Distributed Detection and Localization

A Statistical Signal Processing Approach

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Content

- Introduction

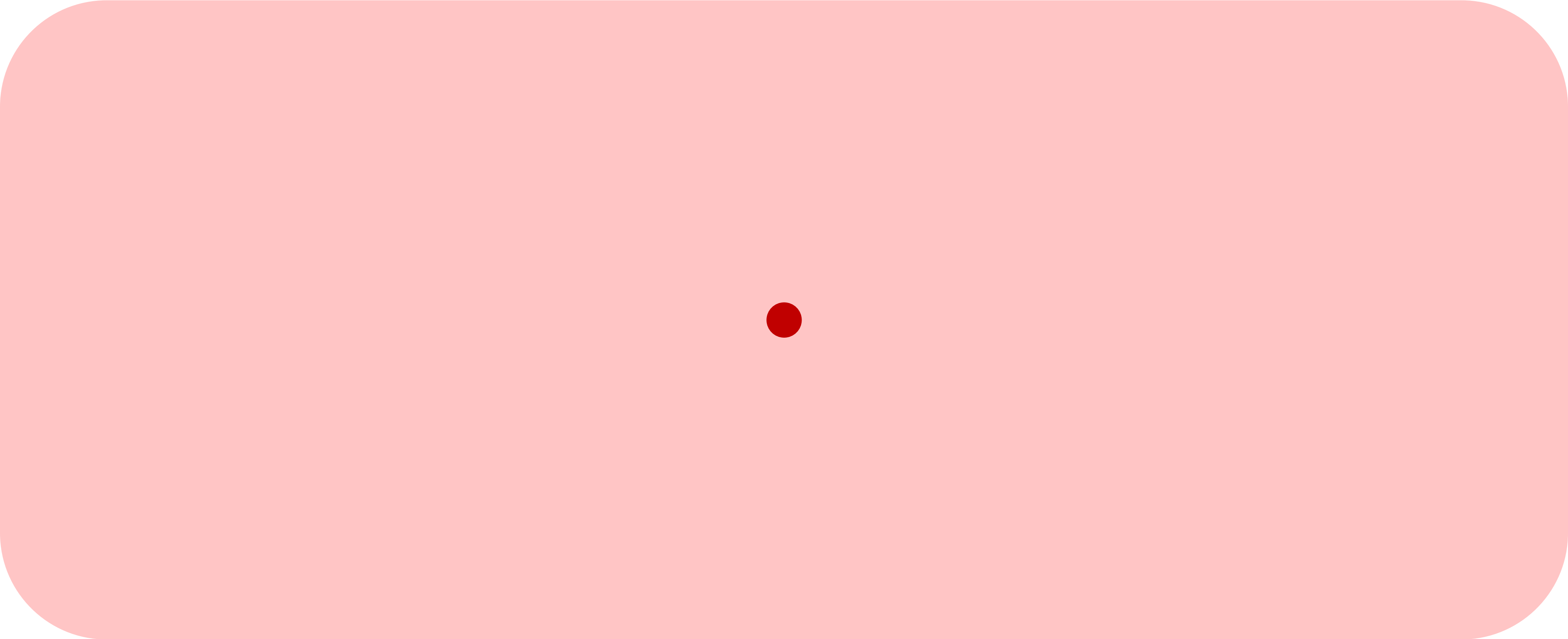
- Sensor Modeling
    - Part I – Detection
    - Part II – Detection and Localization

- (Wireless) Sensor Networks
    - Part I – Distributed Detection
    - Part II – Distributed Detection and Localization

