \mathcal{G} \forall t$ and call $\bar{P} = \mathbb{E}[P]$.

- If $\mathcal{G}_{\bar{P}}$ is rooted that consensus is achieved *w.p.1*
- If also $P(t)^T$ is stochastic for every t , then *average* consensus is achieved *w.p.1*

Remark:

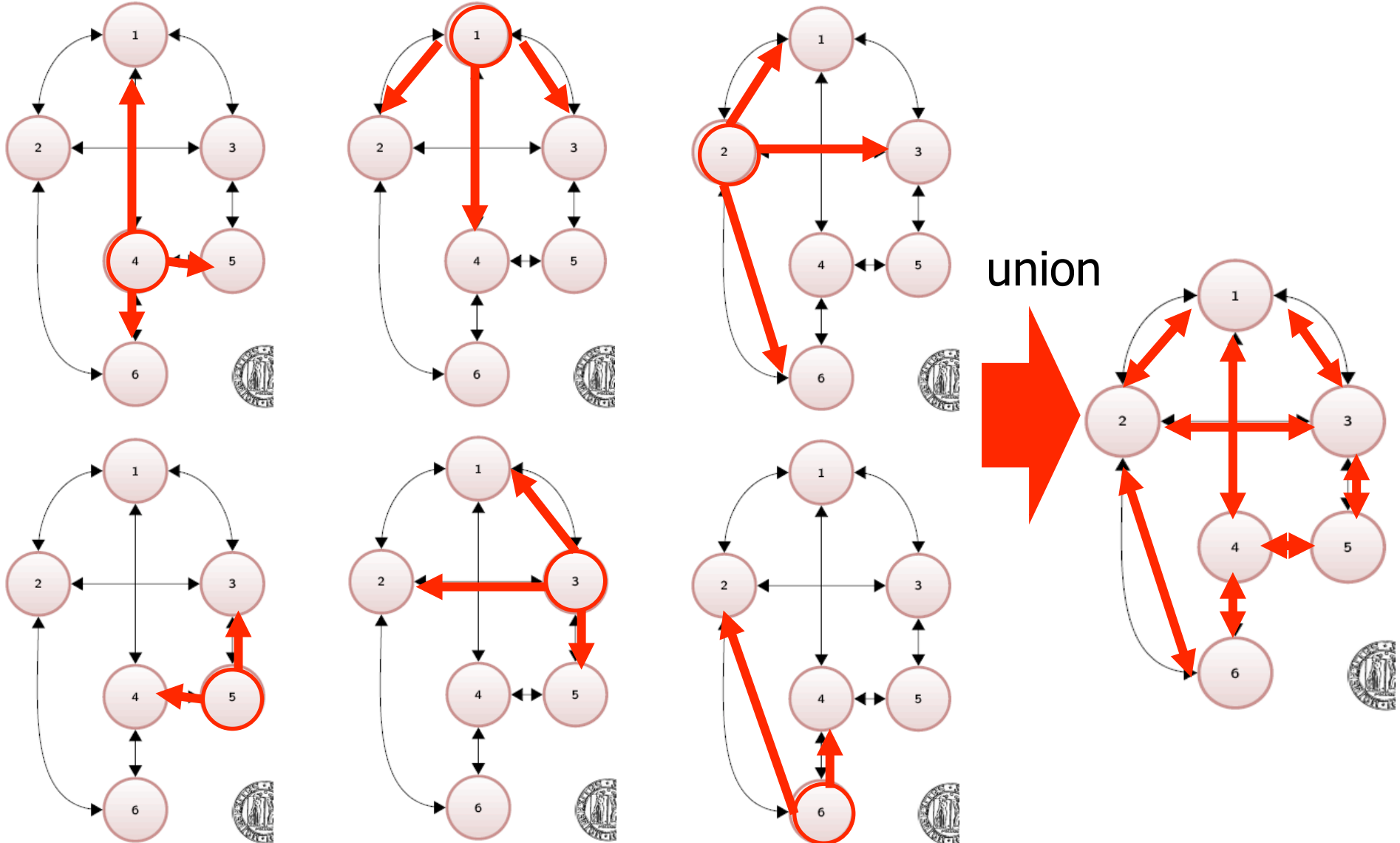
It is **not** sufficient \bar{P} doubly stochastic to guarantee *average* consensus

$$x(t+1) = P(t)x(t) = P(t)P(t-1) \cdots P(0)x(0) = Q(t)x(0) \quad (Q(t) = P^t \text{ if } P(t) = P)$$

$$Q(t) \rightarrow \mathbf{1}\rho^T, \quad \mathbb{E}[\rho] = \frac{1}{N}\mathbf{1}, \quad \text{Var}(\rho) \sim \frac{1}{N}$$

F. Fagnani, S. Zampieri, “Randomized consensus algorithms over large scale networks”, IEEE Journal on Selected Areas in Communications, 2008

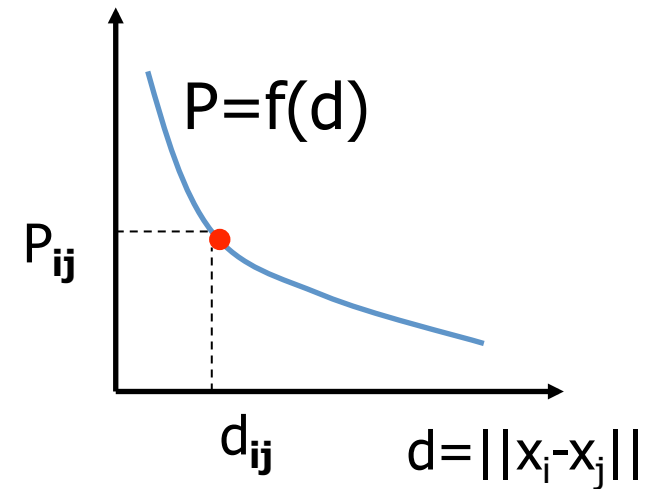
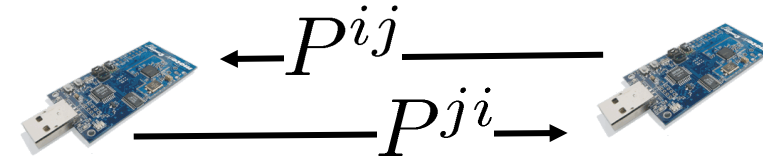
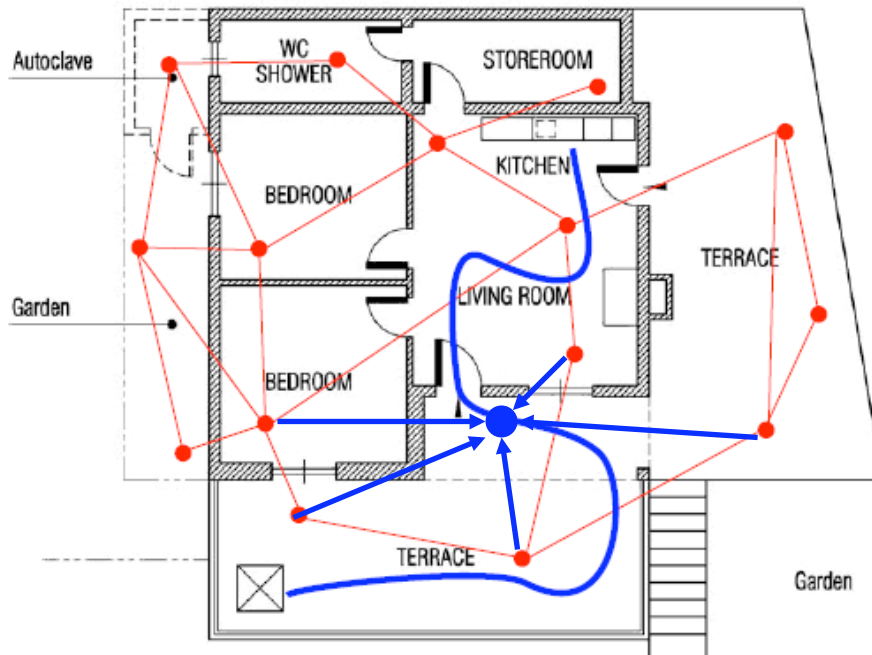
How to apply these results: broadcast communication



