Quantized Fusion Rules for Energy-Based Distributed Detection in Wireless Sensor Networks

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Overview

1. Introduction

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Motivation

- Distributed detection has been attracting significant interest in the context of WSNs [Chamberland 2007] and [Barbarossa 2013].

Challenges

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  1. Efficiently utilizes the scarce bandwidth.
  2. Overcomes the limitations of a fading wireless channel.

Literature Review

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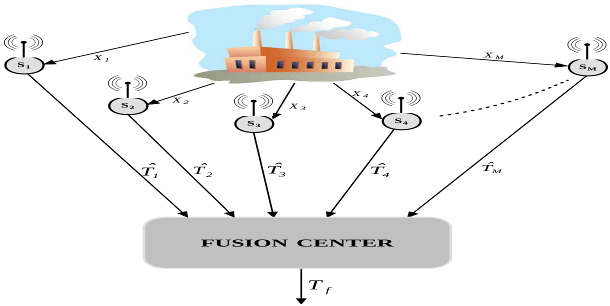
- The channel fading effect on distributed detection was tackled by Chenn [Chenn 2006].
- Barbarossa and Sardelliti addressed both issues of limited bandwidth and channel imperfections. They optimized the transmission power for the detection of a known signal [Barbarossa 2013].

Overview

2. Problem Formulation cont'd ...



- M sensor nodes reporting to a FC tasked with the detection of any intruders.
- The intruder leaves a signature signal unknown to the WSN but deterministic.
- The i^{th} SN collects N samples corrupted by (AWGN) zero mean and known variance σ_i^2.

2. Problem Formulation cont'd ...

System Model

- Depending on the underlying hypothesis:

$$\begin{aligned} \mathcal{H}_0 : x_i(n) &= w_i(n) \\ \mathcal{H}_1 : x_i(n) &= s_i(n) + w_i(n) \end{aligned}$$

2. Problem Formulation cont'd ...

Optmimum detection

- The intruder's signal is unknown at the SNs, hence the i^{th} SN estimates the energy of the received signal:

$$T_i = \sum_{n=1}^{N} |x_i(n)|^2 . \qquad (1)$$

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- SNs should send their measurements to the FC, where the ultimate detection decision will be made.
- Available bandwidth is limited.
- This approach is not always feasible in the context of WSNs .

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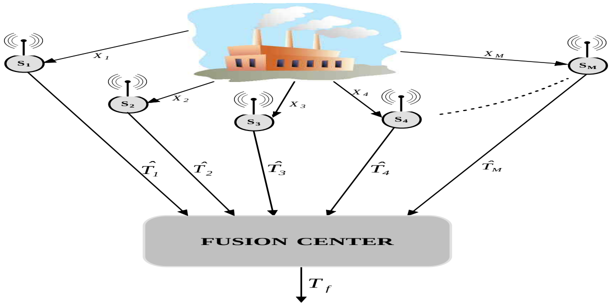

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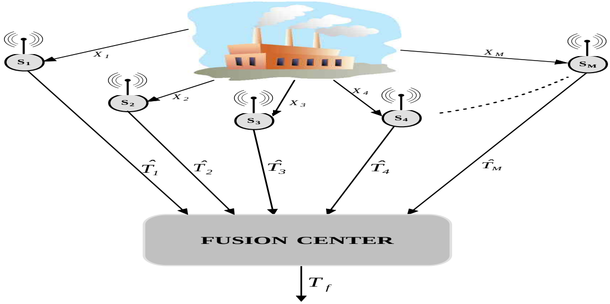

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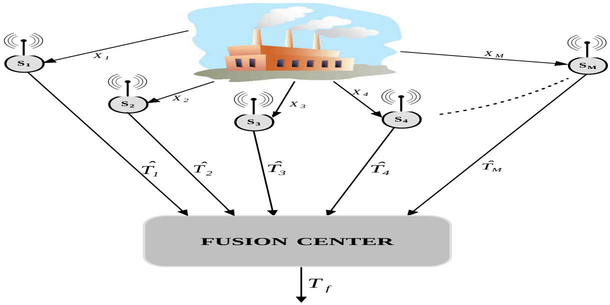

Optmimum detection

- WSN adopts a distributed detection algorithm.
- SNs send their quantized soft decisions (i.e., the quantized local test statistics) to the FC.
- FC combines them to arrive at the global decision.