Introduction

Binary Event

Binary Event



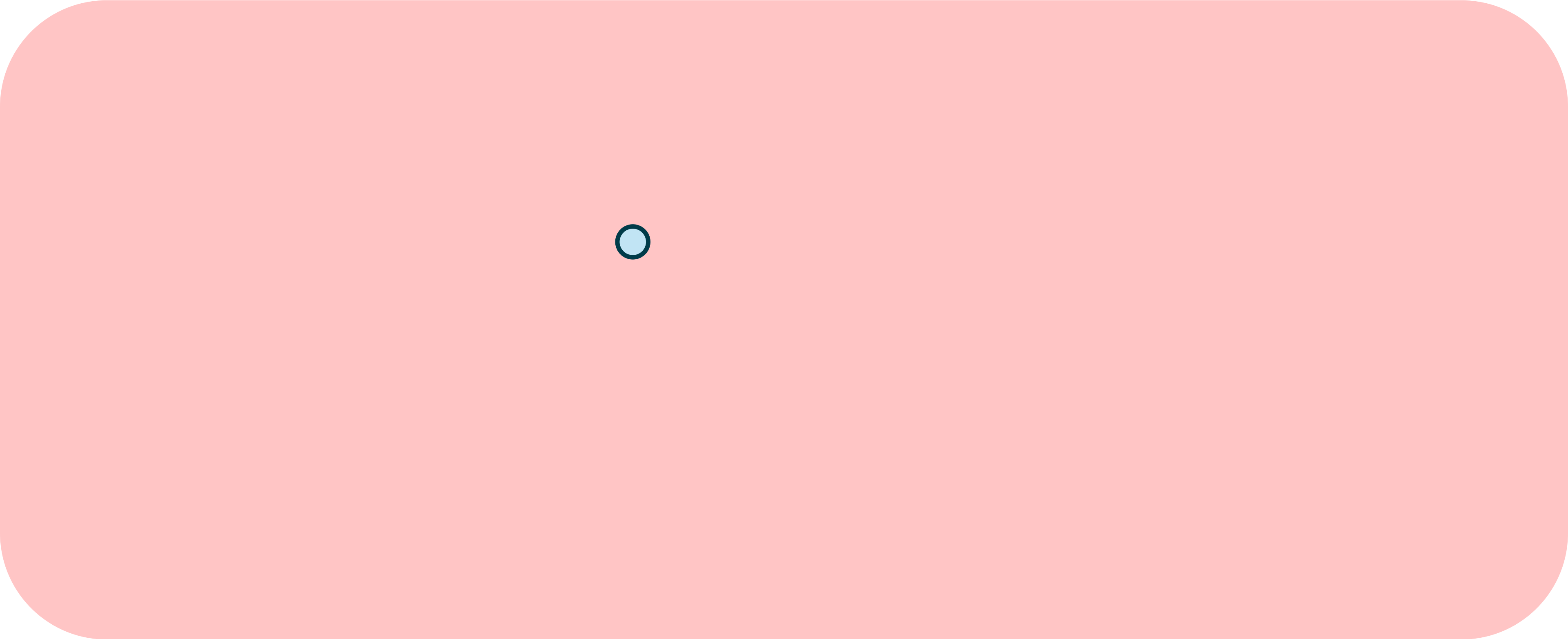
Binary Event

Binary Event

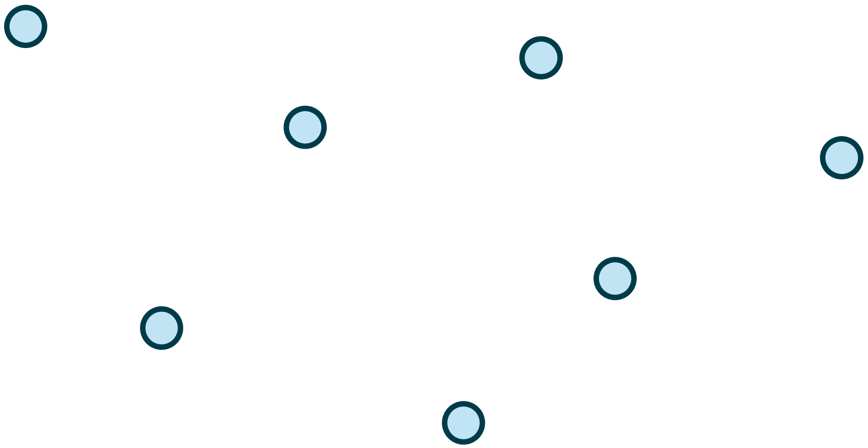
Binary Event

Detection
Single Sensor

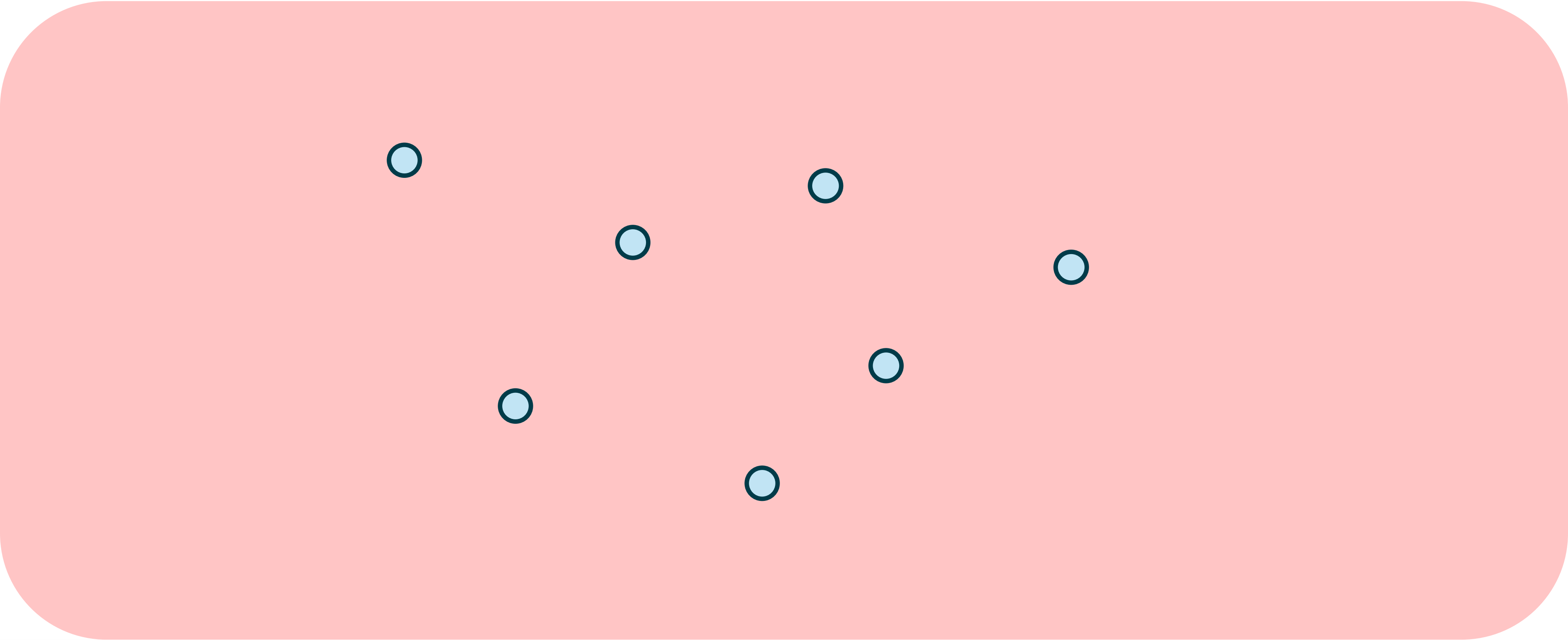
Detection
Single Sensor



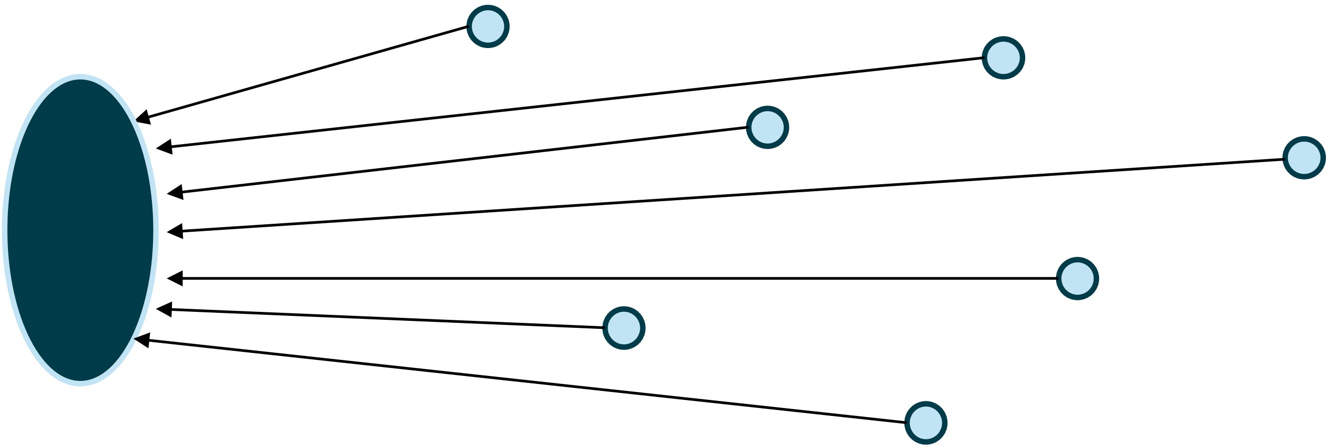
Distributed Detection Sensor Network



Distributed Detection
Sensor Network



Distributed Detection
Sensor Network with Fusion Center



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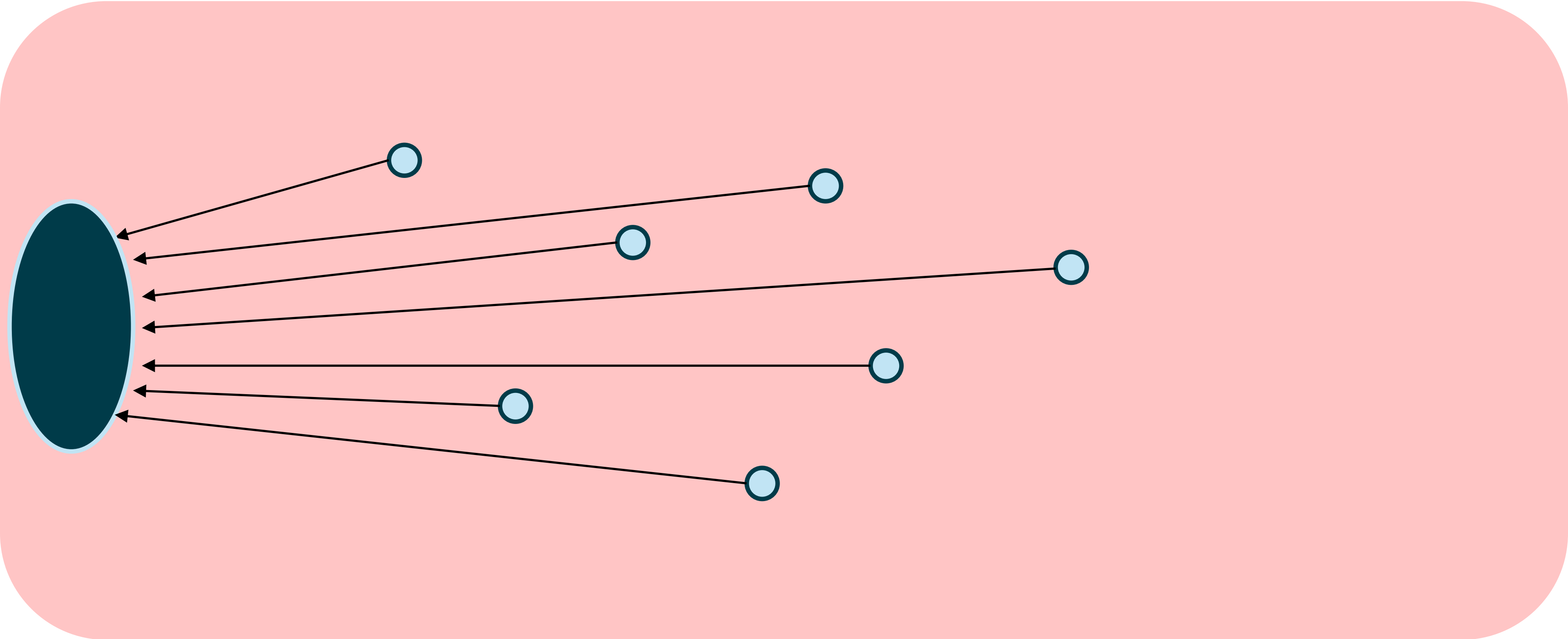

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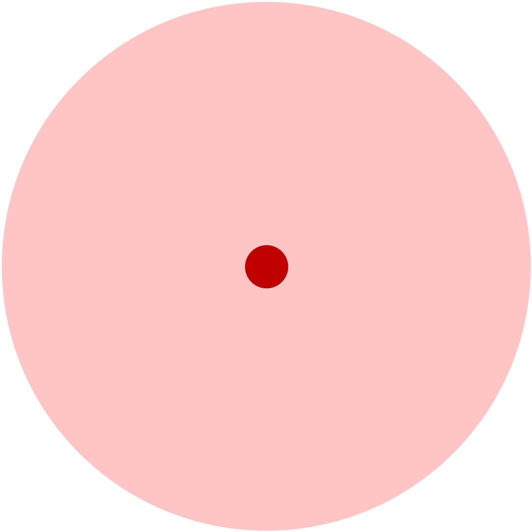

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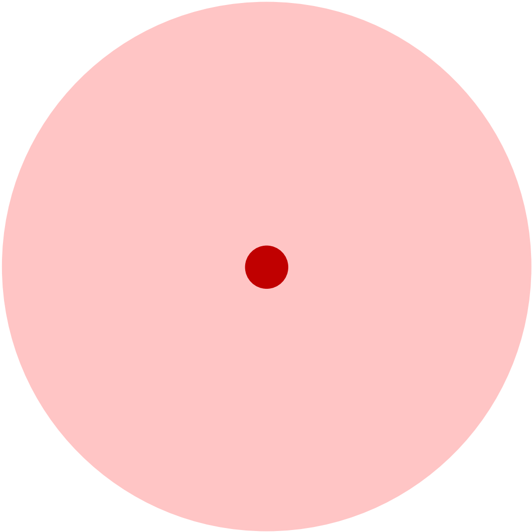
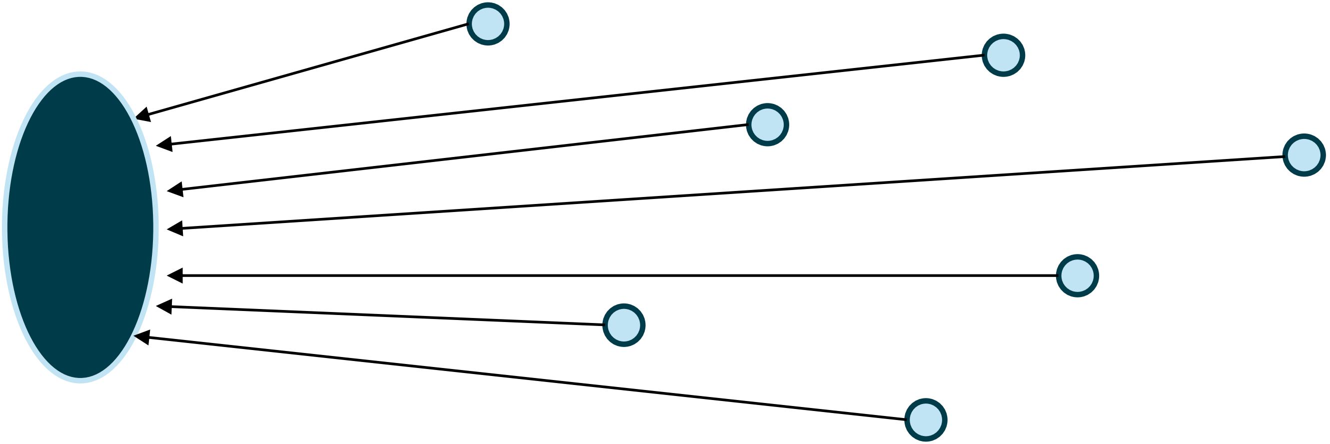
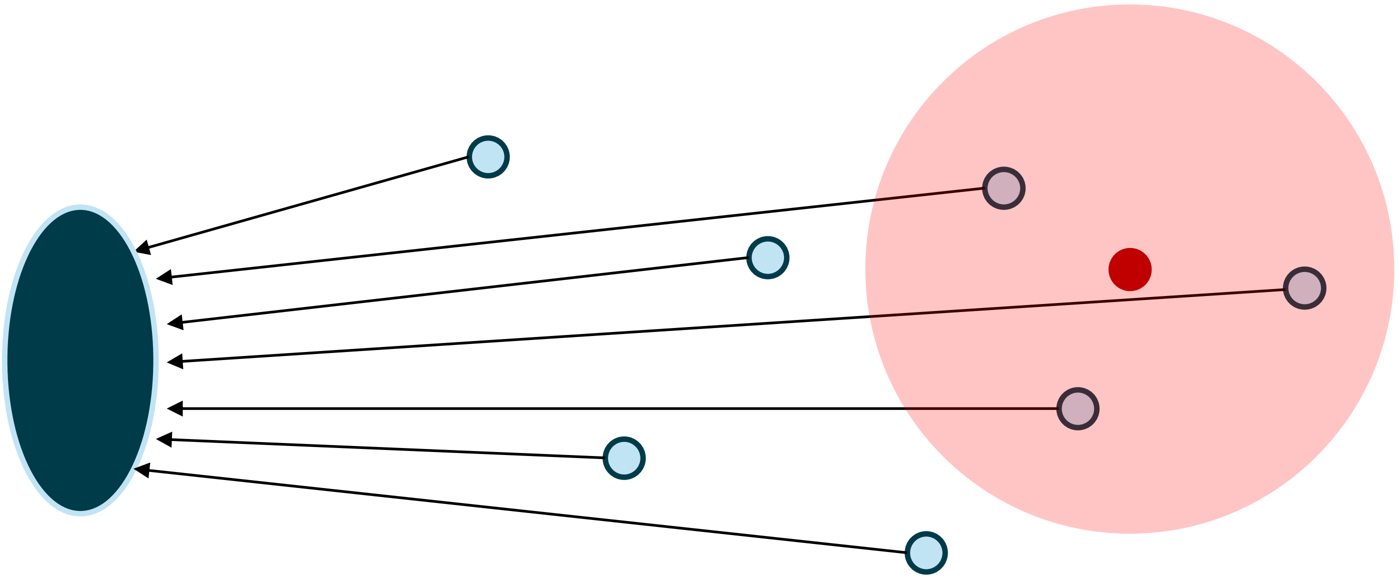


