DESIGN OF SENSOR SYSTEMS WITH FUSION FOR DETECTION APPLICATIONS

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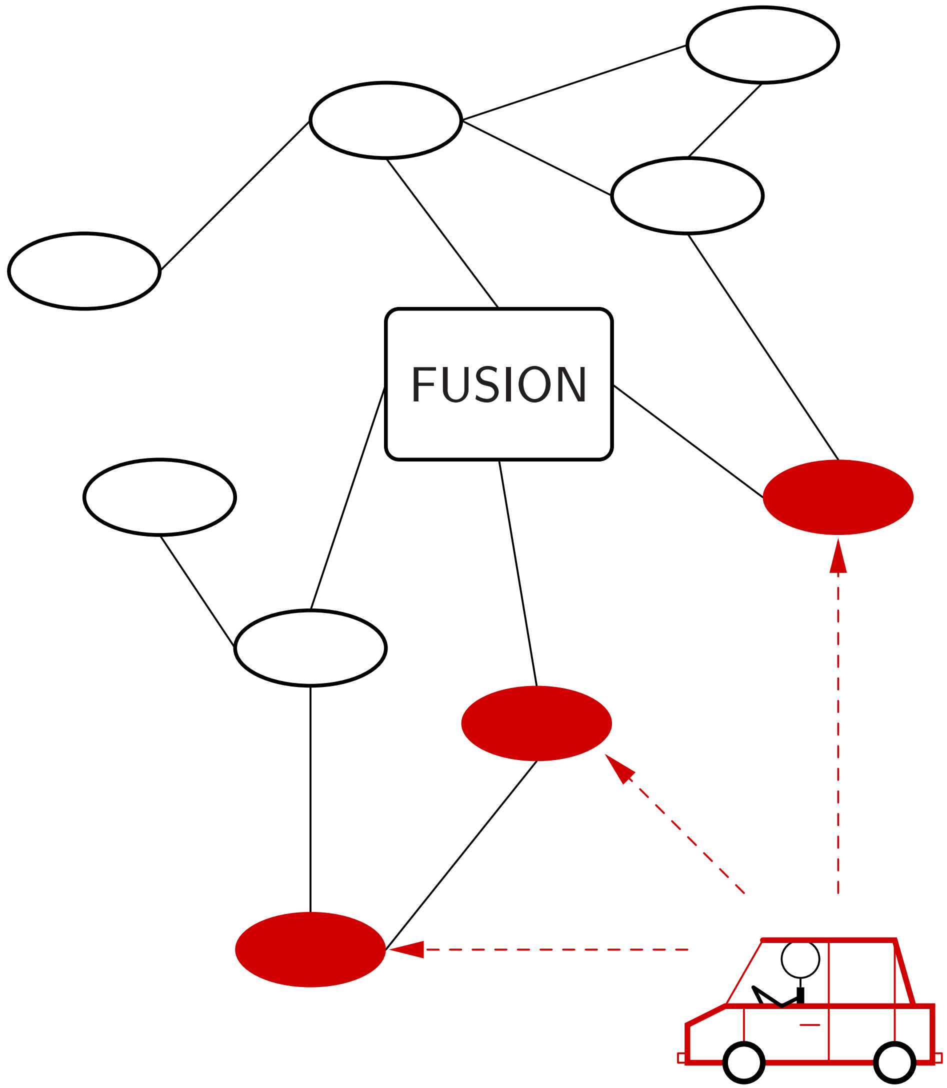
System-Theoretic Framework for Sensor Networks

- Research to date on sensors networks largely been focused on:
  - techniques for building sensors
  - protocols for networking them
- Sensor networks are NOT simply ad hoc wireless networks with more stringent energy constraints
- Need to incorporate sensing (actuation) into the design and optimization of these networks for specific applications
- Need a core system-theoretic framework to provide guidelines

Detection Applications of Wireless Sensing Systems

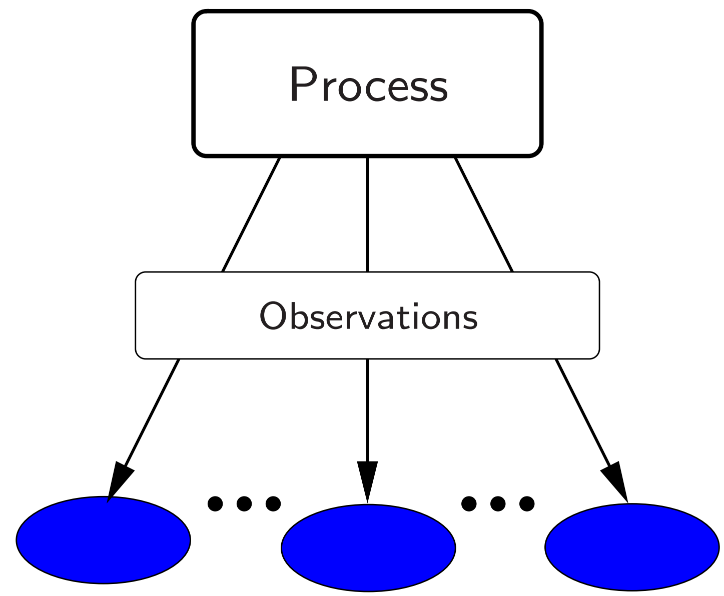
- Health care
- Manufacturing
- Monitoring civil infrastructures
- Quality control
- Security
- Surveillance
- Tracking endangered species
- Traffic monitoring

Detection is often primary step in sensing process



Types of Detection Problems

- Static decision making
  - one block of observations per sensor
  - possible motivation: energy savings from taking occasional "snapshots" of environment
- Process monitoring
  - detecting when observed process goes out of bound
- Dynamic decision making
  - sequential detection – determining block length on-line
  - quickest change detection
- Binary versus M-ary