Outline

- Motivations and target applications
- Overview of consensus algorithms
- Application of consensus to WSN:
 - Sensor calibration
 - Clock synchronization
 - Map-Building
 - Perimeter Patrolling
- Open vistas and conclusions

Sensor calibration issues in RF-based localization

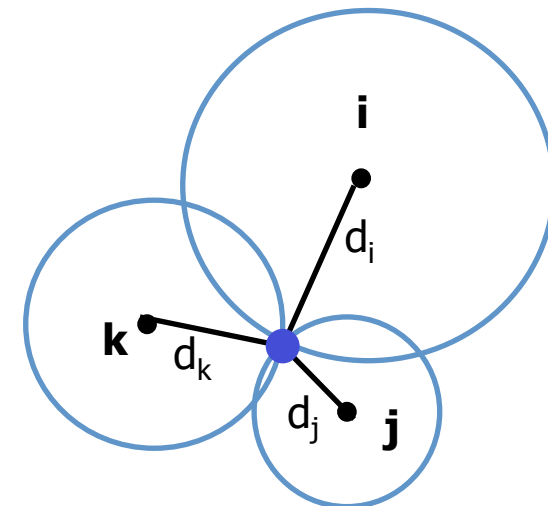


Systematic calibration errors

$$P_{rx}^{ij} = g(x_i, x_j) + o_i$$

$$P_{rx}^{ji} = g(x_j, x_i) + o_j$$

$$g(x_i, x_j) = g(x_j, x_i)$$



WSN sensor calibration

Ideally:

- Estimate o_i : \hat{o}_i
- Use \hat{o}_i to compensate the offset: $o_i - \hat{o}_i = 0$

Remember the previous example

$$P_{rx}^{ij} = g(x_i, x_j) + o_i - \hat{o}_i$$

$$P_{rx}^{ij} - P_{rx}^{ji} = o_i - o_j$$

Calibration as consensus problem

Remark

If P is stochastic the linear algorithm can be written in both forms:

$$x_i(t+1) = p_{ii}x_i(t) + \sum_{j \in \mathcal{N}(i)} p_{ij}x_j(t)$$

$$x_i(t+1) = x_i(t) + \sum_{j \in \mathcal{N}(i)} p_{ij}(x_j(t) - x_i(t)) \quad o_i - \hat{o}_i(t) = x(t)$$

$$o_i - \hat{o}_i(t+1) = o_i(t) - \hat{o}_i(t) + \frac{1}{2} ((o_i - \hat{o}_i(t)) - (o_j - \hat{o}_j(t)))$$

$$o_i - \hat{o}_i(t+1) = o_i(t) - \hat{o}_i(t) + \frac{1}{2} ((o_i + g(x_i, x_j) - \hat{o}_i(t)) - (o_j + g(x_i, x_j) - \hat{o}_j(t)))$$

$$\hat{o}_i(t+1) = \hat{o}_i(t) - \frac{1}{2} (P^{ij} - P^{ji} - \hat{o}_i(t) + \hat{o}_j(t))$$

update
equation

$$\hat{o}_i(t) \rightarrow o_i - \frac{1}{N} \sum_i o_i = o_i - \alpha \approx o_i$$

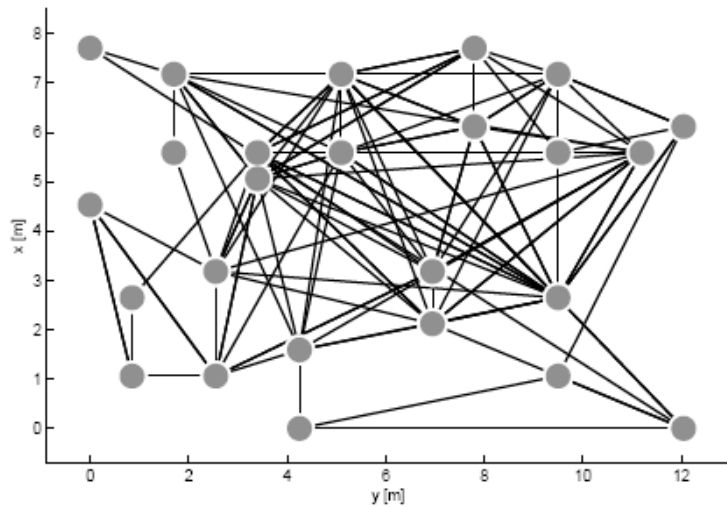
Steady state

Experimental Testbed

25 TMote-Sky nodes with Chipcon CC2420 RF Transceiver randomly placed inside a single conference room:



Network topology and nodes displacement:



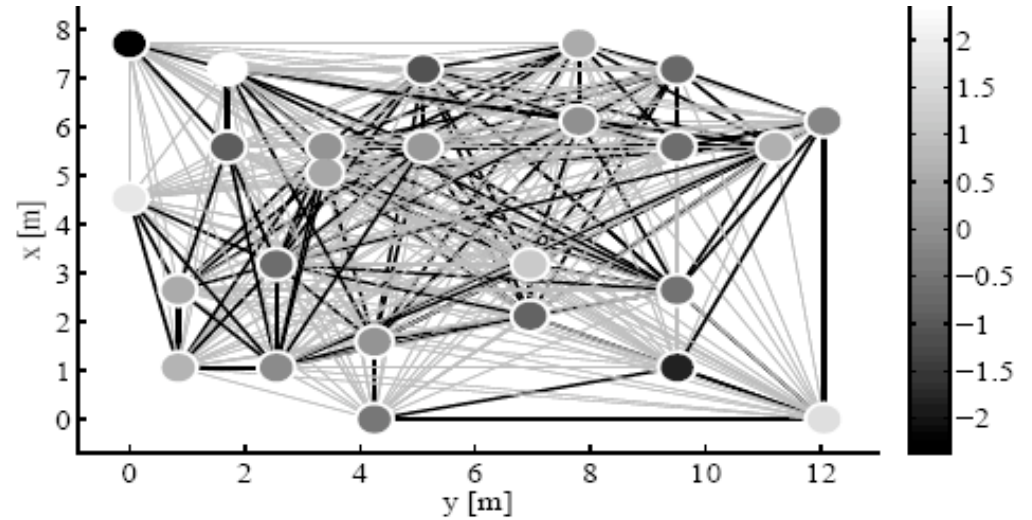
Kept just the links that safely carried the 75% of the sent messages over them