Distributed Detection and Localization
Sensor Network with Fusion Center



Distributed Detection and Localization
Sensor Network with Fusion Center



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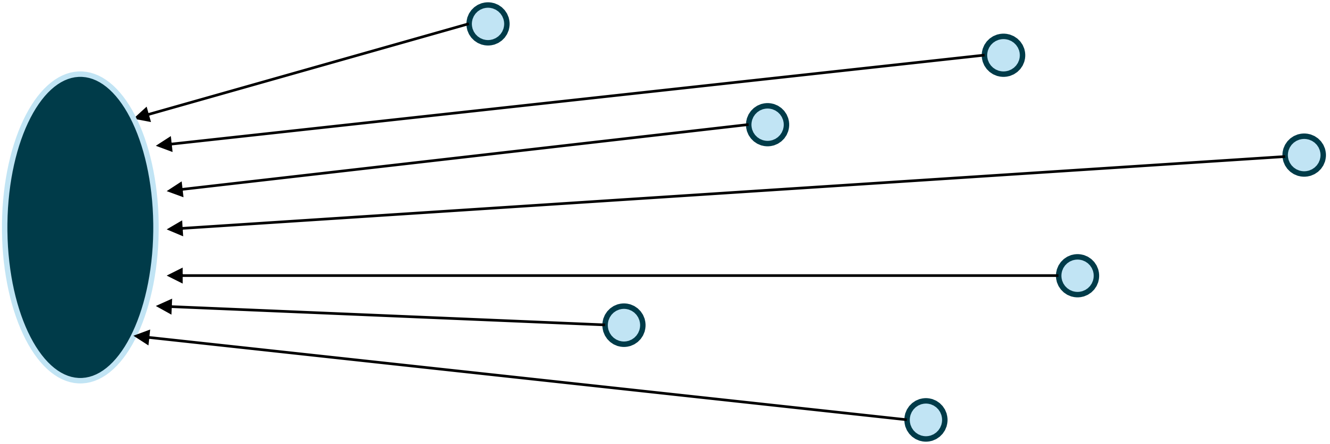
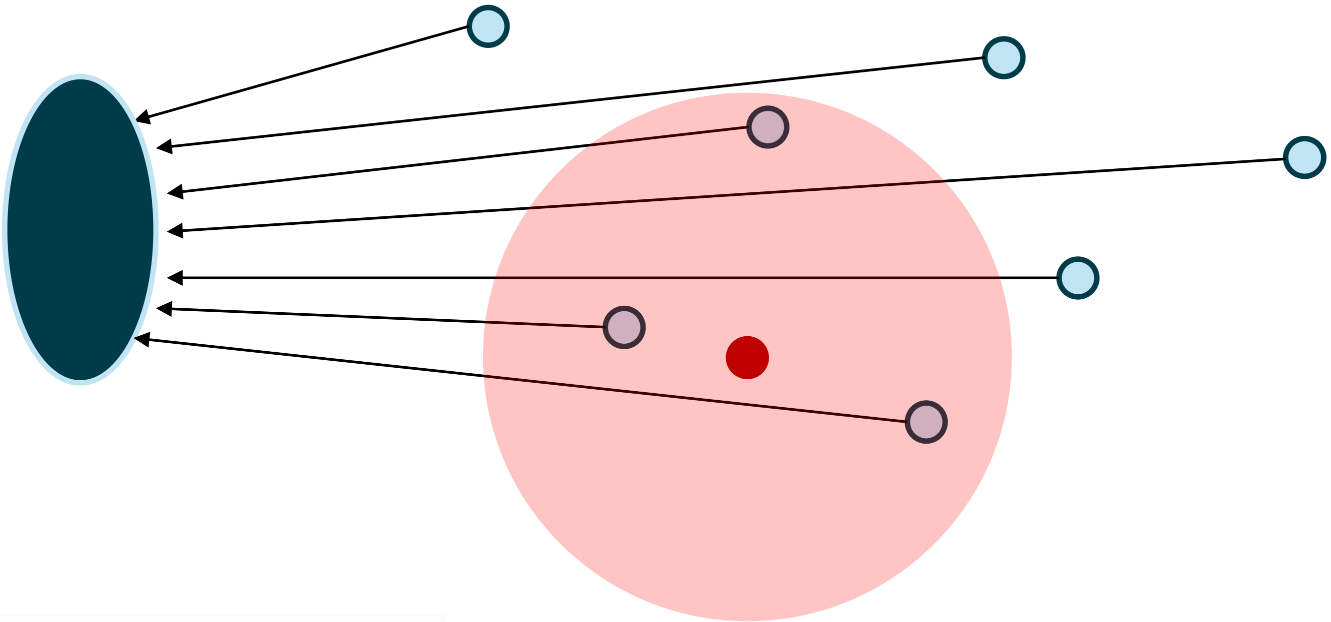
Sensor Network with Fusion Center



Distributed Detection and Localization
Sensor Network with Fusion Center



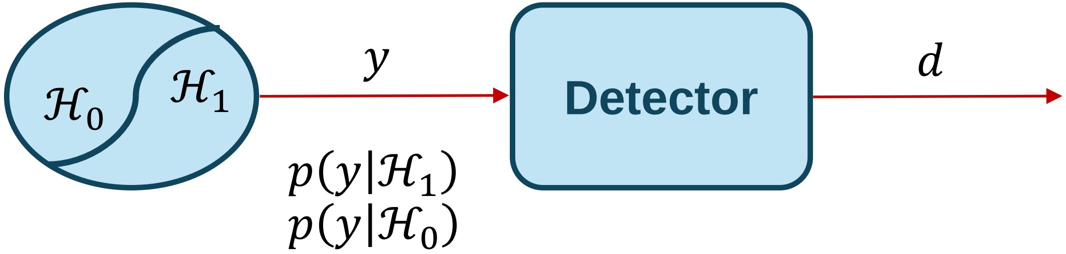
Applications

- Collaborative Spectrum Sensing in Cognitive Radio
- Event Detection in Underwater Acoustic Sensor Networks
- Leak Detection and Localization in Oil&Gas production/distribution systems

Sensor Modeling

Part I - Detection

Detection Theory – Decision Theory – Hypothesis Testing



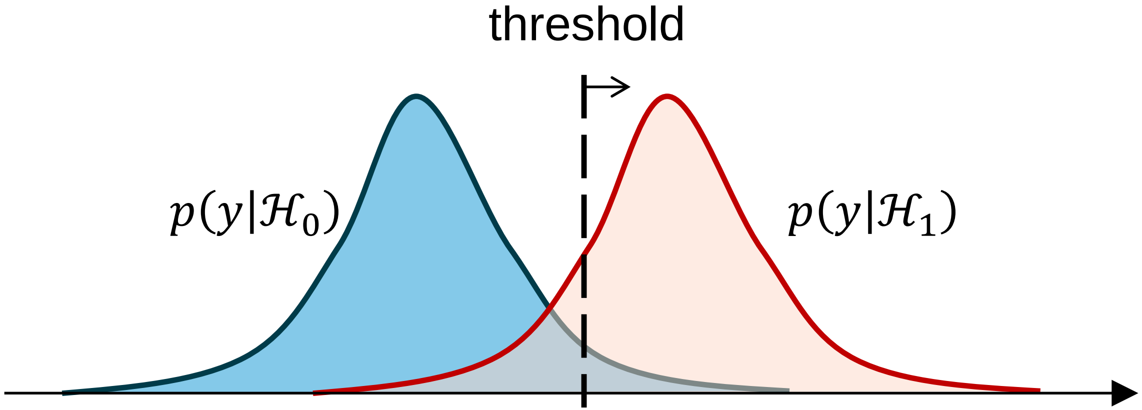
True Hp \ Estimated Hp	$\mathcal{H}_0$	$\mathcal{H}_1$
$\mathcal{H}_0$	Correct Decision	Type I Error (False Alarm)
$\mathcal{H}_1$	Type II Error (Missed Detection)	Correct Decision (Detection)

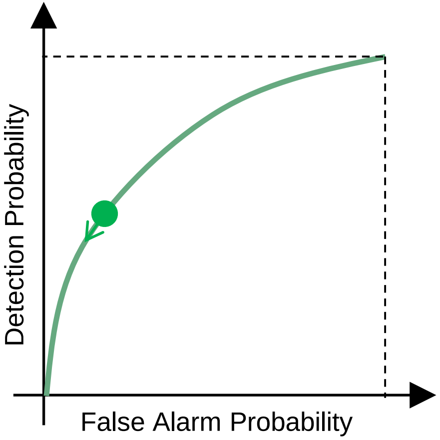
$$P_D = p(d = \mathcal{H}_1|\mathcal{H}_1)$$

$$P_F = p(d = \mathcal{H}_1|\mathcal{H}_0)$$

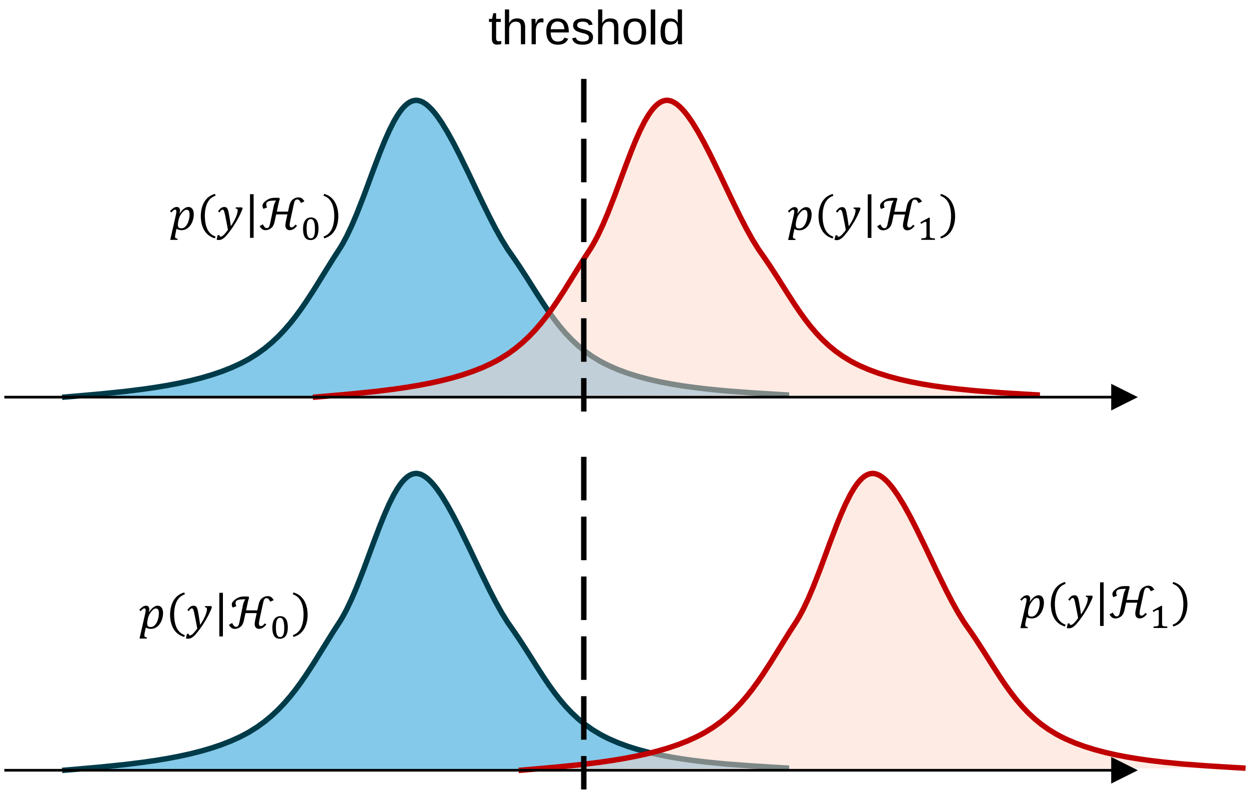
$$P_M = p(d = \mathcal{H}_0|\mathcal{H}_1) = 1 - P_D$$

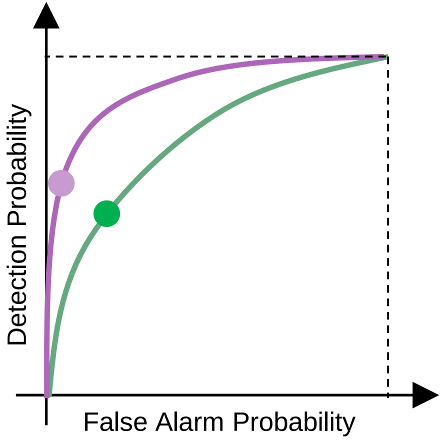
Receiver Operating Characteristic (ROC)