Proposition

- We propose to quantize T_i with L_i bits and transmit to the FC with power p_i over a wireless channel.

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- The number of quantization bits at the i^{th} SN must satisfiy the channel capacity constraint:

$$L_i \leq \frac{1}{2}\log_2\left(1+\frac{p_i h_i^2}{\zeta_i}\right) \text{bits}, \;\; i = 1, 2, \ldots, M.$$

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- The wireless channel conditions between the i^{th} SN and the FC:
  1. Suffers from zero mean AWGN with a variance of ζ_i.
  2. Experiences flat fading with a channel gain h_i (assumed to be iid).

Overview

Part I

Soft Decision Fusion Rules

3. Soft Decision Fusion Rules cont'd ...

Optimal Fusion Rule cont'd ...

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- The optimal fusion rule follows from the likelihood ratio test:

$$\mathrm{LRT}(\boldsymbol{T}) = \frac{p\{T_1, T_2, ..., T_M | \mathcal{H}_1\}}{p\{T_1, T_2, ..., T_M | \mathcal{H}_0\}} \geq \gamma \tag{3}$$

where $p\{T_1, T_2, ..., T_M | \mathcal{H}_j\}$ is the joint probability distribution of local soft decisions under the j^{th} hypothesis.

3. Soft Decision Fusion Rules cont'd ...

Optimal Fusion Rule cont'd ...

- T_i can be adequately approximated by a Gaussian distribution with the following mean and variance:

$$\mathrm{E}\left\{T_i|\mathcal{H}_0\right\} = N\sigma_i^2, \qquad \mathrm{Var}\left\{T_i|\mathcal{H}_0\right\} = 2N\sigma_i^4 \tag{4}$$

$$\mathrm{E}\left\{T_i|\mathcal{H}_1\right\} = N\sigma_i^2\left(1+\xi_i\right), \qquad \mathrm{Var}\left\{T_i|\mathcal{H}_1\right\}=2N\sigma_i^4\left(1+2\xi_i\right) \tag{5}$$

where $\xi_i = \sum_{n=1}^{N} s_i^2\left(n\right)/N\sigma_i^2$ is the SNR at the i^{th} SN.

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- Noise at different SNs assumed independent, LLR takes the form:

$$T_f = \sum_{i=1}^{M}\left(\frac{\left(T_i - N\sigma_i^2\right)^2}{2N\sigma_i^4} - \frac{\left(T_i - N\sigma_i^2\left(1+\xi_i\right)\right)^2}{2N\sigma_i^4\left(1+2\xi_i\right)}\right) \geq \gamma' \tag{6}$$

3. Soft Decision Fusion Rules cont'd ...

Optimal Fusion Rule

- The LLR can be further simplified

$$T_f = \sum_{i=1}^{M} a_i \left(T_i - b_i \right)^2 \tag{7}$$

$$a_i = \frac{\xi_i}{N\sigma_i^4 \left(1 + 2\xi_i\right)}, \quad b_i = \frac{N\sigma_i^2}{2}.$$

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- where $\gamma' = 2\ln\left(\prod_{i=1}^{M}\gamma\left(\frac{\sqrt{2N\sigma_i^4}}{\sqrt{2N\sigma_i^4(1+2\xi_i)}}\right)\right)$.

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  2. Equal fusion
  3. Optimum linear fusion

Suboptimal Fusion Rules

Weighted Fusion Rule

- Replace a_i by $a_i^w = 1/2N\sigma_i^4$ and we let $b_i^w = b_i = \frac{N\sigma_i^2}{2}$. This rule approaches the optimal one when the SNR is large.

$$T_f = \sum_{i=1}^{M} a_i \left(T_i - b_i \right)^2 \tag{8}$$

Equal Weight Fusion Rule

Optimum Linear Fusion Rule

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Optimum Linear Fusion Rule

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Optimum Linear Fusion Rule

- $T_f^l = \sum_{i=1}^{M} \alpha_i T_i,$ where $\alpha_i = \frac{\xi_i}{N\sigma_i^2(1+2\xi_i)}$.