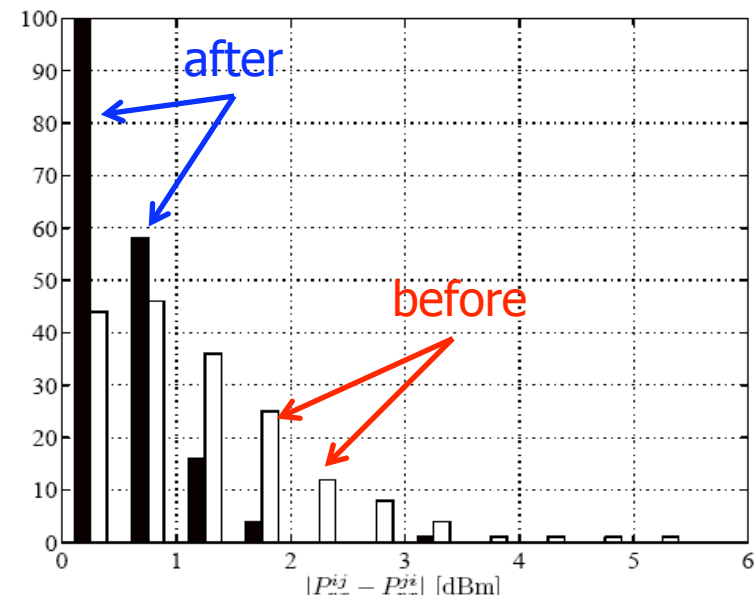
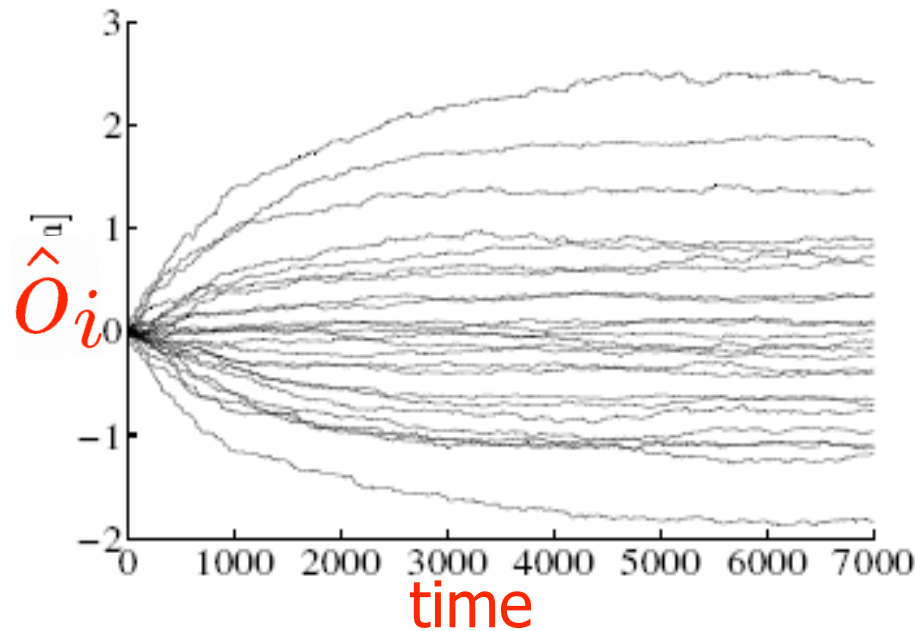
Experimental results

Links divided in 2 categories:

- Training links (black)
- Validation links (gray)



Error distribution



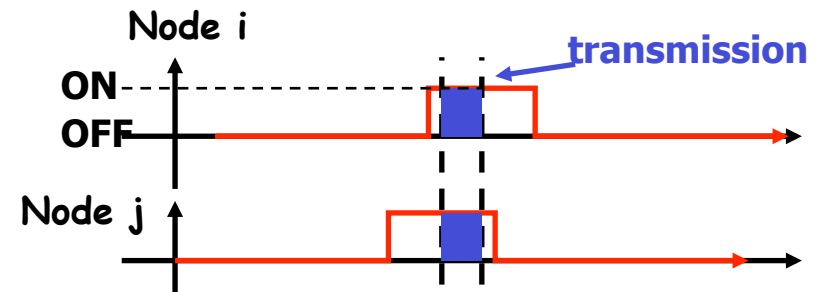
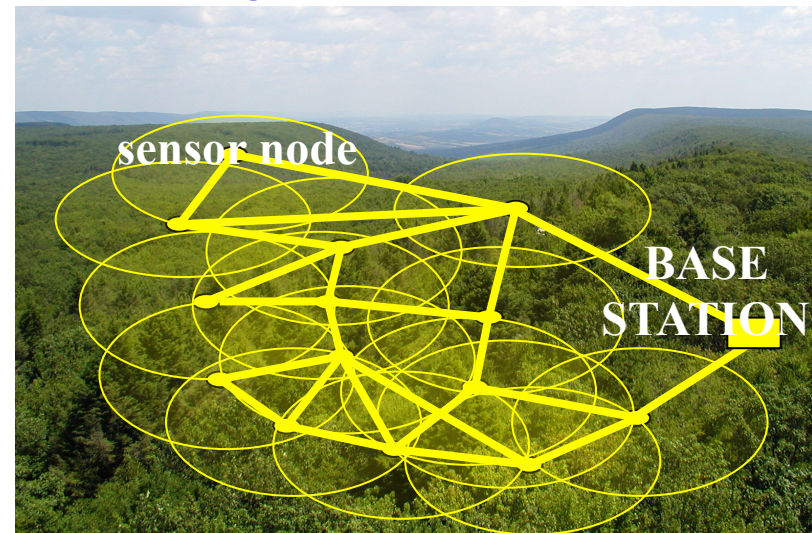
Clock Synchronization in WSN

Cromotherapy

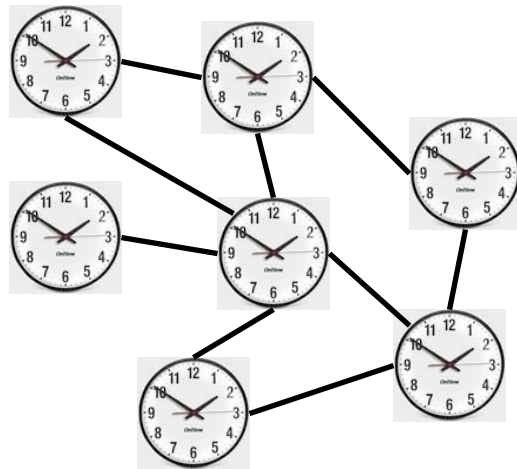
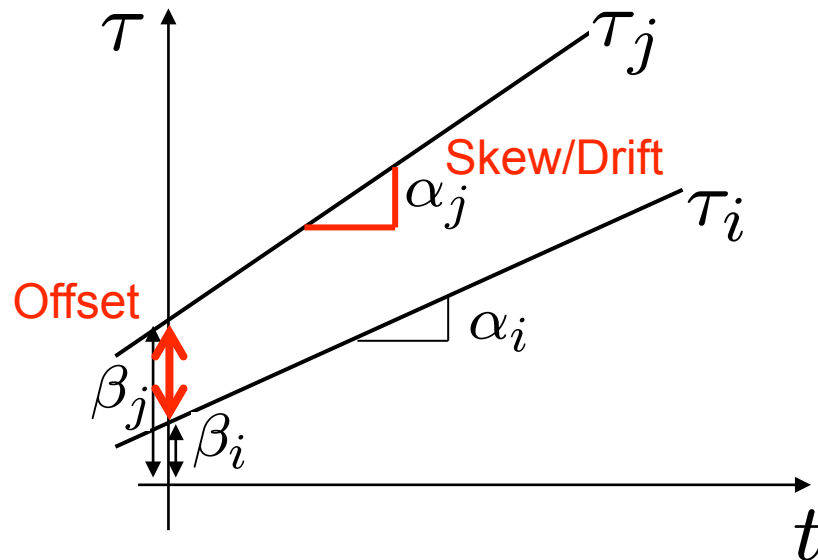