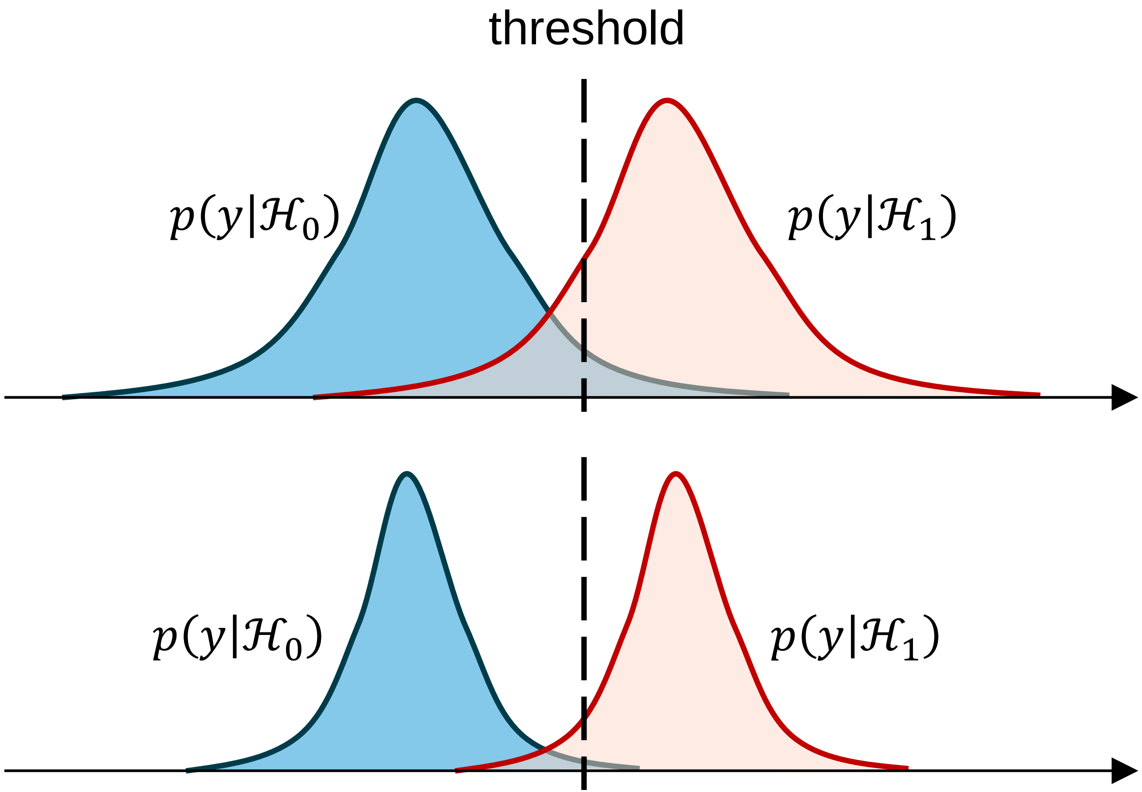


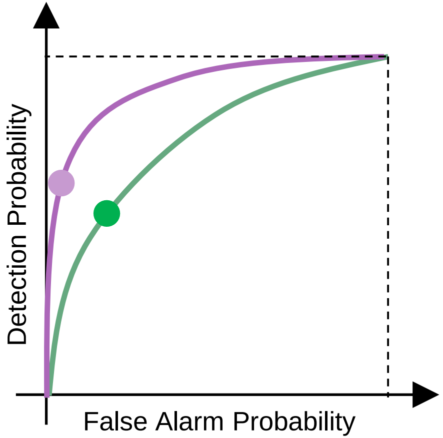
ROC – Increasing the Signal Power



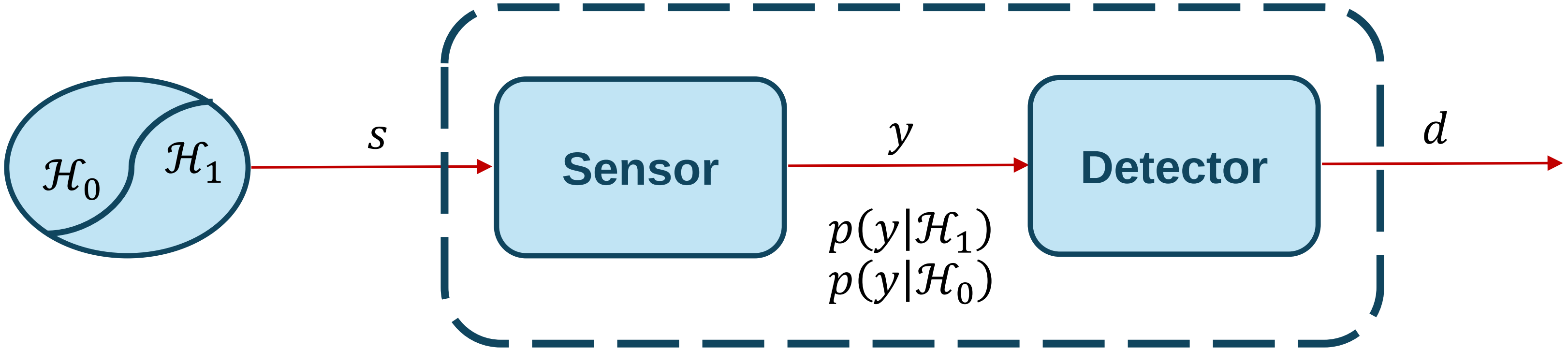


ROC – Reducing the Noise Power





Sensor Model



True Hp \ Estimated Hp	$\mathcal{H}_0$	$\mathcal{H}_1$
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$$P_D = p(d = \mathcal{H}_1|\mathcal{H}_1)$$

$$P_F = p(d = \mathcal{H}_1|\mathcal{H}_0)$$

Local Test – Optimum Test – Likelihood Ratio Test (LRT)

- LRT is the optimum test in the Neyman-Pearson framework and in the Bayesian framework
  - $y|\mathcal{H}_0 \sim p(y|\mathcal{H}_0)$
  - $y|\mathcal{H}_1 \sim p(y|\mathcal{H}_1)$

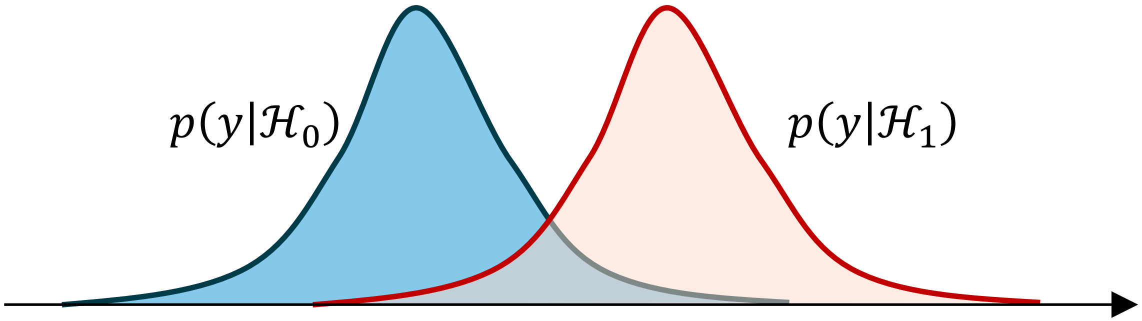
- Compute the likelihood ratio or equivalently the log-likelihood ratio (**LLR**)
  - $\lambda(y) = \ln\left(\frac{p(y|\mathcal{H}_1)}{p(y|\mathcal{H}_0)}\right)$

- Compare the LLR with a threshold
  - $\lambda(y) \gtreqless \gamma$

- Requires complete knowledge of the conditional probabilities $p(y|\mathcal{H}_0)$ and $p(y|\mathcal{H}_1)$

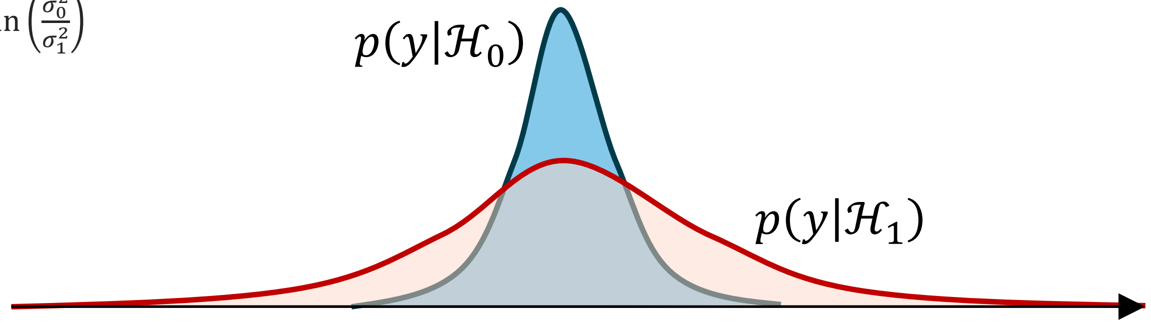
LRT – Example 1 (Shift in Mean)

- Statistical Signal Model
  - $y|\mathcal{H}_0 \sim \mathcal{N}(0; \sigma^2)$ $\qquad p(y|\mathcal{H}_0) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{y^2}{2\sigma^2}}$
  - $y|\mathcal{H}_1 \sim \mathcal{N}(\mu;\ \sigma^2)$ $\qquad p(y|\mathcal{H}_1) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y-\mu)^2}{2\sigma^2}}$
- Compute the LLR
  - $\lambda(y) = \ln\left(\frac{p(y|\mathcal{H}_1)}{p(y|\mathcal{H}_0)}\right) = \frac{\mu}{\sigma^2} y - \frac{\mu^2}{2\sigma^2}$
- **LRT** is equivalent to **Level Test**
  - $y \gtreqless \gamma$



LRT – Example 2 (Shift in Variance)

- Statistical Signal Model
  - $y|\mathcal{H}_0 \sim \mathcal{N}(0; \sigma_0^2)$ $\quad p(y|\mathcal{H}_0) = \frac{1}{\sqrt{2\pi\sigma_0^2}} e^{-\frac{y^2}{2\sigma_0^2}}$
  - $y|\mathcal{H}_1 \sim \mathcal{N}(0; \sigma_1^2)$ $\quad p(y|\mathcal{H}_1) = \frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{y^2}{2\sigma_1^2}}$
- Compute the LLR
  - $\lambda(y) = \ln\left(\frac{p(y|\mathcal{H}_1)}{p(y|\mathcal{H}_0)}\right) = \frac{1}{2}\frac{\sigma_1^2 - \sigma_0^2}{\sigma_0^2\sigma_1^2} y^2 + \frac{1}{2}\ln\left(\frac{\sigma_0^2}{\sigma_1^2}\right)$
- **LRT** is equivalent to **Energy Test**
  - $y^2 \gtrless \gamma$



Practical Tests

- (Optimum) **LRT**

$$\ln\left(\frac{p(y|\mathcal{H}_1)}{p(y|\mathcal{H}_0)}\right) \gtreqless \gamma$$