System Performance

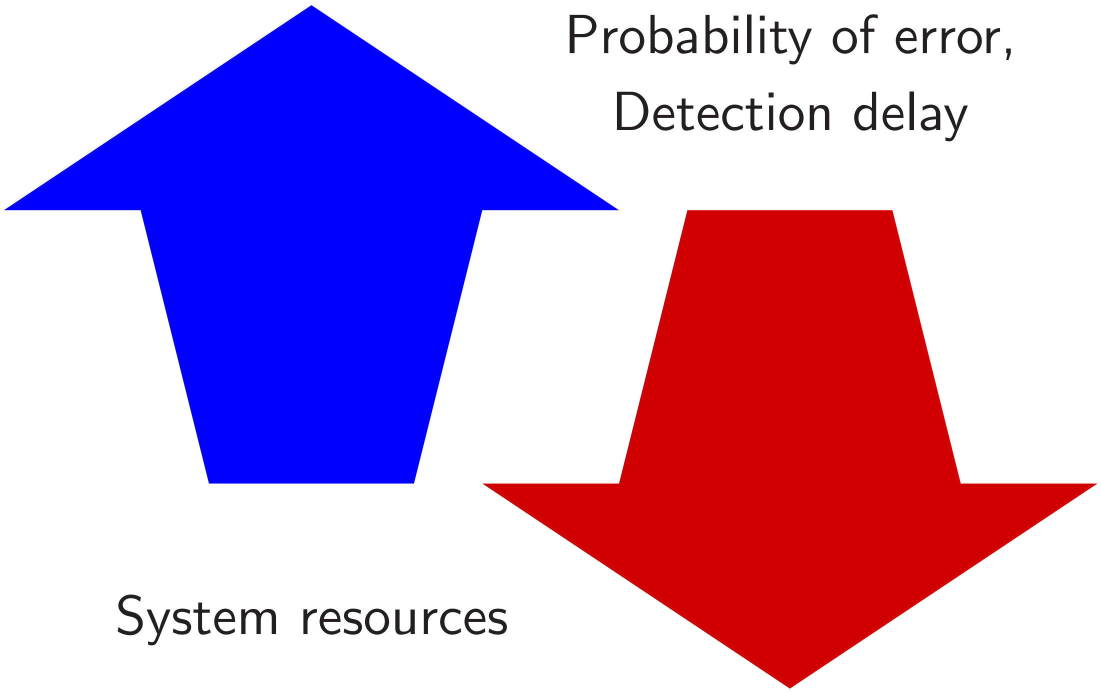
Performance metrics

- probability of error
- detection delay

Resource constraints

- bandwidth
- energy
- complexity

Natural tradeoff problem



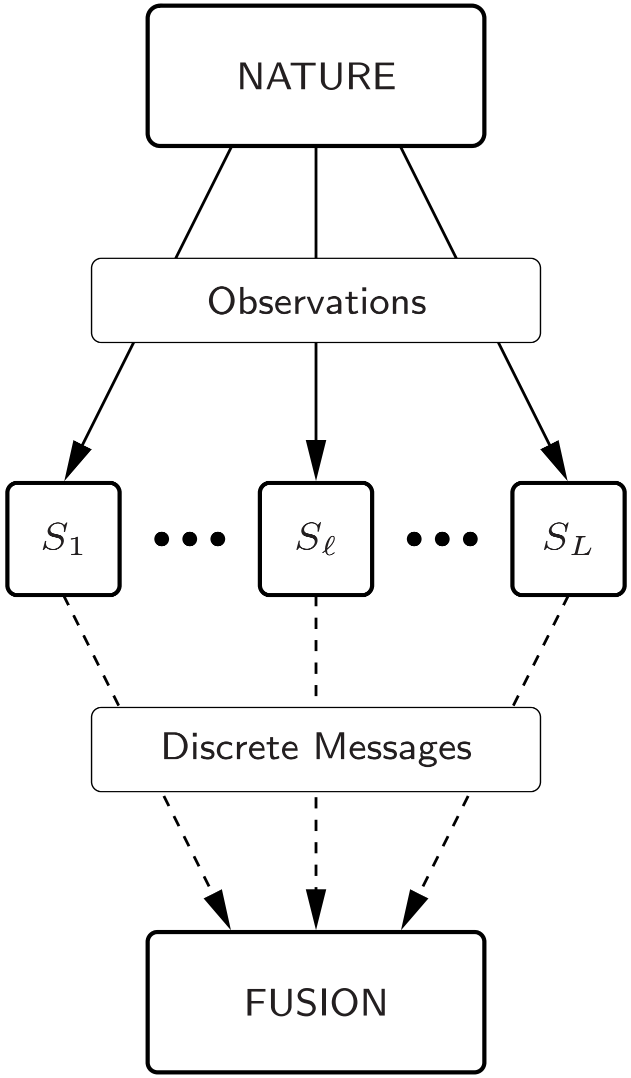
Basic Problem Formulation

- Binary hypothesis – H_0 and H_1
- Fusion architecture – sensors send a function of their observations to fusion center where decision is made
- Static detection – each sensor has single observation
- Bayesian setting – minimize P_e at fusion center

$$P_e = \alpha \mathsf{P}(H_0) + \beta \mathsf{P}(H_1)$$

- Neyman-Peason setting – minimize β subject to $\alpha \leq \alpha_0$

Classical Decentralized Detection Framework



Resource constraints captured by imposing finite alphabet constraints on sensor outputs