Part II

Quantized Soft Decision Fusion Rules

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Quantized Optimal Fusion Rule cont'd ...

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- Now let the quantized test statistic ($\hat{T}_i$) at the i^{th} sensor be modeled (with L_i bits) as

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- v_i is the quantization noise with uniform distribution in the interval $[-B, B]$ and variance

$$\sigma_{v_i}^2 = \frac{B^2}{3 \times 2^{2L_i}}. \tag{10}$$

Quantized Soft Decision Fusion Rules cont'd ...

Quantized Optimal Fusion Rule

- Approximating $\hat{T}_i$'s as Gaussian distribution, the LLR optimum fusion rule can be shown to be:

$$T_f^q = \sum_{i=1}^{M} a_i^q \left(\hat{T}_i - b_i^q \right)^2 \tag{11}$$

$$a_i^q = \frac{\xi_i}{N\sigma_i^4 \left(1+2\xi_i+\frac{\sigma_{v_i}^2}{2N\sigma_i^4}\right)\left(1+\frac{\sigma_{v_i}^2}{2N\sigma_i^4}\right)} \qquad b_i^q = \frac{N\sigma_i^2}{2} - \frac{\sigma_{v_i}^2}{4\sigma_i^2}.$$

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Observations

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- Interesting observation is that $T_f^q \to T_f$ as $N \to \infty$, regardless of $\sigma_{v_i}^2$.
- Bandwidth can be saved but at the expense of increasing both the number of collected measurements and also the detection delay.

Overview

Quantized Soft Decision Fusion Rules cont'd...

Quantized Sub-Optimum Fusion Rules

$$T_f^q = \sum_{i=1}^{M} a_i^q \left(\hat{T}_i - b_i^q \right)^2$$

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- The suboptimal (quantized) fusion rules can be easily shown to be:

$$L_i \leq \frac{1}{2} \log_2 \left(1 + \frac{p_i h_i^2}{\zeta_i} \right) \text{bits}, \; i = 1, 2, \ldots, M.$$

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  - Equal fusion: $a_i^q = a^{eq} = 1$ and $b^{eq} = b^{wq} = b_i^q$.

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Quantized Linear Fusion Rule

$$T_f^l = \sum_{i=1}^{M} \alpha_i^q \hat{T}_i$$

- The weights of suboptimal (quantized) linear fusion rules can be easily shown to be:

$$\alpha_i^q = \frac{\xi_i}{2\sigma_i^2 \left[1 + 2\xi_i + \frac{\sigma_{v_i}^2}{N\sigma_i^2}\right]}. \tag{12}$$

E. Nurellari, D. McLernon, M. Ghogho and S. Aldalahmeh, "Optimal quantization and power allocation for energy-based distributed sensor detection," *Proc. EUSIPCO*, Lisbon, Portugal, 1-5 Sept. 2014.

Overview

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Optimization Problem cont'd ...

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- Using the central limit theorem, T_f^q can be approximated by a Gaussian distribution:

$$T_f^q \sim \begin{cases} \mathcal{N}\left(\mathrm{E}\left\{T_f^q | \mathcal{H}_0\right\}, \mathrm{Var}\left\{T_f^q | \mathcal{H}_0\right\}\right) \text{ under } \mathcal{H}_0 \\ \mathcal{N}\left(\mathrm{E}\left\{T_f^q | \mathcal{H}_1\right\}, \mathrm{Var}\left\{T_f^q | \mathcal{H}_1\right\}\right) \text{ under } \mathcal{H}_1 \end{cases} \tag{14}$$

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- We can optimize the transmission powers (p_i) to maximize P_d under the constraint of a maximum aggregate transmit power budget (P_t):

$$\begin{aligned} \boldsymbol{p}_{opt} = &\ \arg \max_{\boldsymbol{p}} P_d(\boldsymbol{p}) \\ \text{subject to} &\sum_{i=1}^{M} p_i \leq P_t \text{ for } \ p_i \geq 0, \ i = 1, \ldots, M \end{aligned} \tag{15}$$

where $\boldsymbol{p} = [p_1, p_2, \ldots, p_M]$.