- Test commonly employed in absence of other relevant information
  - **Level Test**

$$y \gtreqless \gamma$$

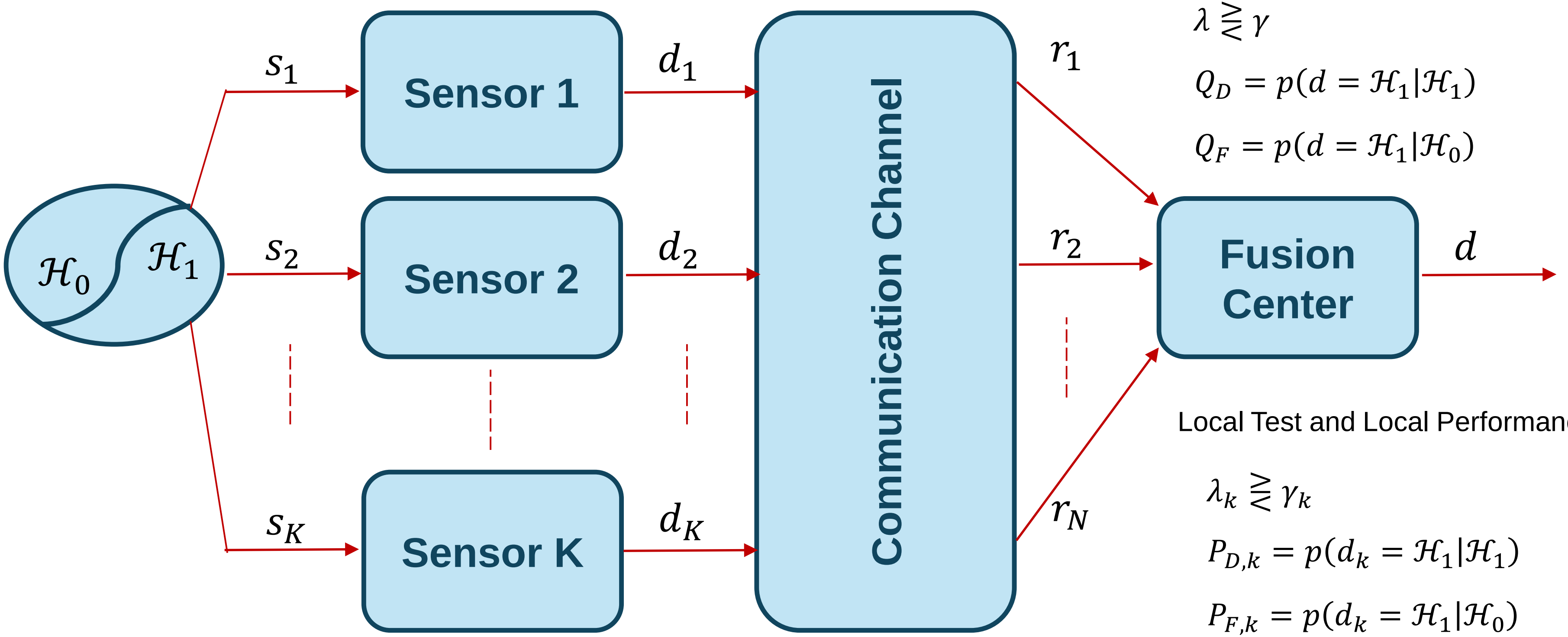
  - **Energy Test**

$$y^2 \gtreqless \gamma$$

(Wireless) Sensor Networks

Part I – Distributed Detection

Sensor-Network Architecture



Global Test and Global Performance

$$\lambda \gtreqless \gamma$$

$$Q_D = p(d = \mathcal{H}_1 | \mathcal{H}_1)$$

$$Q_F = p(d = \mathcal{H}_1 | \mathcal{H}_0)$$

Local Test and Local Performance

$$\lambda_k \gtreqless \gamma_k$$

$$P_{D,k} = p(d_k = \mathcal{H}_1 | \mathcal{H}_1)$$

$$P_{F,k} = p(d_k = \mathcal{H}_1 | \mathcal{H}_0)$$

Sensor-Network Architecture

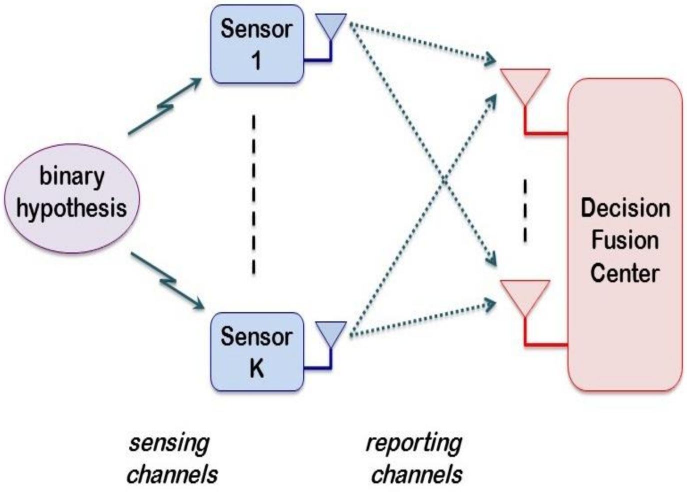
- Possible assumptions on the information processing at sensor location
  - **Hard decisions**, local binary decision $d_k \in \{0,1\}$
  - **Soft decisions**, level of confidence, multibit quantization of the LRT $d_k \in \{0,1,\dots,2^n - 1\}$
  - **Analog information**, in the ideal case of infinite precision, LLR information is sent (e.g. $d_k = \lambda_k(y_k)$)

- Possible assumptions on the reporting channel
  - Perfect channel: $r_k = d_k$
  - Parallel Access Channel (**no interference**): $r_k = f_k(d_k)$
  - Multiple Access Chanel (**interference**): $r = f(d_1, d_2, \dots, d_K)$
  - MIMO Chanel (**interference and multiple antennas**): $r_n = f_n(d_1, d_2, \dots, d_K)$

  - Common channel models:
    - Binary Symmetric Channel
    - Additive White Gaussian Noise Channel
    - Rayleigh-Fading Channel

- The fusion center takes a global decision depending on a specific **fusion rule**: $\lambda(r_1, r_2, \dots, r_N) \gtreqless \gamma$

MIMO Decision Fusion in WSNs



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- D. Ciuonzo, G. Romano, P. Salvo Rossi, "Optimality of Received Energy in Decision Fusion over a Rayleigh Fading Diversity MAC with Non-Identical Sensors," *IEEE Trans. Signal Process.* (2013)
- D. Ciuonzo, G. Romano, P. Salvo Rossi, "Performance Analysis and Design of Maximum Ratio Combining in Channel-Aware MIMO Decision Fusion," *IEEE Trans. Wireless Commun.* (2013)
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- D. Ciuonzo, P. Salvo Rossi, S. Dey, "Massive MIMO Channel-Aware Decision Fusion," *IEEE Trans. Signal Process.* (2015)
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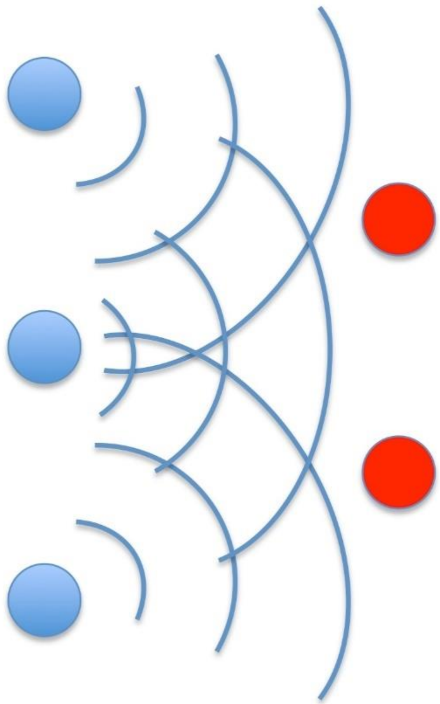
- P. Salvo Rossi, D. Ciuonzo, T. Ekman, H. Dong, "Energy Detection for MIMO Decision Fusion in Underwater Acoustic Wireless Sensor Networks," *IEEE Sensor J.* (2015)
- P. Salvo Rossi, D. Ciuonzo, K. Kansanen, T. Ekman, "Performance Analysis of Energy Detection for MIMO Decision Fusion in Wireless Sensor Networks over Arbitrary Fading Channels," *IEEE Trans. Wireless Commun.* (2016)

Why MIMO in WSNs?

- Introduces **spatial diversity**
  - Fading mitigation
- Is **spectrally efficient**
  - Resource saving
- Comes (almost) for **free**
  - Exploiting interference
  - No additional cost except for appropriate processing



System Model

$$\boldsymbol{y} = \boldsymbol{H}\boldsymbol{x} + \boldsymbol{w}$$

$$\lambda(\boldsymbol{y}) \gtrless \gamma$$

$$Q_D = p(\lambda > \gamma | \mathcal{H}_1)$$

$$Q_F = p(\lambda > \gamma | \mathcal{H}_0)$$

- $\boldsymbol{y} = (y_1, \dots, y_N)^T$ is the **received-signal vector**
- $y_n \in \mathbb{C}$ is the complex-valued signal received at the *n*th RX antenna

- $\boldsymbol{H} = \left(\left(H_{1,1}, \dots, H_{1,K}\right)^T, \dots, \left(H_{N,1}, \dots, H_{N,K}\right)^T\right)^T$ is the **channel matrix**
- $H_{n,k} \sim \mathcal{N}_{\mathbb{C}}(0; 1)$ is the channel coefficient between the *k*th sensor and the *n*th RX antenna

- $\boldsymbol{x} = (x_1, \dots, x_K)^T$ is the **transmitted vector**
- $x_k \in \{-1, +1\}$ is the BPSK symbol transmitted by the *k*th sensor

- $\boldsymbol{w} = (w_1, \dots, w_N)^T$ is the **noise vector**
- $w_n \sim \mathcal{N}(0; \sigma_w^2)$ is the AWGN at the *n*th RX antenna

$$\mathrm{SNR}_{tx} = \frac{K}{\sigma_w^2} \qquad \mathrm{SNR}_{tx}^* = \frac{1}{\sigma_w^2}$$

$$\mathrm{SNR}_{rx} = \frac{KN}{\sigma_w^2} \qquad \mathrm{SNR}_{rx}^* = \frac{N}{\sigma_w^2}$$

Performance Benchmarks

- **Observation Bound**: noisy sensing with perfect reporting

$$Q_F = \sum_{k=g}^{K} \binom{K}{k} P_F^k (1 - P_F)^{K-k} \qquad Q_D = \sum_{k=g}^{K} \binom{K}{k} P_D^k (1 - P_D)^{K-k}$$

- **Communication Bound**: perfect sensing with noisy reporting

- **Optimal Fusion Rule**: LRT

$$\lambda(\boldsymbol{y}) = \ln \left(\frac{\sum_{x \in \{\pm 1\}^K} e^{-\frac{\|\boldsymbol{y} - \boldsymbol{H}\boldsymbol{x}\|^2}{\sigma_w^2}} \prod_{k=1}^{K} p(x_k | \mathcal{H}_1)}{\sum_{x \in \{\pm 1\}^K} e^{-\frac{\|\boldsymbol{y} - \boldsymbol{H}\boldsymbol{x}\|^2}{\sigma_w^2}} \prod_{k=1}^{K} p(x_k | \mathcal{H}_0)} \right)$$

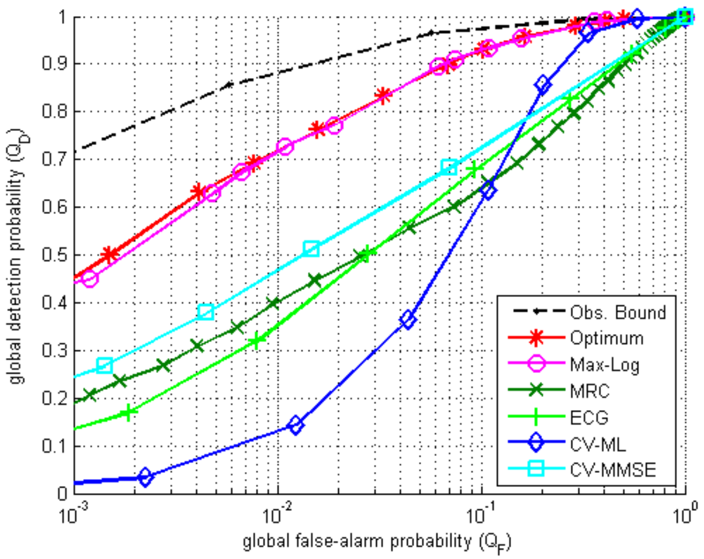
  – High computational complexity: exponential with the number of sensors $\mathcal{O}(2^K N)$
  – Numerical instability: large dynamic range is problematic with fixed-point implementations
  – Excessive knowledge requirements: local performance, channel matrix, noise variance