$$\gamma_\ell(Y_\ell) \in \{1, 2, \ldots, D_\ell\}$$

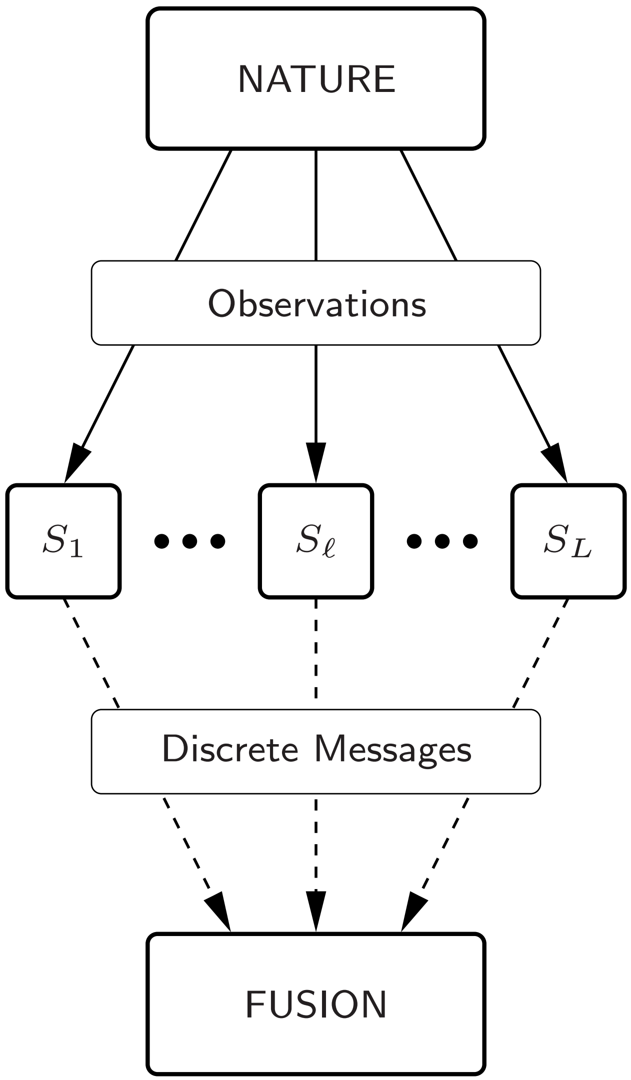
Perfect reception of sensor outputs at fusion center

Jointly optimize sensor mappings and fusion rule

Optimization problem is in general hard, but tractable under conditional independence assumption

Solution does not scale with number of sensors

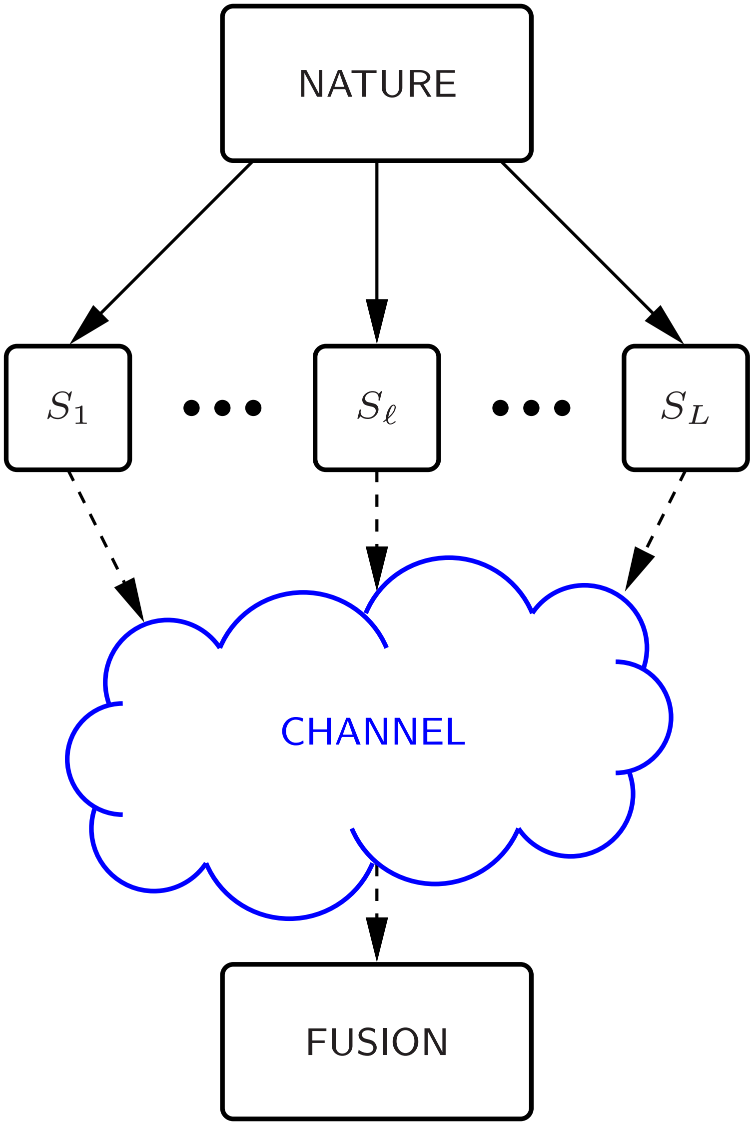
Classical Framework



Drawbacks of classical framework in context of modern sensor systems

- assumes idealized channel and overlooks physical layer
- resource constraints not captured adequately for efficient design
- focus on optimal decision rules; should be on system design strategies