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where $\boldsymbol{p} = [p_1, p_2, \ldots, p_M]$.

- We adopt the spatial branch-and-bound strategy using the YALMIP optimization tools.

Overview

Simulations setup

- We simulate a WSN of M SNs detecting an intruder with $s_i(n) = A$, where $A = 0.1$.
- The communication noise variances set to $\zeta_i = 0.1 \ \forall i$ (for simplicity).
- The measurement noise variances are generated randomly and used throughout the simulations.
- The average measurement SNR for the network is defined as $\xi_a = 10 \log_{10} \left(\frac{1}{M} \sum_{i=1}^{M} \xi_i \right)$.
- In all simulations we assume perfect knowledge of ξ_i.

Simulation Results 1/6

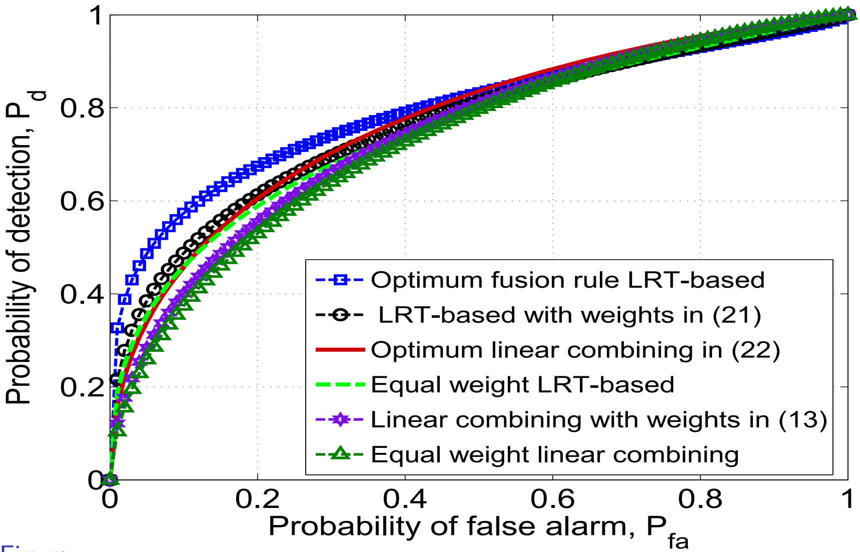

Figure: Receiver operating characteristics of six different fusion rules for $N = 10$, $M = 10$, $\xi_a = -8.5$ dB and $B = 0.5$.

Simulation Results 2/6

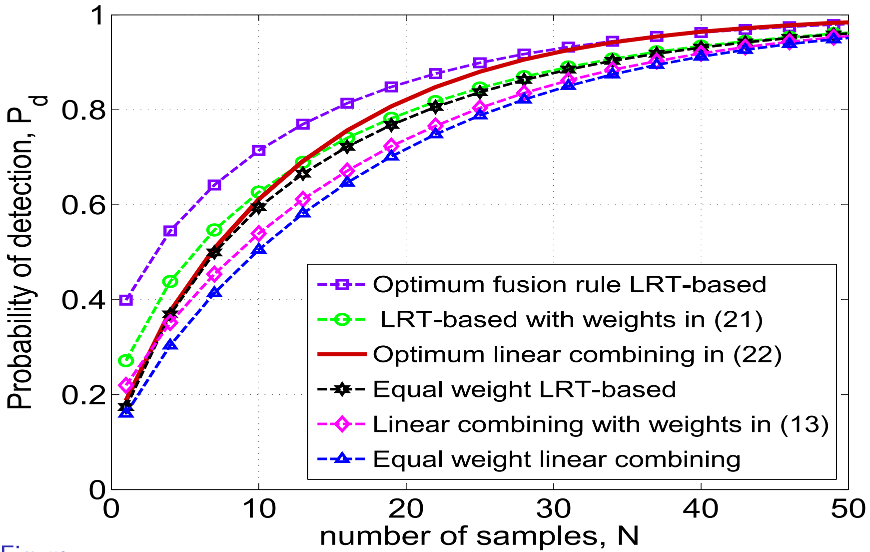

Figure: Probability of detection (P_d) versus number of samples (N) with $M = 20$, $P_{fa} = 0.1, B = 0.5$ and $\xi_a = 8.5$ dB.