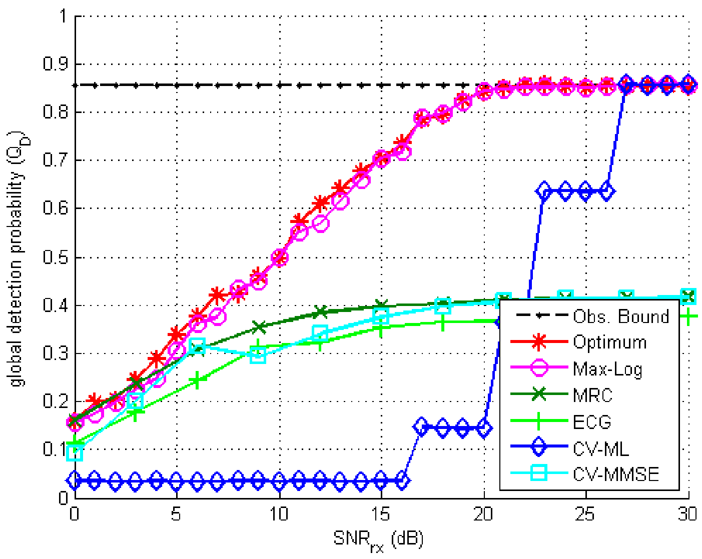
Alternative Fusion Rules

- Decode-and-Fuse approach
  - Maximum Ratio Combining
    (optimum at low SNR, linear complexity $\mathcal{O}(N)$, requires partial channel)
  - Equal Ratio Combining
    (no optimality, linear complexity $\mathcal{O}(N)$, requires less partial channel)
  - Max-Log
    (optimal, reduced exponential complexity, full knowledge)

- Decode-then-Fuse approach
  - Chair-Varshney Rule with Maximum Likelihood Estimation
    (optimum at high SNR, reduced exponential complexity, requires local performance and channel matrix)
  - Chair-Varshney Rule with Minimum Mean Square Error Estimation
    (no optimality, polynomial complexity $\mathcal{O}(NK^2 + N^2)$, full knowledge)

Performance





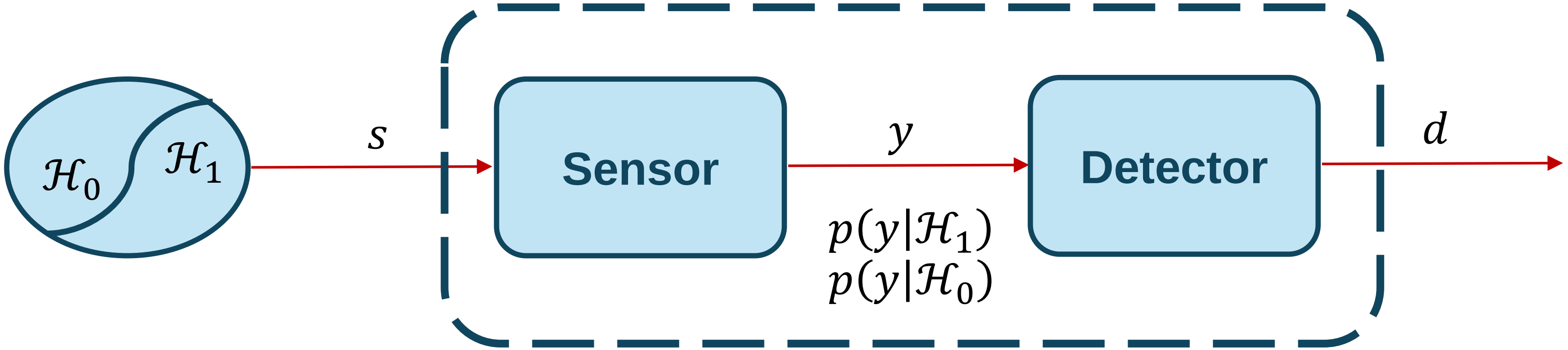

KONGSBERG

Sensor Modeling

Part II – Distributed Detection and Localization

KONGSBERG

Sensor Model



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$$P_F = p(d = \mathcal{H}_1|\mathcal{H}_0)$$

Sensing Model

$$y = \theta \cdot g(\boldsymbol{x}; \boldsymbol{x}_T) + w$$

- y is the **measurement** at the sensor
- $w \sim \mathcal{N}(0; \sigma_w^2)$ is the **noise** at the sensor
- $\boldsymbol{x}$ is the **location** of the sensor

- θ is the **intensity** of the target to be detected
  - Unknown and Deterministic: $\theta \in \Omega_\theta$
    e.g. $\theta \in [-\theta_0, +\theta_0]$
  - Unknown and Stochastic: $\theta \sim p(\theta)$
    e.g. $\theta \sim \mathcal{N}(0; \sigma_T^2)$
- $g(\cdot;\cdot)$ is the (distance-dependent) amplitude attenuation function (**AAF**) or spatial signature
- $\boldsymbol{x}_T$ is the **target location**

Amplitude Attenuation Function (AAF)

- Comes from **domain knowledge**

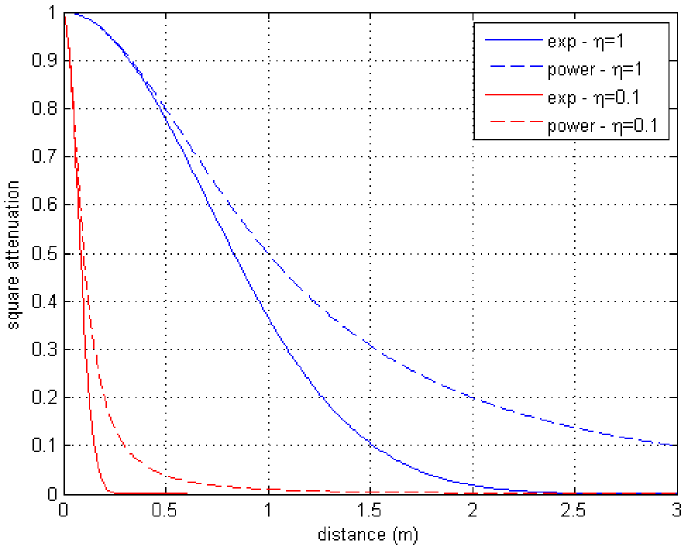
- Represents the physical phenomenon and related propagation

- Common AAF with EM signals:
  - **Exponential** AAF

$$g^2(\boldsymbol{x}; \boldsymbol{x}_T) = e^{-\frac{\|x - x_T\|^2}{\eta^2}}$$

  - **Power-Law** AAF

$$g^2(\boldsymbol{x}; \boldsymbol{x}_T) = \frac{1}{1 + \frac{\|x - x_T\|^2}{\eta^2}}$$

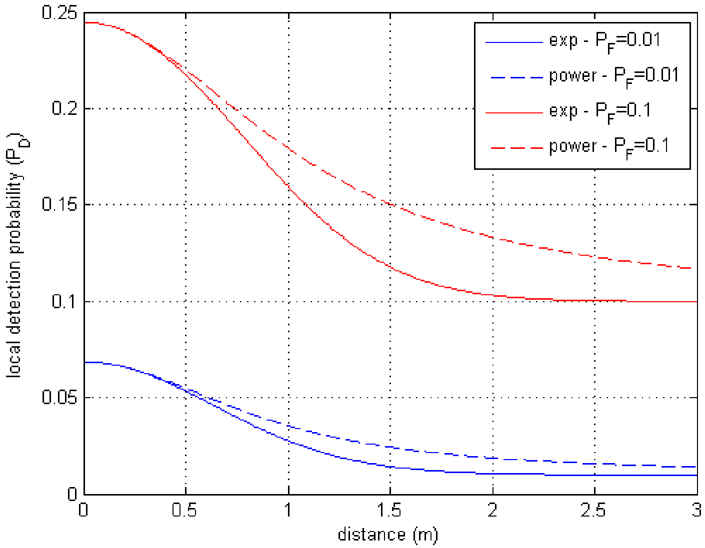


Local Test

- Statistical Signal Model
  - $y|\mathcal{H}_0 \sim \mathcal{N}(0; \sigma_W^2)$ $\quad p(y|\mathcal{H}_0) = \frac{1}{\sqrt{2\pi\sigma_W^2}} e^{-\frac{y^2}{2\sigma_W^2}}$
  - $y|\mathcal{H}_1 \sim \mathcal{N}(0; \sigma_T^2 g^2(\boldsymbol{x}; \boldsymbol{x}_T) + \sigma_W^2)$ $\quad p(y|\mathcal{H}_1) = \frac{1}{\sqrt{2\pi(\sigma_T^2 g^2(\boldsymbol{x}_k; \boldsymbol{x}_T) + \sigma_W^2)}} e^{-\frac{y^2}{2(\sigma_T^2 g^2(x; \boldsymbol{x}_T) + \sigma_W^2)}}$
- Compute the LLR
  - $\lambda(y) = \ln\left(\frac{p(y|\mathcal{H}_1)}{p(y|\mathcal{H}_0)}\right) = \frac{\Gamma_S}{2} \frac{g^2(\boldsymbol{x};\boldsymbol{x}_T)}{\sigma_T^2 g^2(\boldsymbol{x};\boldsymbol{x}_T) + \sigma_W^2} y^2 + \frac{1}{2} \ln\left(\frac{1}{1 + \Gamma_S g^2(\boldsymbol{x};\boldsymbol{x}_T)}\right)$ $\quad \Gamma_S \triangleq \frac{\sigma_T^2}{\sigma_W^2}$ sensing SNR
- **LRT** is equivalent to **Energy Test**
  - $y^2 \gtrless \gamma$

Local Performance

- Assume fixed local FA probability
- Assume fixed AAF
- Evaluate local detection probability vs target distance

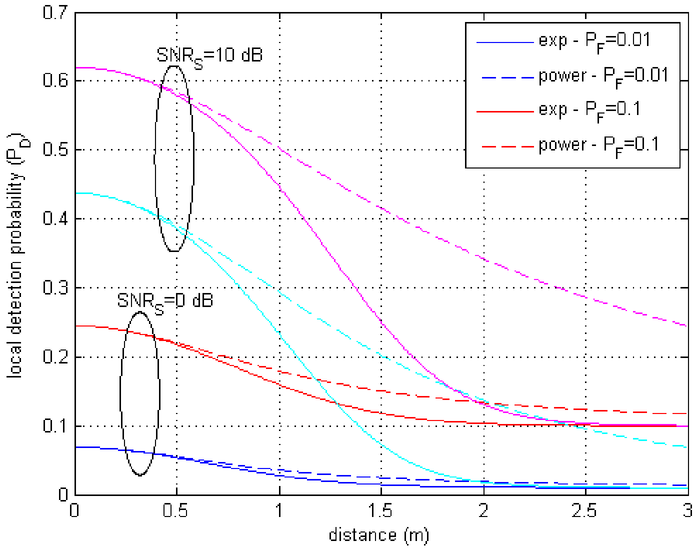


- $P_F = 2Q\left(\sqrt{\frac{\gamma}{\sigma_w^2}}\right)$
- $P_D = 2Q\left(\sqrt{\frac{\gamma}{\sigma_T^2 g^2(x;x_T)+\sigma_w^2}}\right)$

Local Performance

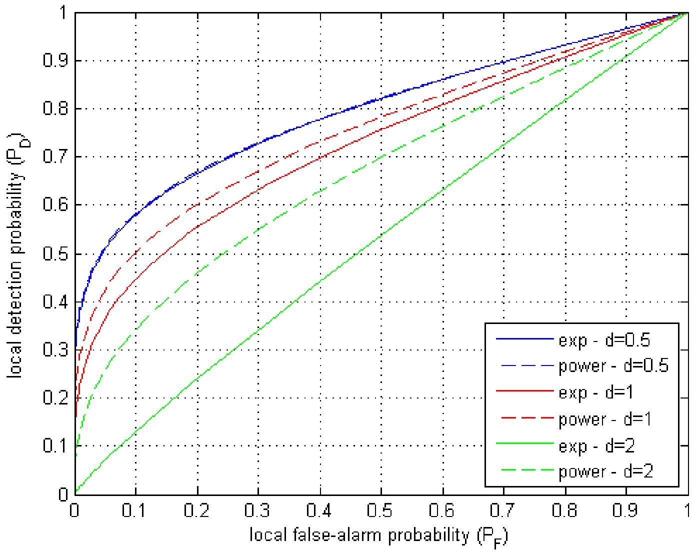
- Assume fixed local FA probability
- Assume fixed AAF
- Evaluate local detection probability vs target distance
- Performance improves with sensing SNR