Synchronized sequence of RGB colors on wireless lamps

Low Power TDMA communication for battery powered nodes



Clock Synchronization (1/2)



Local clocks

$$\tau_i(t) = \alpha_i t + \beta_i \quad i = 1, \dots, N$$

Virtual reference clock

$$\tau^*(t) = \alpha^* t + \beta^*$$

Local clock estimate

$$\hat{\tau}_j(t) = \hat{\alpha}_j \tau_i + \hat{\omega}_j \quad i = 1, \dots, N$$

$$\hat{\tau}_j(t) = \underbrace{\hat{\alpha}_j \alpha_j}_{\alpha^*} t + \underbrace{\hat{\alpha}_j \beta_i}_{\beta^*} + \hat{\omega}_j$$

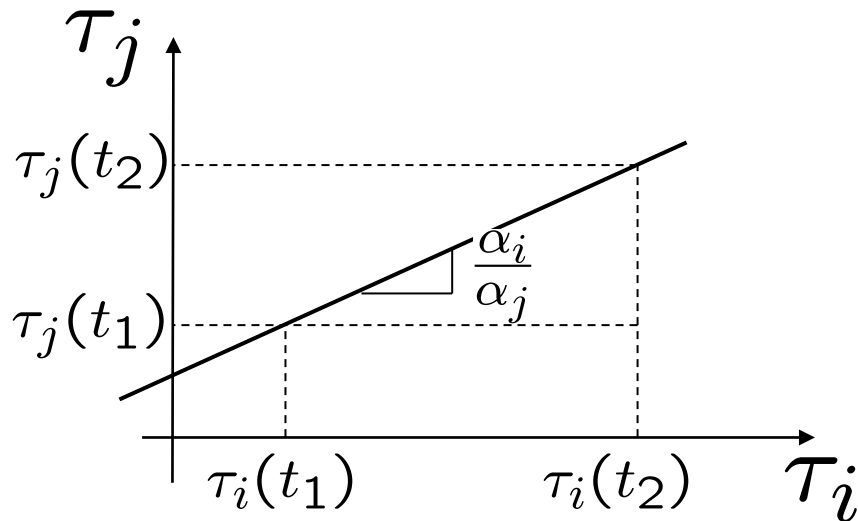
GOAL: find $(\hat{\alpha}_j, \hat{\omega}_j)$ such that

$$\lim_{t \rightarrow \infty} \hat{\tau}_i(t) = \tau^*(t), \quad \forall i = 1, \dots, N$$

Strategy:

- 1) set $x_j^\alpha = \alpha_j \hat{\alpha}_j$ and $x_j^\beta = \hat{\omega}_j + \hat{\alpha}_j \beta_j$ write consensus
- 2) find update equations for $\hat{\alpha}_j(t)$ and $\hat{\omega}_j(t)$
- 3) $\alpha_i \hat{\alpha}_i(t) \rightarrow \frac{1}{N} \sum_{i=1}^N \alpha_i$ and $\hat{\omega}_j(t) + \hat{\alpha}_j(t) \beta_j \rightarrow \beta^*$

Clock Synchronization (2/2)



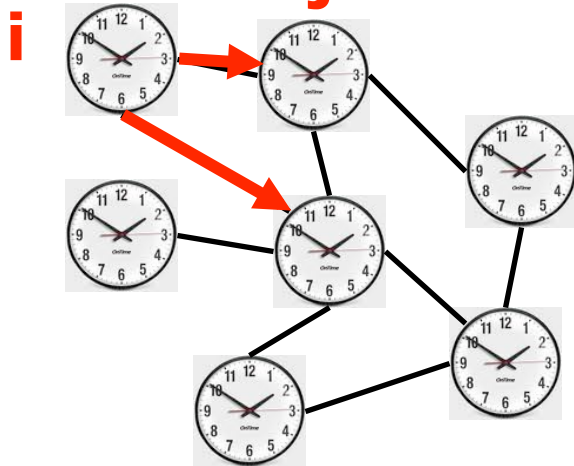
$$\hat{\tau}_j(t) = \underbrace{\hat{\alpha}_j}_{x_j^\alpha} \alpha_j t + \underbrace{\hat{\alpha}_i \beta_i}_{x_j^\beta} + \hat{o}_j$$

$$x_j^\alpha(t^+) = \frac{1}{2} x_j^\alpha(t) + \frac{1}{2} x_i^\alpha(t)$$

$$\hat{\alpha}_j(t^+) \alpha_j = \frac{1}{2} \hat{\alpha}_j(t) \alpha_j + \frac{1}{2} \hat{\alpha}_i(t) \alpha_i$$

$$\hat{\alpha}_j(t^+) = \frac{1}{2} \hat{\alpha}_j(t) + \frac{1}{2} \hat{\alpha}_i(t) \left(\frac{\alpha_i}{\alpha_j} \right)$$

$(\tau_i(t_1), \hat{\tau}_i(t_1), \hat{\alpha}_j)$ **j**



Drift compensation

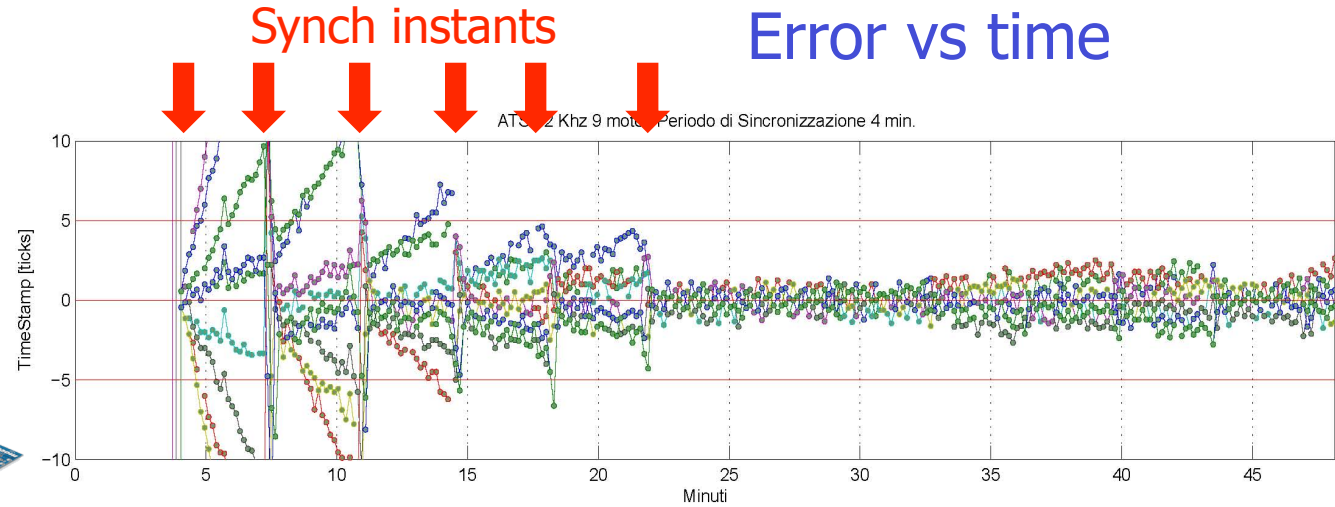
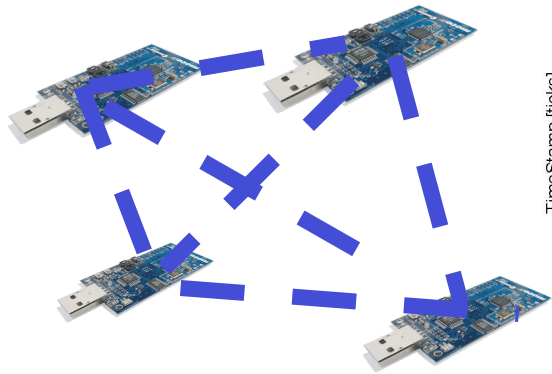
$$\hat{\alpha}_j(t^+) = \frac{1}{2} \hat{\alpha}_j(t) + \frac{1}{2} \hat{\alpha}_i(t) \frac{\tau_i(t_2) - \tau_i(t_1)}{\tau_j(t_2) - \tau_j(t_1)}$$