Simulation Results 3/6

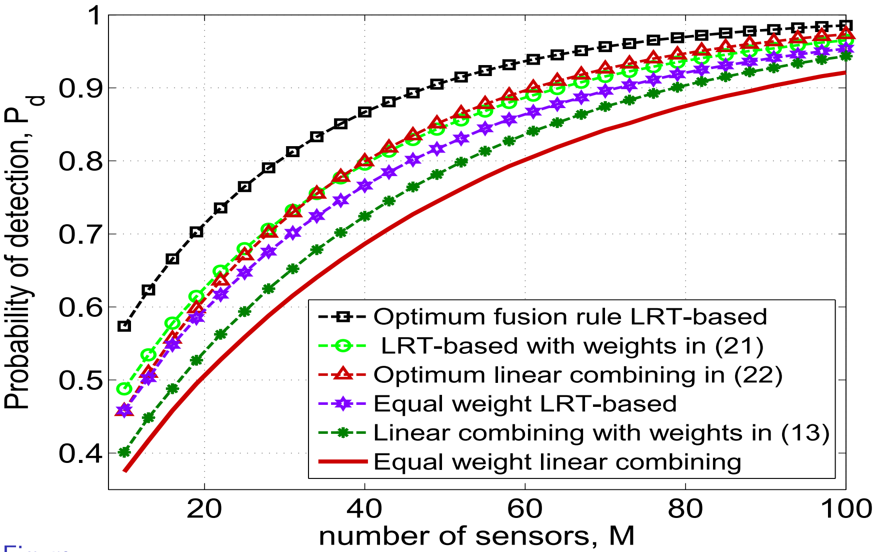

Figure: Probability of detection (P_d) versus number of sensors (M) for $N = 10$, $P_{fa} = 0.1$, $\xi_a = 8.5$ dB and $B = 0.5$.

Simulation Results 4/6

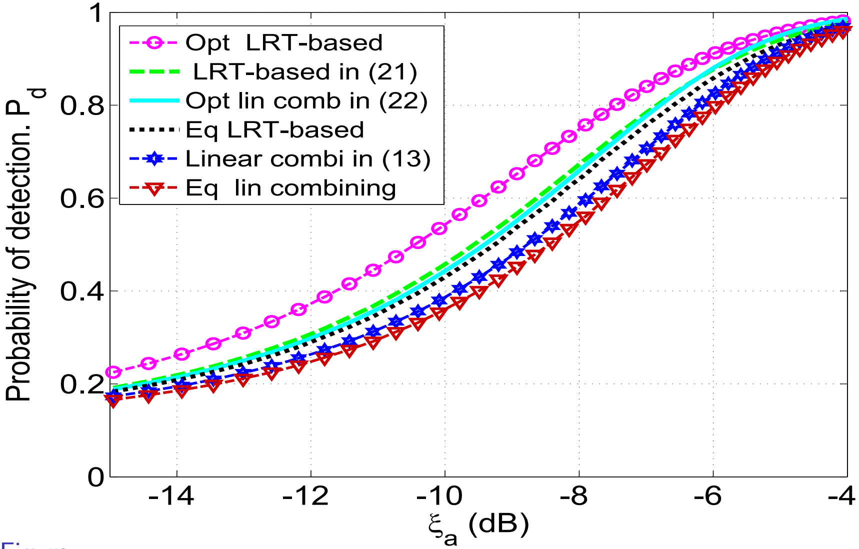

Figure: Probability of detection (Pd) versus the signal to noise ratio (ξ_a) for $M = 20$, $N = 10$, $P_{fa} = 0.1$ and $B = 0.5$.