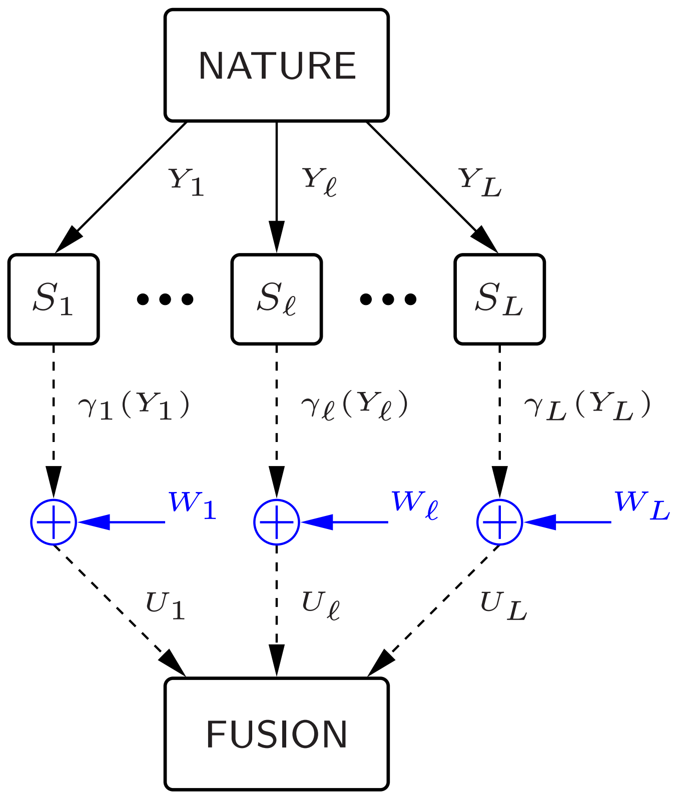
Alternative Framework



Features of alternative framework

- resource constraints represented more generally in "channel" from sensors to fusion center
- asymptotics – large number of sensors
- focus on good solutions that scale well
- number/density of nodes as parameter to be optimized
- conditionally dependent observations

Example 1: Noisy Sensor-Fusion Channels



Y_ℓ observation

γ_ℓ transmission map

W_ℓ additive noise

$$U_\ell = \gamma_\ell(Y_\ell) + W_\ell$$

A total power constraint

$$\sum_{\ell=1}^{L} f(\gamma_\ell) \leq A$$

where $f(\gamma_\ell)$ is the expected power consumed by node ℓ

L number of sensor nodes
not fixed a priori

Noisy Channels – Problem Definition

An admissible strategy $\mathcal{G}$ is a vector function $(\gamma_1, \dots, \gamma_L)$ such that

$$F(\mathcal{G}) = \sum_{\ell=1}^{L} f(\gamma_\ell) \leq A$$

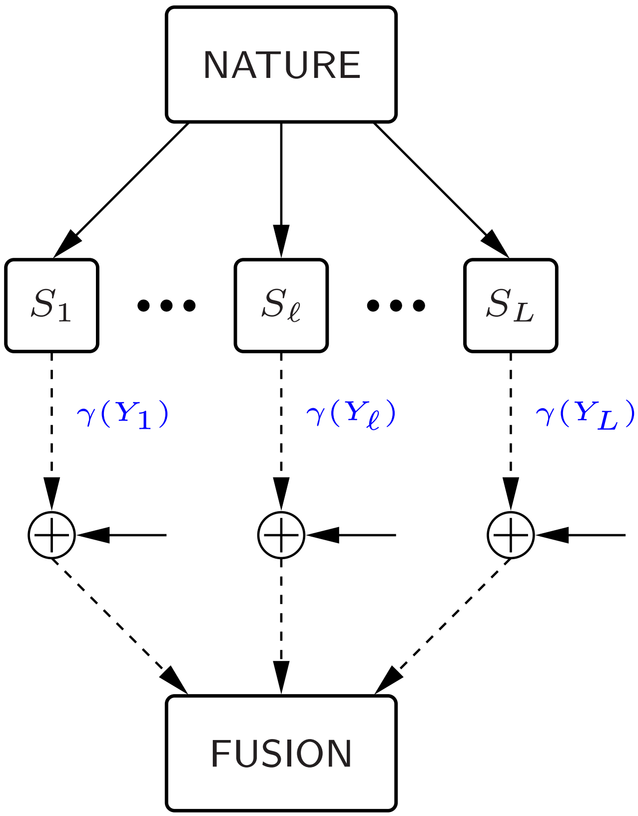
where $f(\gamma_\ell) > 0$ represents the expected power consumed by node ℓ

Problem *Find collection of strategies* $\{\mathcal{G}_A\}$*, one for each* A*, that maximizes error exponent*

$$-\lim_{A \to \infty} \frac{\log P_e(\mathcal{G}_A)}{A}$$

where $\mathcal{G}_A$ *denotes strategy such that* $F(\mathcal{G}_A) \leq A$

Normalized Chernoff Information



Large deviations

Using identical sensor nodes is asymptotically optimal with symmetric observations

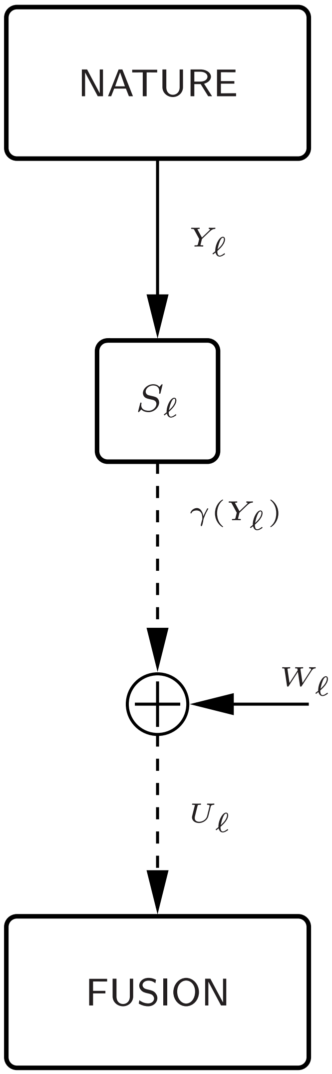
Sensors should be designed to maximize the normalized Chernoff information at input to fusion center

$$-\frac{1}{f(\gamma)} \min_{\lambda \in [0,1]} \log \mathrm{E}_{\mathcal{Q}_{0,\gamma}} \left[\left(\frac{d\mathcal{Q}_{1,\gamma}}{d\mathcal{Q}_{0,\gamma}} \right)^{\lambda} \right]$$

Decoupled design!