- $P_F = 2Q\left(\sqrt{\frac{\gamma}{\sigma_w^2}}\right)$
- $P_D = 2Q\left(\sqrt{\frac{\gamma}{\sigma_T^2 g^2(x;x_T)+\sigma_w^2}}\right)$



Local Performance (ROC)

- Performance worsens with distance
- Performance improves with sensing SNR

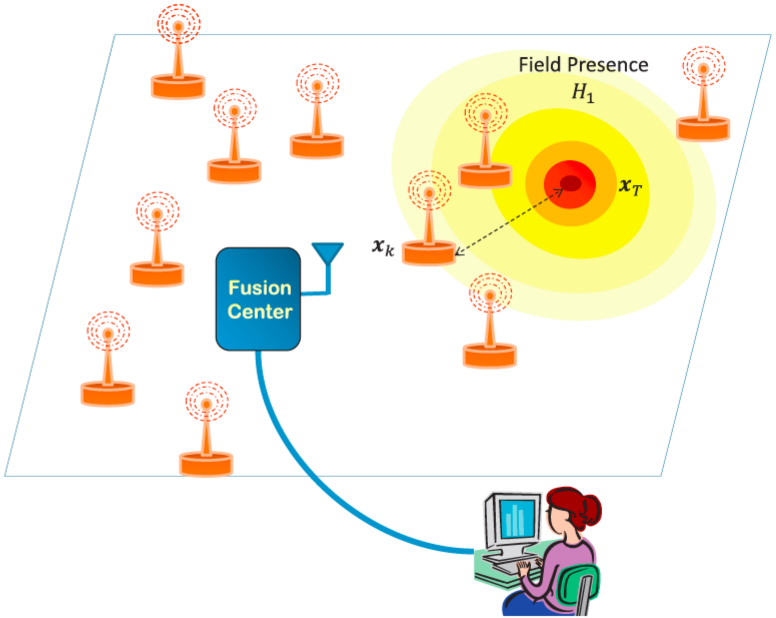


- $P_F = 2Q\left(\sqrt{\frac{\gamma}{\sigma_w^2}}\right)$
- $P_D = 2Q\left(\sqrt{\frac{\gamma}{\sigma_T^2 g^2(\boldsymbol{x};\boldsymbol{x}_T)+\sigma_w^2}}\right)$

(Wireless) Sensor Networks

Part II – Distributed Detection and Localization

MIMO Decision Fusion in WSNs



- D. Ciuonzo, G. Papa, G. Romano, P. Salvo Rossi, P. Willett, “One-Bit Decentralized Detection with a Rao Test for Multisensor Fusion,” *IEEE Signal Process. Lett.* (2013)
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- D. Ciuonzo, A. De Maio, P. Salvo Rossi, “A Systematic Framework for Composite Hypothesis Testing of Independent Bernoulli Trials,” *IEEE Signal Process. Lett.* (2015)
- D. Ciuonzo, P. Salvo Rossi, P. Willett, “Generalized Rao Test for Decentralized Detection of an Uncooperative Target,” *IEEE Signal Process. Lett.* (2017)
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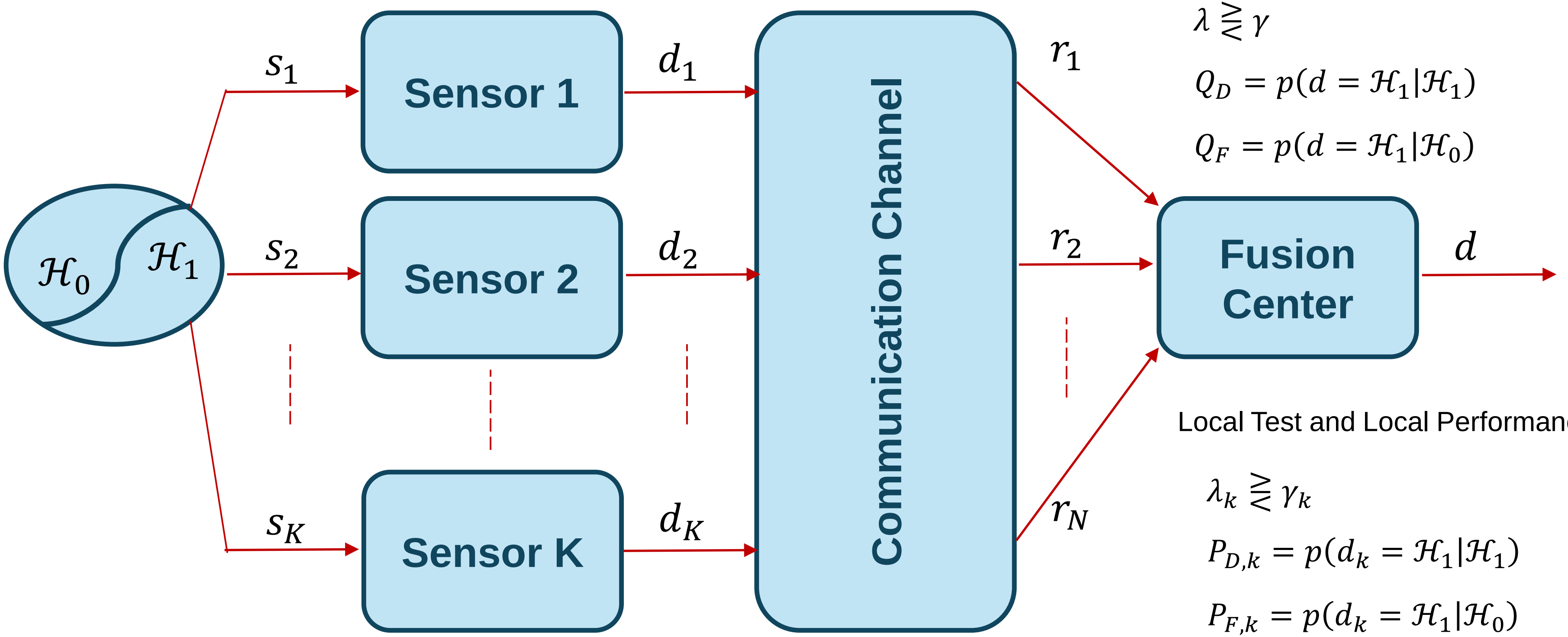
- D. Ciuonzo, P. Salvo Rossi, “Quantizer Design for Generalized Locally-Optimum Detectors in Wireless Sensor Networks,” *IEEE Wireless Commun.* Lett. (in press)

Sensor-Network Architecture



Global Test and Global Performance

$$\lambda \gtreqless \gamma$$

$$Q_D = p(d = \mathcal{H}_1 | \mathcal{H}_1)$$

$$Q_F = p(d = \mathcal{H}_1 | \mathcal{H}_0)$$

Local Test and Local Performance

$$\lambda_k \gtreqless \gamma_k$$

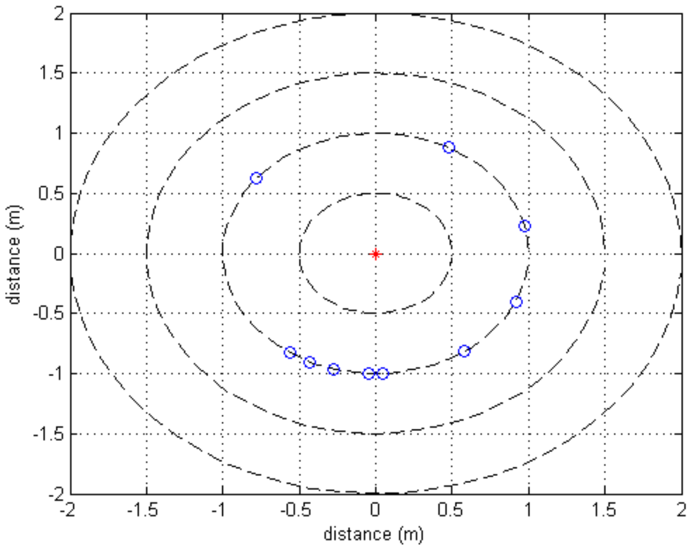
$$P_{D,k} = p(d_k = \mathcal{H}_1 | \mathcal{H}_1)$$

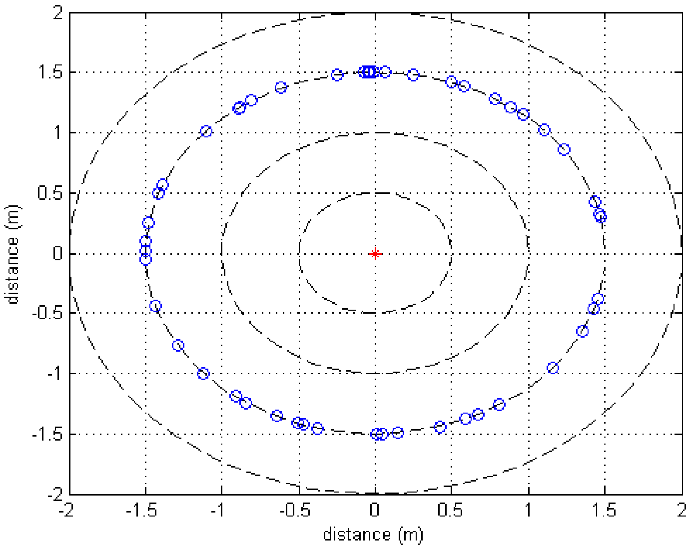
$$P_{F,k} = p(d_k = \mathcal{H}_1 | \mathcal{H}_0)$$

Counting Rule (CR)

- Simple and intuitive strategy is to count the number of reported detections
  - $\lambda = \sum_{k=1}^{K} d_k$
- Advantages
  - System knowledge not required (e.g. local performance, sensing SNR, etc.)
  - It is optimal in the case of homogeneous sensor networks
    $P_{F,k} = P_F$ and $P_{D,k} = P_D$
- Disadvantages
  - Poor performance in practical scenarios of interest
  - No localization provided

Ring Scenario



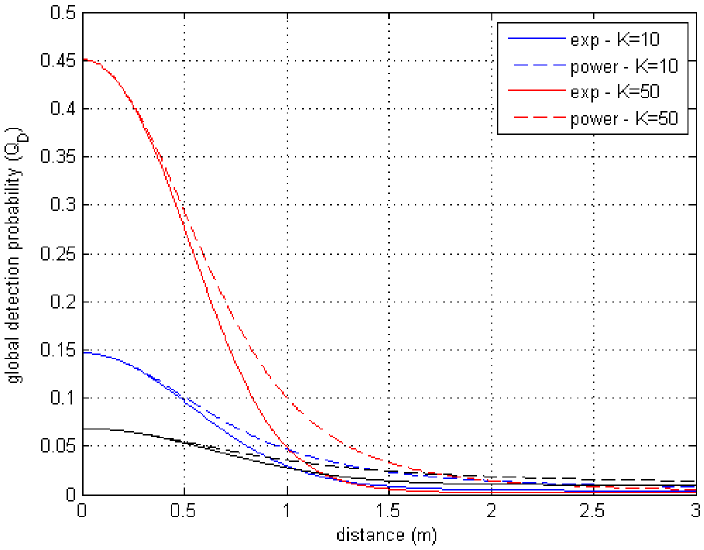


Performance of CR in Ring WSNs

- Assume a WSN with K sensors

- All sensors have the same distance from the target

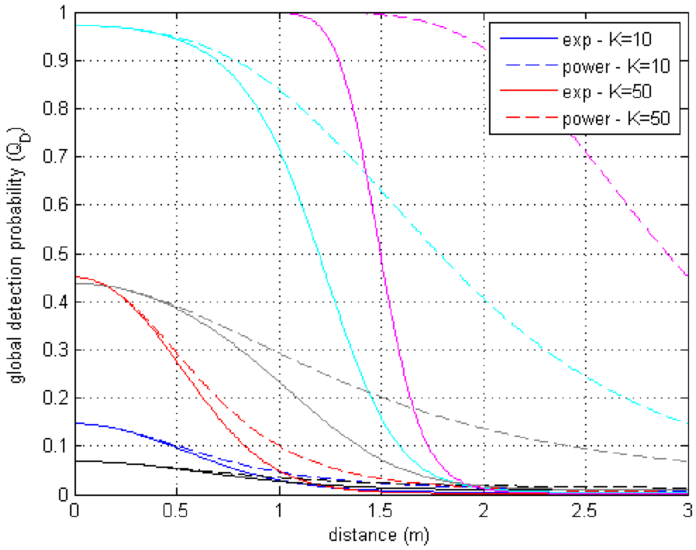
- Performance improves with K



- Unrealistic assumption
  - if present the target is in known position
  - good approximation for large spreading factors