Offset compensation

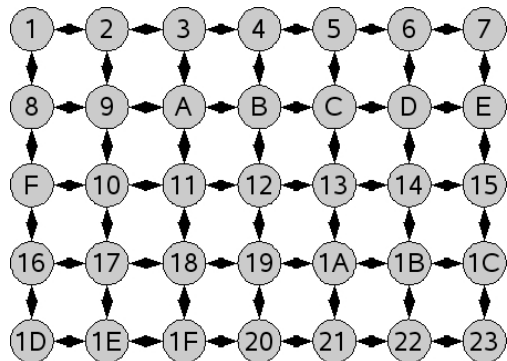
$$\hat{o}_i^+ = \hat{o}_i + \frac{1}{2} (\hat{\tau}_j - \hat{\tau}_i)$$

Clock Synch in WSN: experiments

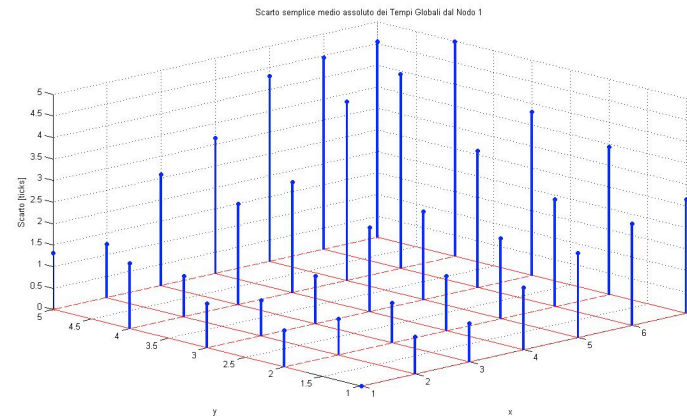
Tmote Sky nodes



7x5 grid (10 hops)



Error vs distance



Clock Synch in WSN: video

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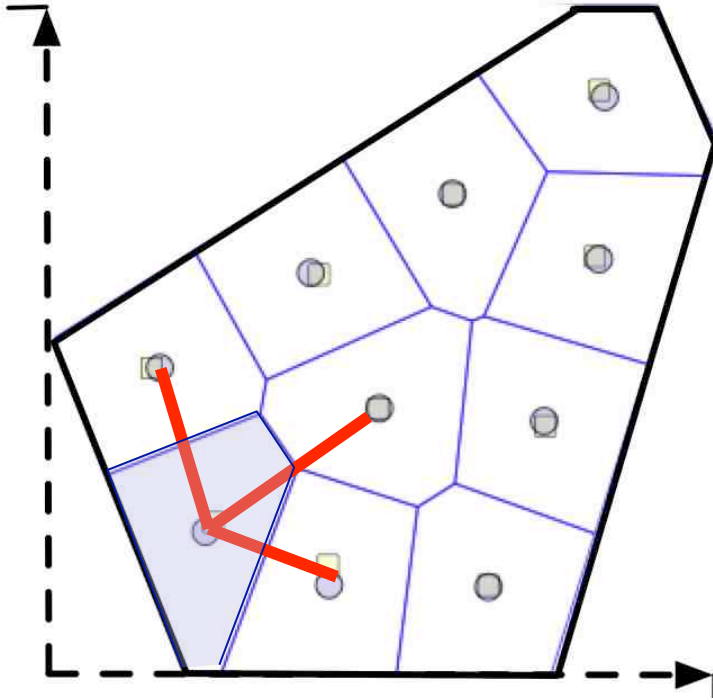
VIDEO

Overlay-based
synchronization protocol

Author: Massimo Marra

Thesis: Design and implementation of a
chromotherapy system
using a wireless sensor network

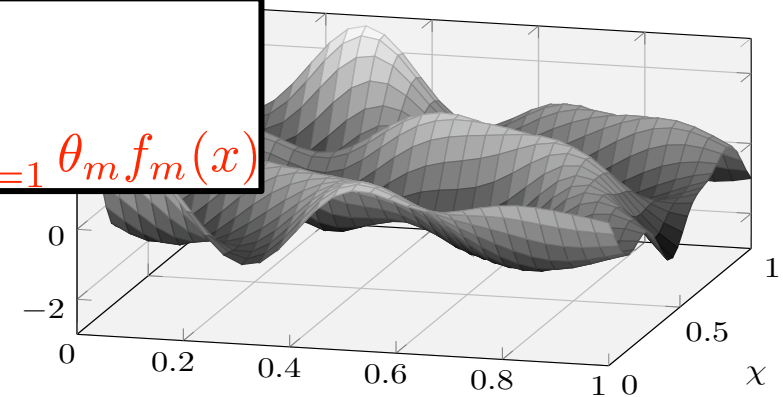
Map-building in robotic networks



Parametric

Model:

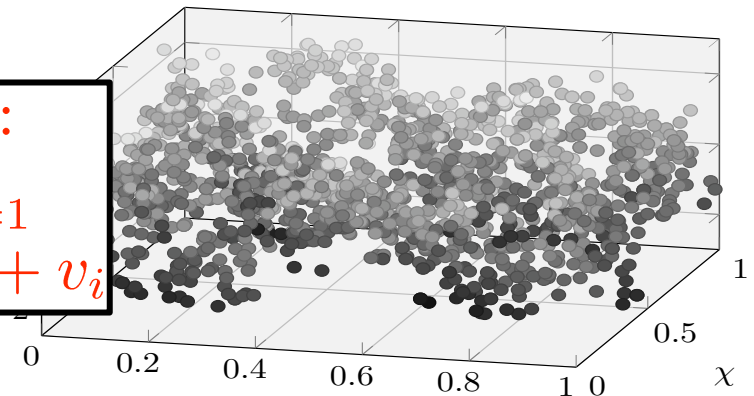
$$f(x) = \sum_{m=1}^M \theta_m f_m(x)$$



Noisy data:

$$\{(x_i, y_i)\}_{i=1}^N$$

$$y_i = f(x_i) + v_i$$



■ Issues:

- Each robot collects local data
- Local communication with robot
- Patrolled area dynamically change

J. Choi, S. Oh, R. Horowitz, "Distributed learning and cooperative control for multi-agent systems", Automatica, 2009
 Mac Schwager, Daniela Rus and Jean-Jacques Slotine "Decentralized, Adaptive Coverage Control for Networked Robots", Int. Jour. Robotics research, 2009

Map-building as least-squares regression

Estimate

$$f(x) = \sum_{m=1}^M \theta_m f_m(x)$$

with unknown parameters $\theta_1, \dots, \theta_M$ from noisy measurements

$$y_i = \sum_{m=1}^M \theta_m f_m(x_i) + v_i, \quad i = 1, \dots, N$$

By stacking all measurements

$$\begin{bmatrix} y(x_1) \\ y(x_2) \\ \vdots \end{bmatrix} = \begin{bmatrix} f_1(x_1) & \dots & f_M(x_1) \\ \vdots & \vdots & \vdots \\ f_1(x_N) & \dots & f_M(x_N) \end{bmatrix} \begin{bmatrix} \theta_1 \\ \vdots \\ \theta_M \end{bmatrix} + \begin{bmatrix} v_1 \\ \vdots \\ v_N \end{bmatrix}$$

or equivalently:

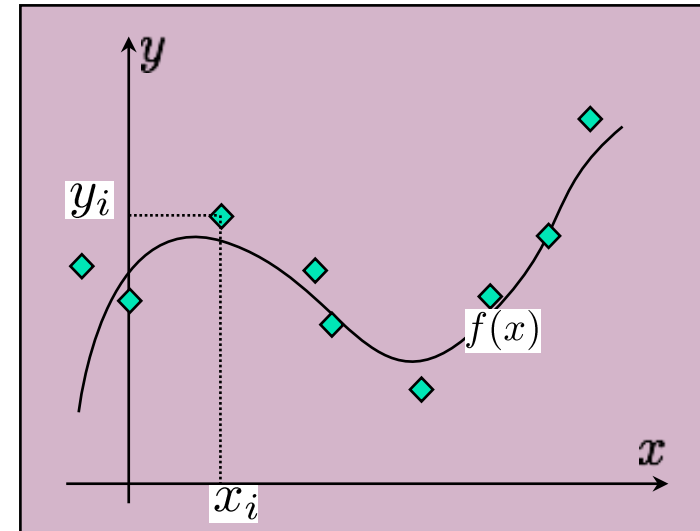
$$y = F\theta + v$$

Goal:

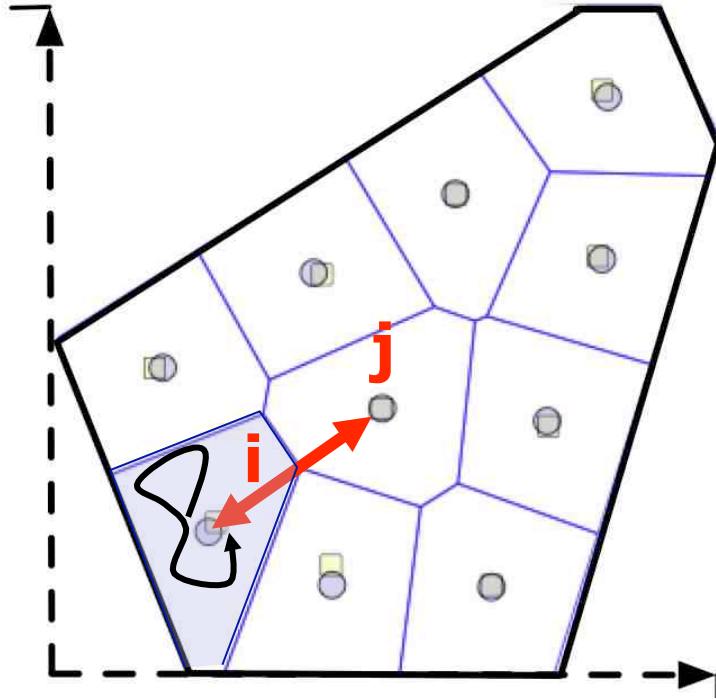
$$\hat{\theta} = \operatorname{argmin}_{\theta} \sum_{i=1}^N v_i^2 = \operatorname{argmin}_{\theta} \|F\theta - b\|^2 = (F^T F)^{-1} F^T y$$

can be written as

$$\hat{\theta} = \left(\sum_{i=1}^N F_i F_i^T \right)^{-1} \left(\sum_{i=1}^N F_i y_i \right) = \left(\frac{1}{N} \sum_{i=1}^N F_i F_i^T \right)^{-1} \left(\frac{1}{N} \sum_{i=1}^N F_i y_i \right)$$



Consensus-based Map-building



Strategy for each robot i :

1) Initialize statistics:

$$Z_0^i = 0 \in R^{M \times M}$$

$$z_0^i = 0 \in R^M$$

2) Collect data and build local statistics:

$$Z_{t+1}^i = Z_t^i + F_t^i F_t^{iT}$$

$$z_{t+1}^i = z_t^i + F_t^i y_t^i$$

3) Choose neighbor j and do gossip consensus:

$$Z_{t+1}^i = Z_{t+1}^j = \frac{1}{2} Z_t^i + \frac{1}{2} Z_t^j$$

$$z_{t+1}^i = z_{t+1}^j = \frac{1}{2} z_t^i + \frac{1}{2} z_t^j$$

4) Estimate map:

$$\hat{\theta}_t^i = (Z_t^i)^{-1} z_t^i$$

5) Repeat steps 2,3,4 (non necessarily in order)

$$F_t^i := \begin{bmatrix} f_1(x_i(t)) \\ f_2(x_i(t)) \\ \vdots \\ f_M(x_i(t)) \end{bmatrix}$$

■ Pros:

- Asynchronous
- Communication graph can change

■ Cons:

- Exchange of $O(M^2)$ data
- Parametric model \leftrightarrow curse of dimensionality

Perimeter Patrolling

Scenario:

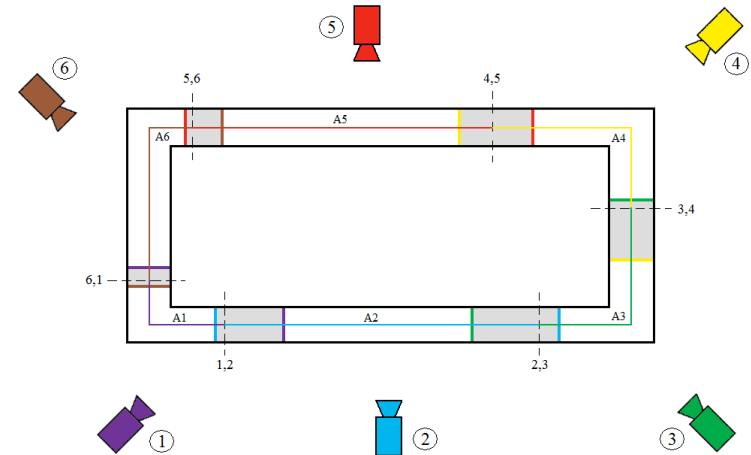
- Perimeter surveillance: 1-D scenario
- Camera position are fixed
- 1 d.o.f. cameras: pan movements only