For the Neyman-Pearson problem, metric based on normalized Kullback-Leibler distance

Designing Sensor Map – Gaussian Example



Y_ℓ Gaussian observation

$$p_{Y|H}(y|H_0) \sim \mathcal{N}\left(-m_y, \sigma_y^2\right)$$
$$p_{Y|H}(y|H_1) \sim \mathcal{N}\left(m_y, \sigma_y^2\right)$$

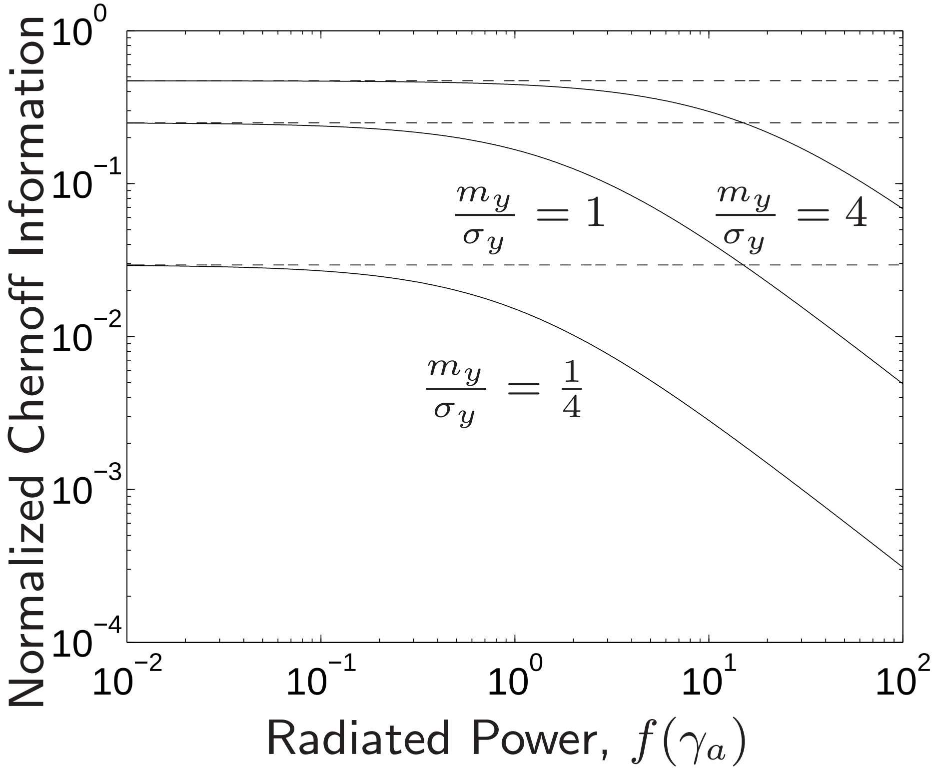
γ transmission map

W_ℓ additive Gaussian noise $\sim \mathcal{N}\left(0, \sigma_w^2\right)$

$$U_\ell = \gamma(Y_\ell) + W_\ell$$

Use normalized Chernoff information to compare candidate γ's

Analog Relay Amplifier



Analog relay amplifier

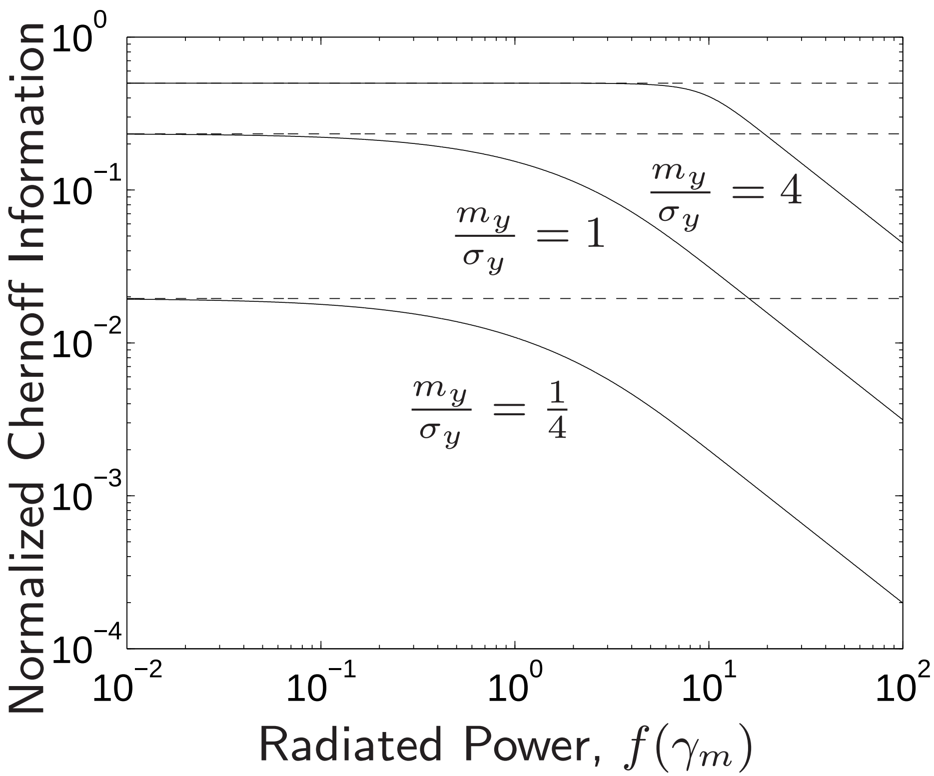
$$\gamma_a(y) = ay$$

$$f(\gamma_a) = a^2 m_y^2 + a^2 \sigma_y^2$$

The Normalized Chernoff information corresponding to analog relay amplifier γ_a is nonincreasing in $f(\gamma_a)$