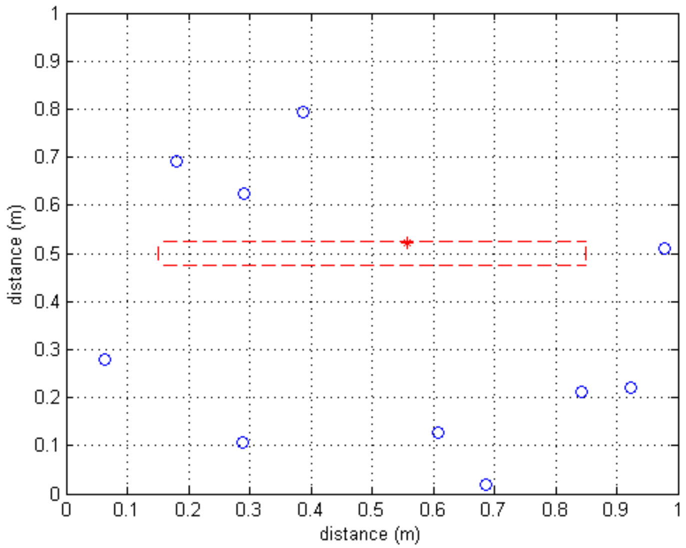
Performance of CR in Ring WSNs

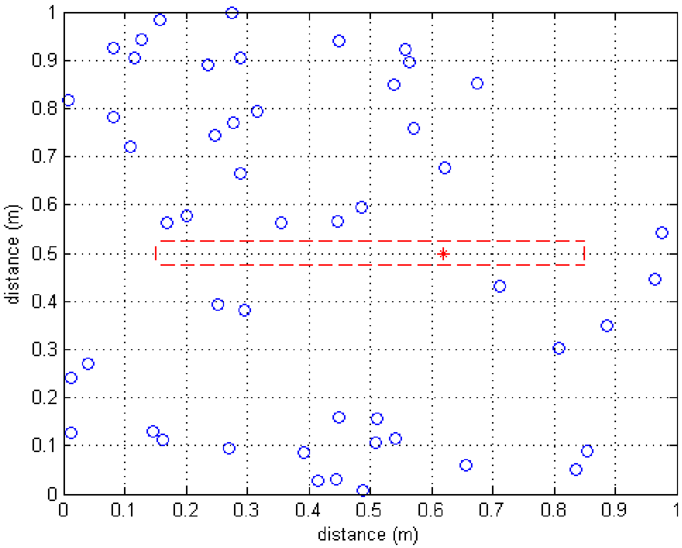
- Assume a WSN with K sensors
- All sensors have the same distance from the target
- Performance improves with K
- Performance improves with sensing SNR



- Unrealistic assumption
  - if present the target is in known position
  - good approximation for large spreading factors

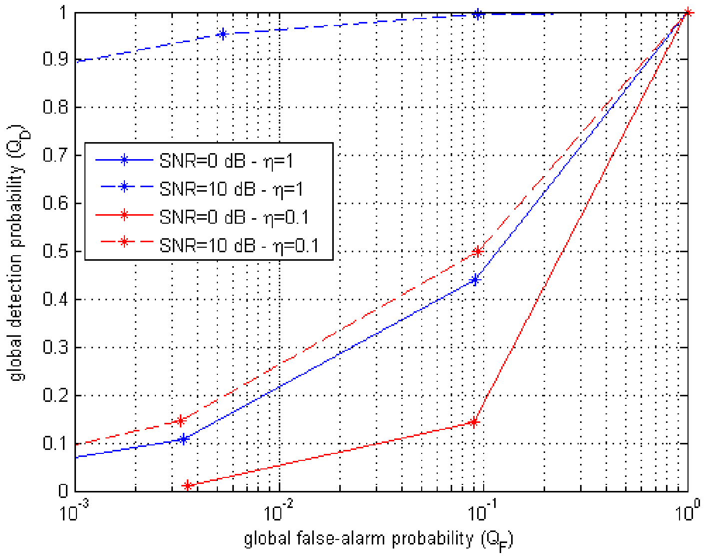
Randomly-Deployed Sensors





Performance of CR in Random WSNs

- Assume a WSN with K sensors
- Sensors are randomly generated in the sensor area
- Target (if present) is randomly generated in the target area
- Performance improves with sensing SNR
- Performance improves with η



Optimum Rule – (Clairvoyant) LRT

- Compute the LLR
  - $\lambda = \ln\left(\frac{p(\boldsymbol{d}|\mathcal{H}_1)}{p(\boldsymbol{d}|\mathcal{H}_0)}\right) = \sum_{k=1}^{K}\left[d_k \ln\left(\frac{P_{D,k}}{P_{F,k}}\right) + (1 - d_k)\ln\left(\frac{1-P_{D,k}}{1-P_{F,k}}\right)\right]$

- Advantages
  - Optimum performance

- Disadvantages
  - Cannot be implemented in practice

    Requires knowledge of both $P_{F,k}$ and $P_{D,k}$ which is unrealistic (because depending on $\boldsymbol{x}_T$ and σ_T^2)

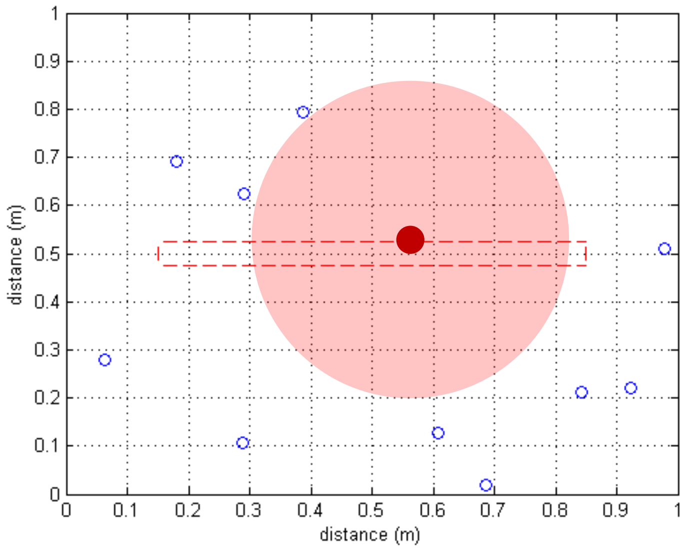
Generalized LRT (GLRT)

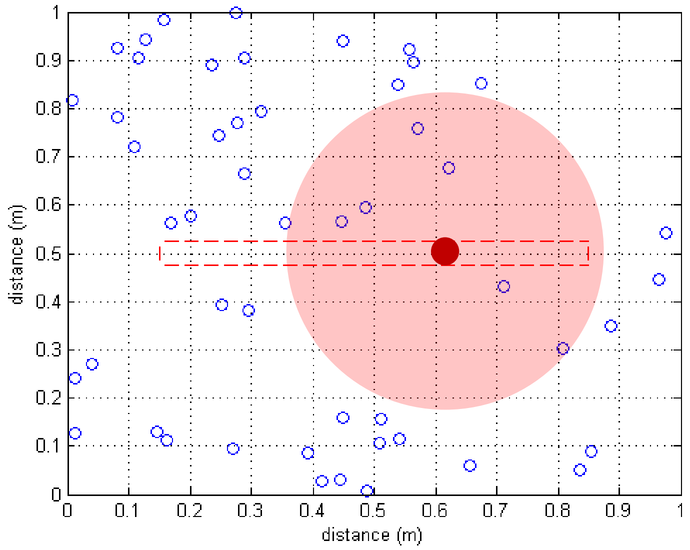
- Compute the LGLR using ML estimation
  - $\lambda = \ln\left(\frac{\max\limits_{x_T;\sigma_T^2} p(\boldsymbol{d}|\mathcal{H}_1;\boldsymbol{x}_T;\sigma_T^2)}{p(\boldsymbol{d}|\mathcal{H}_0)}\right) = \sum_{k=1}^{K}\left[d_k \ln\left(\frac{P_{D,k}(\widehat{\boldsymbol{x}_T};\widehat{\sigma_T^2})}{P_{F,k}}\right) + (1-d_k)\ln\left(\frac{1-P_{D,k}(\widehat{\boldsymbol{x}_T};\widehat{\sigma_T^2})}{1-P_{F,k}}\right)\right]$
  - $\left(\widehat{\boldsymbol{x}_T};\widehat{\sigma_T^2}\right) = \underset{\boldsymbol{x}_T;\sigma_T^2}{\operatorname{argmax}}\, p(\boldsymbol{d}|\mathcal{H}_1;\boldsymbol{x}_T;\sigma_T^2)$

- Advantages
  - System knowledge not required (e.g. local performance, sensing SNR, etc.)
  - Excellent performance for both detection and localization tasks

- Disadvantages
  - Requires optimization procedure for ML estimation (e.g. grid search)

Randomly-Deployed Sensors





Performance of GLRT and CR in Random WSNs

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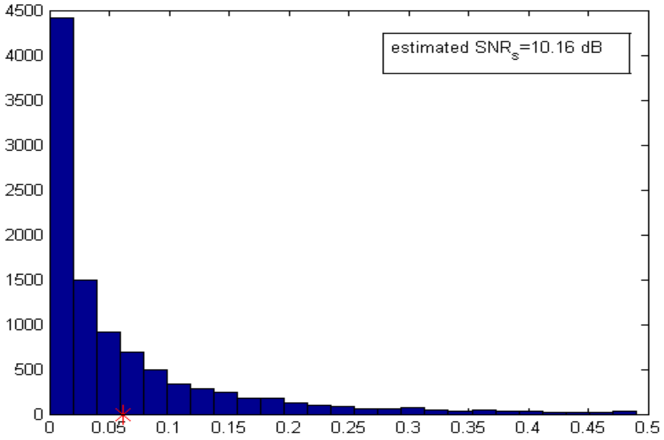
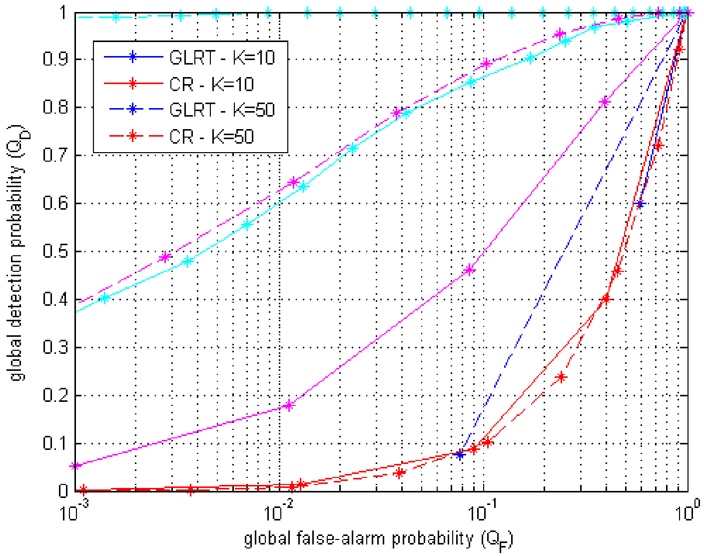
- Sensors are randomly generated in the sensor area
- Target (if present) is randomly generated in the target area
- Performance improves with sensing SNR
- The improvement of GLRT wrt CR is apparent





Alternative Fusion Rules

- Bayesian approach
  - Bayesian LLR
- Locally Optimum Detection (LOD) approach
  - Generalized LOD (GLOD)
- Hybrid approach
  - Bayesian/GLLR
  - Bayesian/LOD

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