Constraints

- Limited mobility range: D_i
- Limited pan speed: v_i

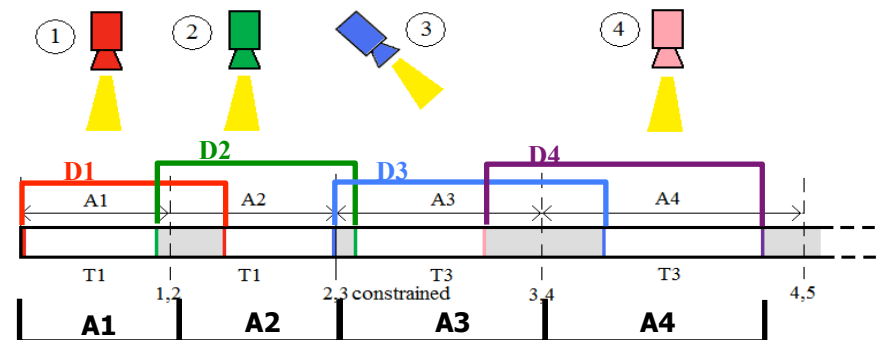
Objective:

- Determine A_i to minimize probability of undetected events



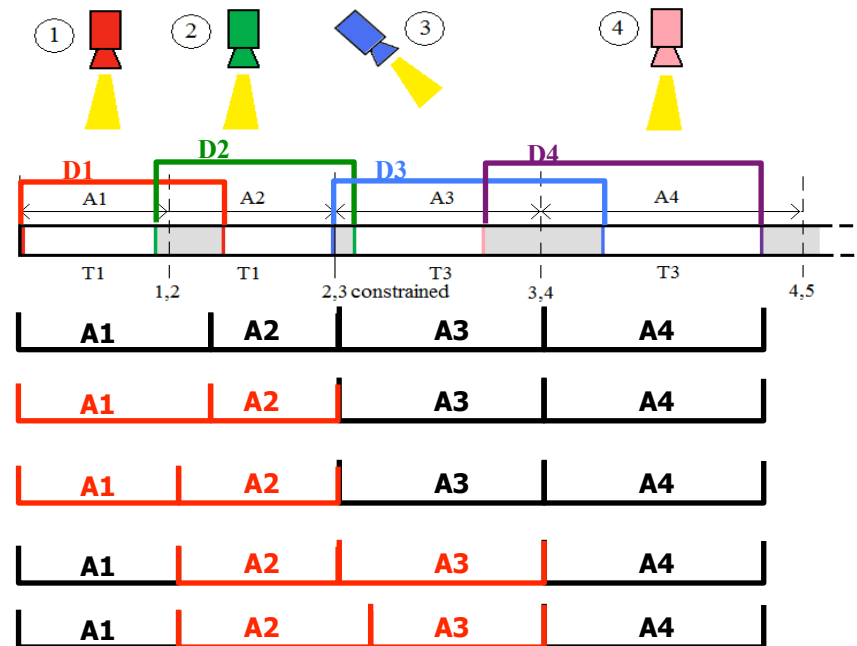
$$\text{Time-of-last-visit: } T_i = \frac{2|A_i|}{v_i}$$

$$T^* := \min_{A_1, \dots, A_N} \max_i \left\{ \frac{|A_1|}{v_1}, \dots, \frac{|A_N|}{v_N} \right\}$$



$$T^* = \frac{|A_1|}{v_1} = \dots = \frac{|A_N|}{v_N}, \text{ (if no mobility constraints } D_i)$$

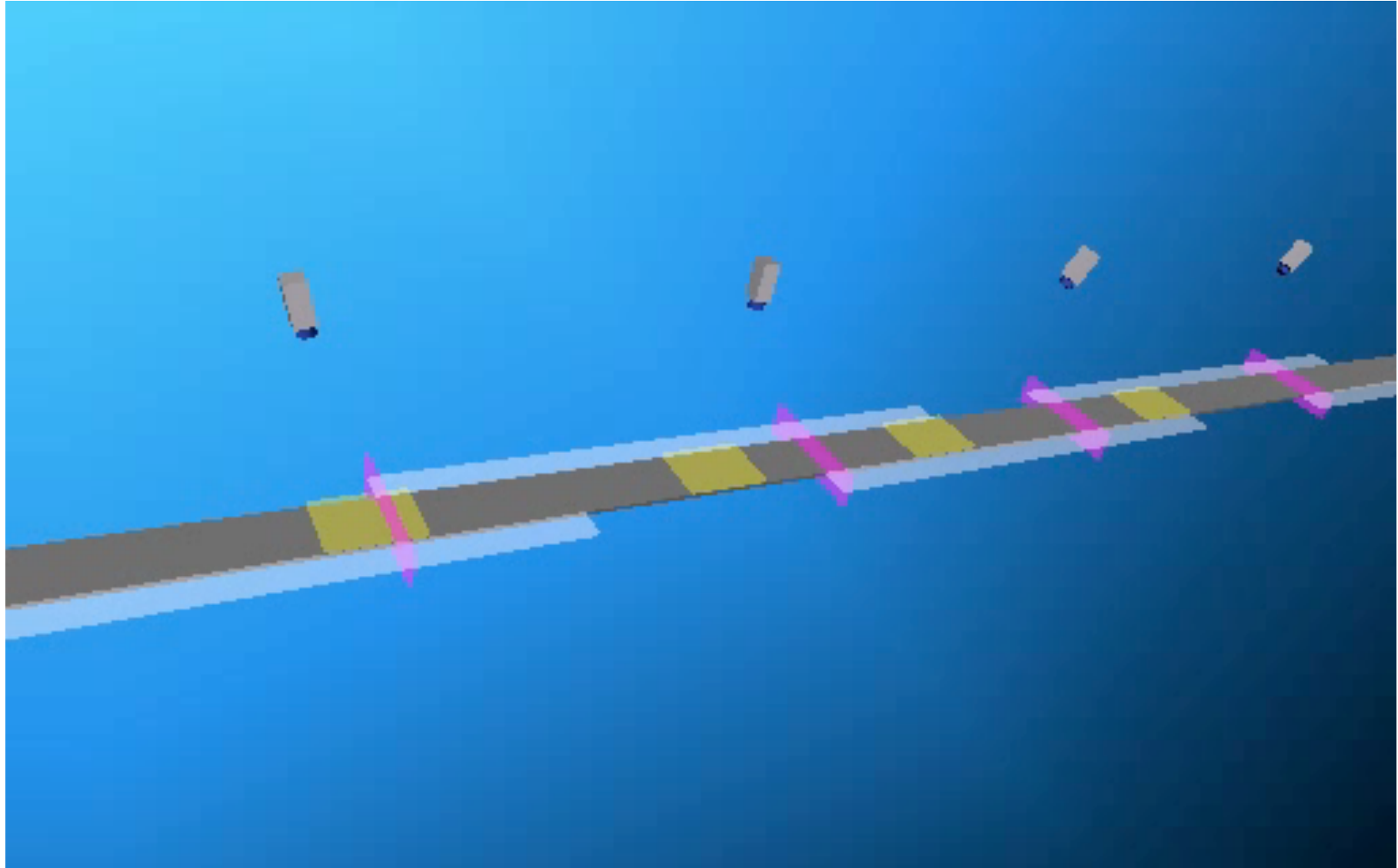
Perimeter Patrolling: asynchronous gossip consensus



Why using an asymptotic algorithm for a simple 1D problem where location of camera is fixed and known?