$$\frac{m_y^2}{2\left(m_y^2 + \sigma_y^2\right)\left(a^2\sigma_y^2 + \sigma_w^2\right)} \xrightarrow{a \downarrow 0} \frac{m_y^2}{2\sigma_w^2\left(m_y^2 + \sigma_y^2\right)}$$

Binary Threshold Node



Binary threshold node

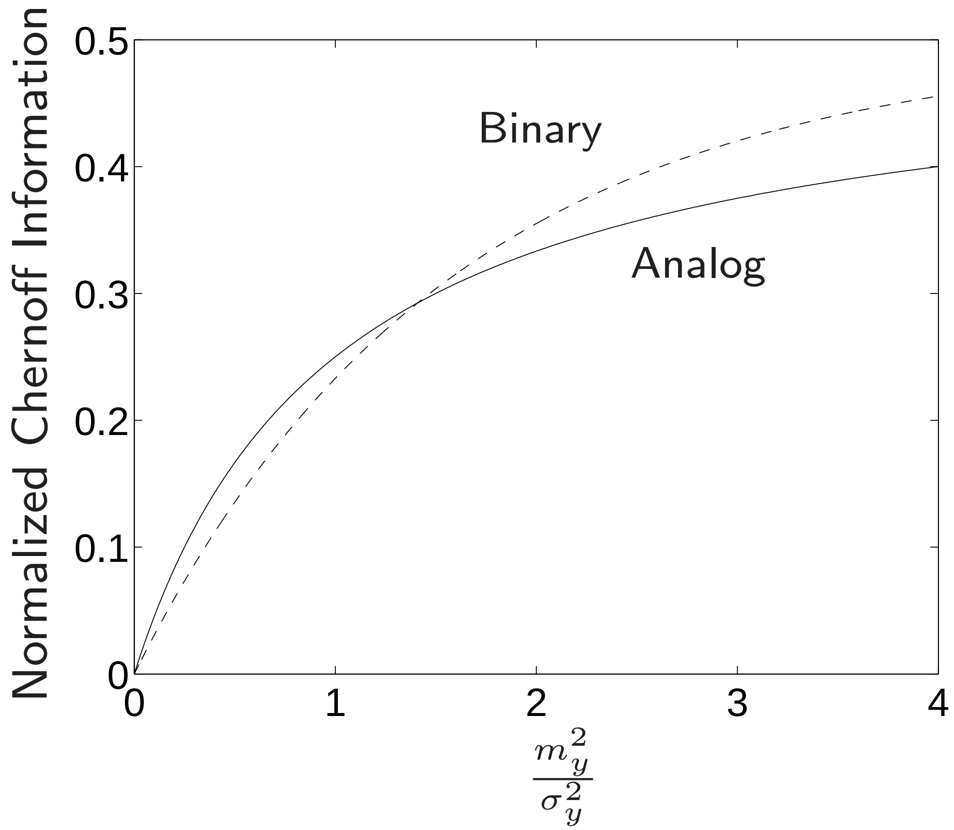
$$\gamma_m(y) = \begin{cases} m : y \geq 0 \\ -m : y < 0 \end{cases}$$

$$f(\gamma_m) = m^2$$

The Normalized Chernoff information corresponding to binary threshold node γ_m is nonincreasing in $f(\gamma_a)$

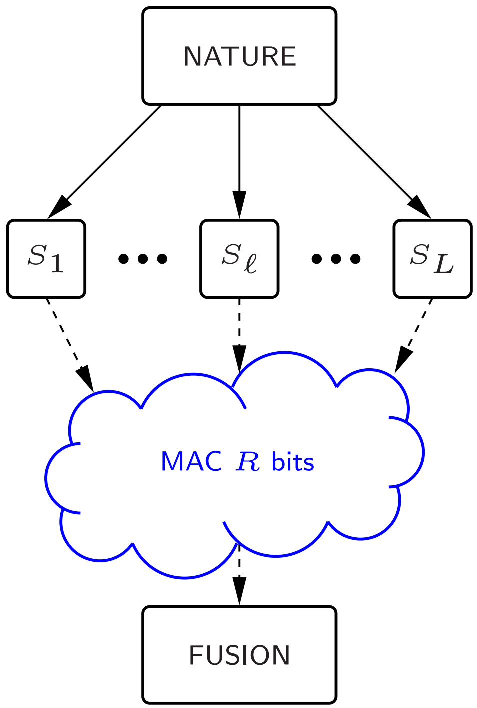
$$-\frac{1}{m^2} \log \int_{-\infty}^{\infty} \sqrt{\mathcal{Q}_{0,\gamma_m}(u)\mathcal{Q}_{1,\gamma_m}(u)}du \xrightarrow{m \downarrow 0} \frac{1}{2\sigma_w^2} \left[Q\left(-\frac{m_y}{\sigma_y}\right) - Q\left(\frac{m_y}{\sigma_y}\right)\right]^2$$

Analog versus Binary Nodes



- Unreliable observations: analog relay amplifiers perform better
- Reliable observations: binary threshold nodes perform better