Simulation Results 5/6

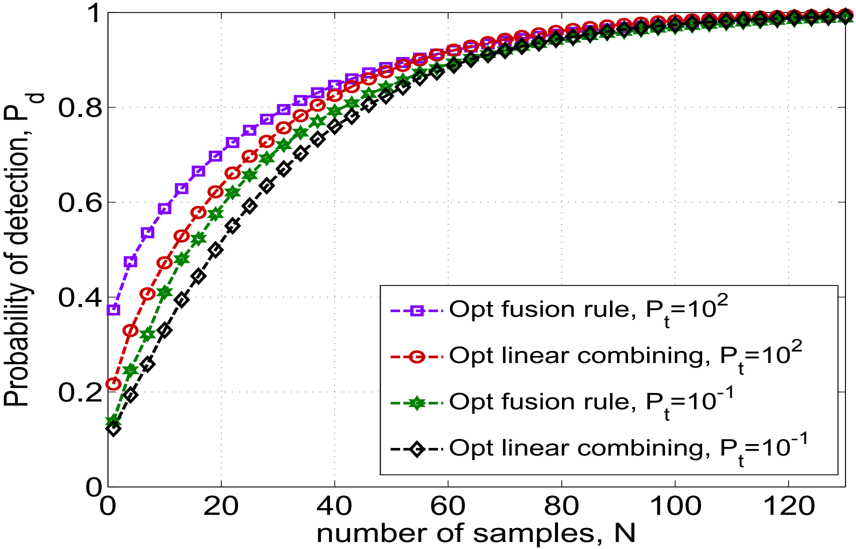

Figure: Probability of detection (Pd) versus the number of samples (N) for $M = 10$ sensors, $P_{fa} = 0.1$, $\xi_a = 8.5$ dB and $B = 1$.

Simulation Result 6/6

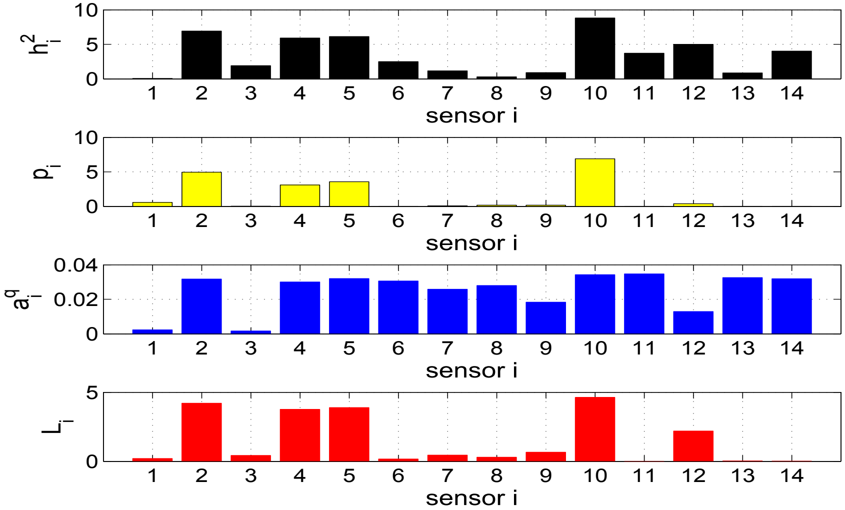

Figure: Optimum sensor transmit power and channel quantization bits allocation for $N = 10$, $P_{fa} = 0.1$, $\xi_a = 8.5$ dB and $P_t = 20$.

Conclusions

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- Realizable suboptimal fusion rules derived from the optimal one were proposed as well, in which more weight in the actual fusion are given to decisions with better sensing quality.
- We show that the effect of quantization on the detection performance can be mitigated by increasing the number of measurements (N), or equivalently incurring more delay in the system.
- Finally, the SN's transmission power has been optimally allocated. Intuitively, more power is given to SNs having better channel gains and consequently increased number of bits.

Questions/Comments?