Just compute the centralized solution once at the beginning

Perimeter Patrolling: video

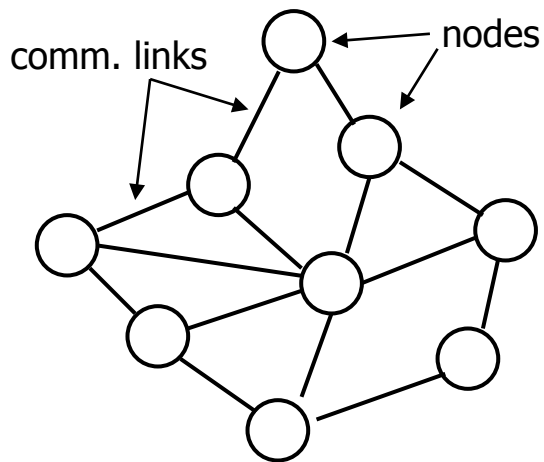


Outline

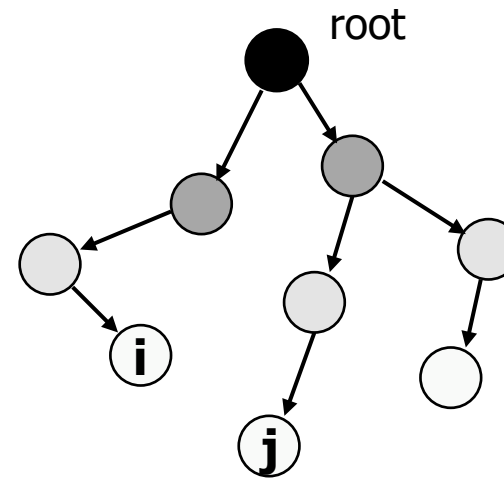
- Motivations and target applications
- Overview of consensus algorithms
- Application of consensus to WSN:
 - Sensor calibration
 - Clock synchronization
 - Map-Building
 - Perimeter Patrolling
- Open vistas and conclusions

Soft Hierarchical Control

Time synchronization example:



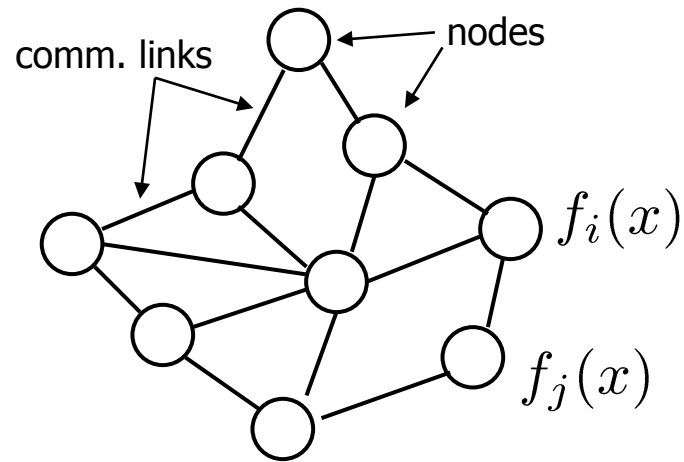
P_{dist} symmetric:
slow convergence but robust



P_{hier} asymmetric:
fast convergence but fragile to node failure

$$P_{soft} = \alpha P_{dist} + (1 - \alpha) P_{hier}, \quad \text{optimal } \alpha \text{ depends on failure rate}$$

Average Consensus and distributed optimization



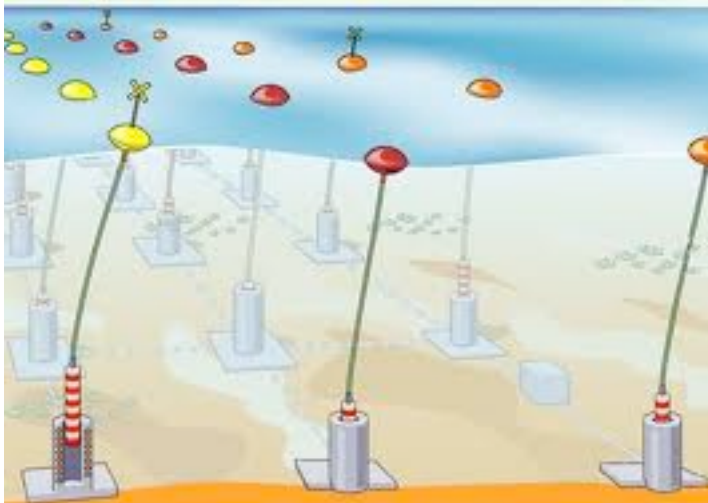
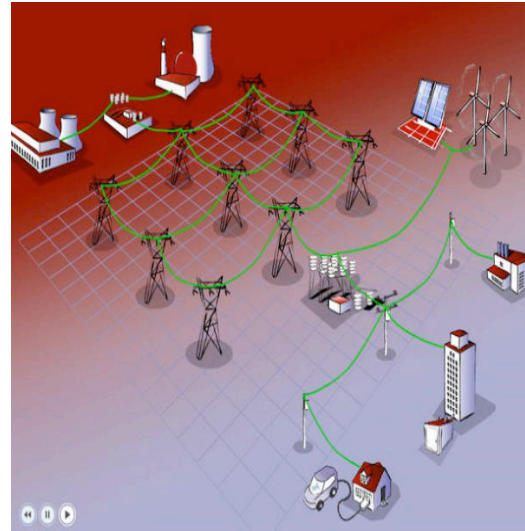
$$x^* = \operatorname{argmin}_x \sum_{i=1}^N f_i(x)$$

$$\text{If } f_i(x) = (x - \theta_i)^2 \text{ then } x^* = \frac{1}{N} \sum_{i=1}^N \theta_i$$

If $f_i(x)$ is convex then:

1. Consensus-based subgradient methods (Nedic, Ozdaglar,...)
2. Alternating Direction Method of Multipliers (Bersekas, Boyd, Giannakis,...)
3. Newton-Raphson consensus (our approach)
4. others ?

Smart Power Grids and Renewable energies



■ Foreseeable future

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

Conclusions

- Consensus is successful tool for multi-agent applications
- Many (important) details swept under the carpet
- Multidisciplinary research is key for success (Communication, CS, Software Engineering, ...)
- Distributed vs hierarchical not well understood in large scale systems
- Smart energy grids: a lot of hype right now but great control opportunity if we stick to reality

References

URL: <http://automatica.dei.unipd.it/people/schenato.html>

■ The Consensus Algorithm

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■ Sensor Calibration

- S. Bolognani, S. Del Favero, L. Schenato, D. Varagnolo. **Consensus-based distributed sensor calibration and least-square parameter identification in WSNs.** *International Journal of Robust and Nonlinear Control*, 2010

■ Perimeter patrolling

- R. Carli, A. Cenedese, L. Schenato. **Distributed Partitioning Strategies for Perimeter patrolling.** *Proceedings of the American Control Conference (ACC11)*, 2011
- M. Baseggio, A. Cenedese, P. Merlo, M. Pozzi, L. Schenato. **Distributed perimeter patrolling and tracking for camera networks.** *Conference on Decision and Control (CDC10)*, pp. --, 2010

■ Distributed map-building

- D. Varagnolo, G. Pillonetto, L. Schenato. **Distributed parametric and nonparametric regression with on-line performance bounds computation.** *Automatica (accepted)*, 20XX