Example 2: MAC Fusion with Sum Rate Constraint

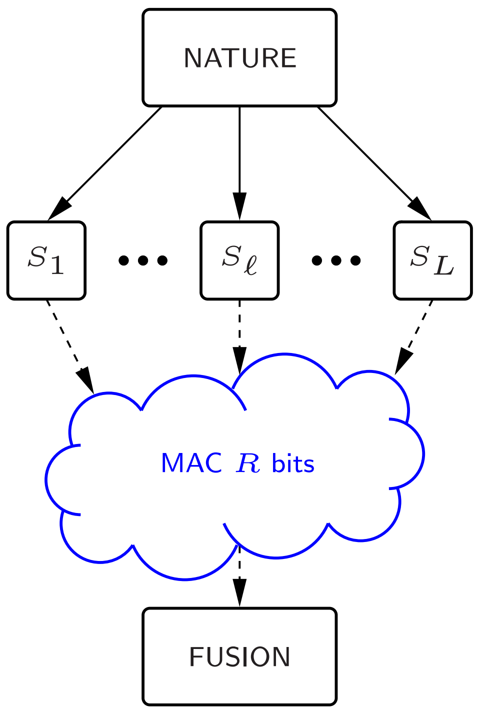


- Sum power constraint replaced by sum bit rate constraint
- MAC channel can carry R bits from sensors to fusion center
- $f(\gamma) = \lceil \log_2 D_\gamma \rceil$
- Asymptotics as $R \to \infty$

Sensor map should be chosen to maximize

$$-\frac{1}{\lceil \log_2 (D_\gamma) \rceil} \min_{\lambda \in [0,1]} \left\{ \log \mathrm{E}_{\mathcal{Q}_{0,\gamma}} \left[\left(\frac{d\mathcal{Q}_{1,\gamma}}{d\mathcal{Q}_{0,\gamma}} \right)^\lambda \right] \right\}.$$

Optimality of Binary Sensors



If there exists a binary function γ_b such that

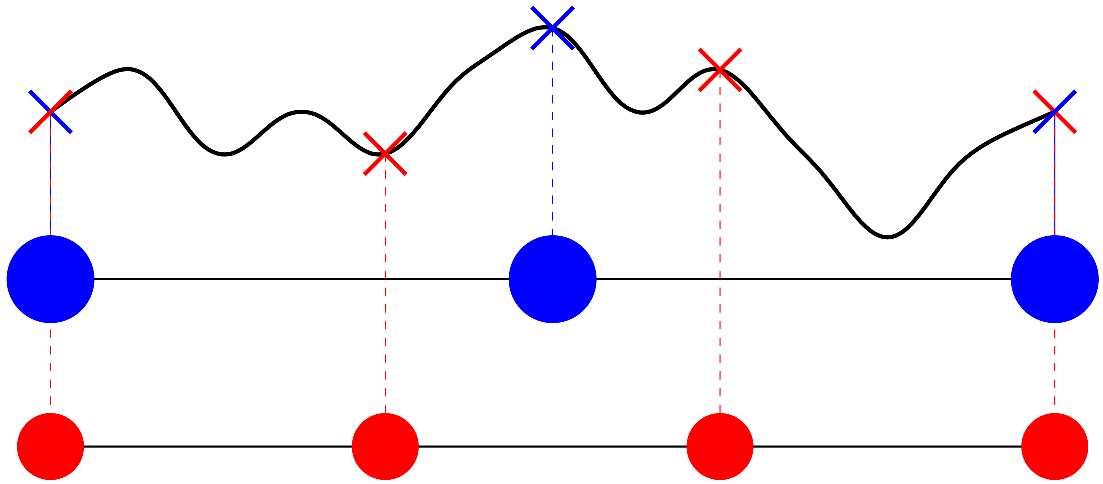
$$C\left(\gamma_\mathsf{b}(Y)\right) \geq \frac{C(Y)}{2}$$

then having R sensor nodes, each sending one bit of information, is asymptotically optimal

This condition can be verified for many observation models of interest

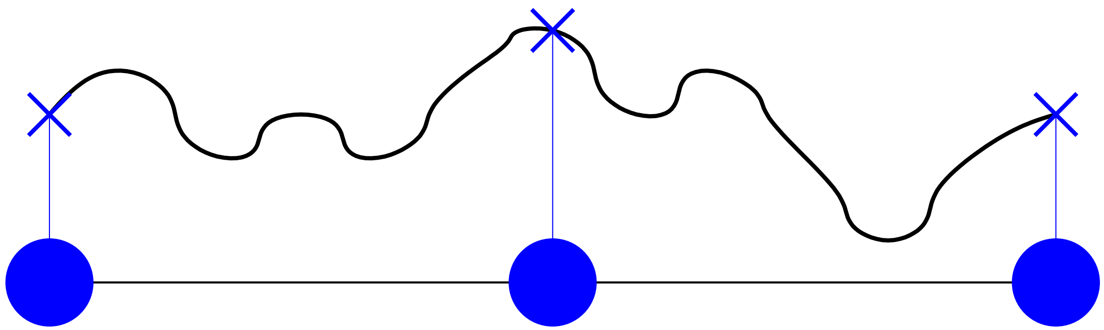
Having more sensor nodes outperforms the benefits of getting detailed information from each node

Correlated Sensors – Density Analysis



- Sensor nodes on line, sampling correlated spatial stochastic process
- Power density constraint: power per unit distance fixed, i.e., power per node decreases linearly with node density
- Correlation between node observations increases with node density
- Q: How dense should the network be?

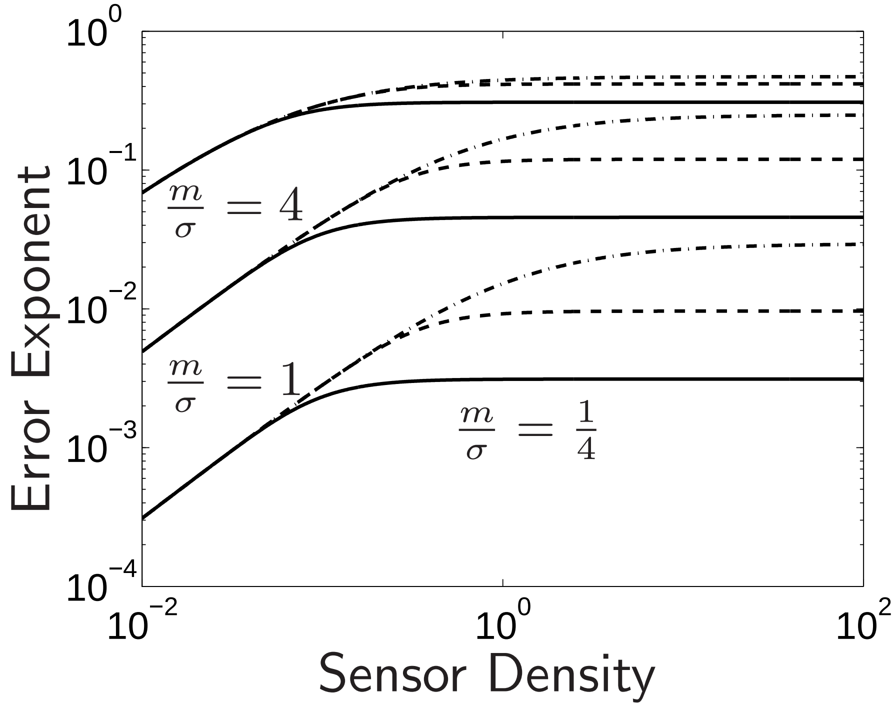
Problem Formulation



- Observed spatial process is one of two possible stationary signals $\mathbf{X}_0(s)$ and $\mathbf{X}_1(s)$
- Signal is corrupted by stationary observation noise process $\mathbf{V}(s)$
- Two possible models for correlation at sensors
  - Model I: Deterministic signal with Gauss-Markov noise
  - Model II: Zero mean Gauss-Markov signal with white noise

Deterministic Signal with Gauss-Markov Noise

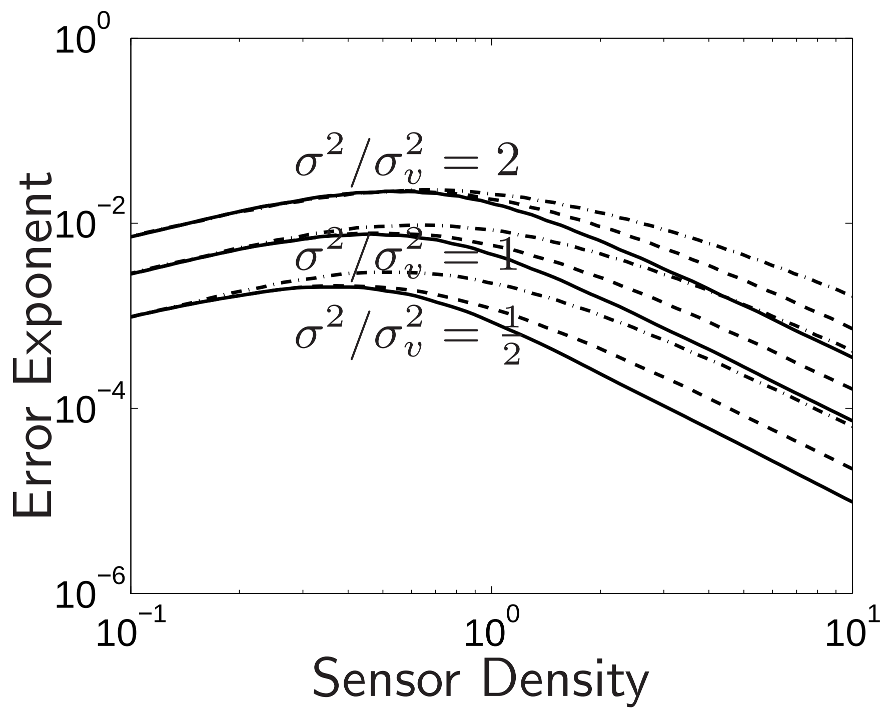
- Corr. Coeff. $\rho \in \{0, 0.4, 0.8\}$, power per unit distance $c = 1$, $\sigma_w^2 = 1$
- The fusion center does not need to know ρ for optimum asymptotic performance!



- Higher densities are always better!

Zero-Mean Gauss-Markov Signal with White Noise

- Corr. Coeff.$\rho \in \{0.2, 0.5, 0.8\}$, power per unit distance $c = 1$, $\sigma_w^2 = 1$
- The fusion center needs to know ρ for optimum asymptotic performance



- Optimum value for density!

Design and Optimization Strategies

- Optimum solution may be too complicated and not robust – focus on good suboptimum solutions that are robust and scalable
- Soften optimization metrics – error exponents, deflection, etc.
- Decouple optimization problem – choose sensor operations to optimize local metrics
- Allow number (density) of sensors to be system design parameter that needs to be optimized before deployment
- Fully exploit modes of operation of sensor to minimize resource consumption for while meeting application performance criteria
- Design communication protocol with detection application in mind – e.g., some bits are more important than others

Some Questions and Challenges

- What if the observations statistics are not known precisely?
- How should sensor outputs be communicated on channel? Is it necessary to convert to bits/packets?
- What is the role of coding?
- How much do we gain by allowing sensors to talk to each other in the fusion configuration?
- What is the right architecture for the network? Decentralized with fusion or distributed?
- What feedback should we provide to sensor designers?

References

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