Cross-Layer Resource Allocation in Sensor Networks for Distributed Detection with Soft Decision Fusion

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***Abstract*—Cross-layer adaptation offers the possibility to optimize resource utilization in wireless sensor networks with respect to application-specific performance metrics. In this paper, a transmission power allocation algorithm is presented that is adapted to distributed detection in wireless sensor networks with soft decision fusion. Specifically, the objective is to minimize the global probability of detection error given a fixed level of total transmission power in the network. The cross-layer approach for the allocation of transmission power is based on a measure of individual sensor detection quality as well as location information. It leads to significant performance gains compared to uniform power assignment.**

I. Introduction

Distributed detection is one of the primary applications of wireless sensor networks and often the first step in an overall sensing process [1]–[3]. In the parallel fusion network, the sensor nodes process their observations independently and make preliminary decisions about the state of the observed environment, e.g., absence or presence of a target. The sensors transmit the local decisions to a fusion center that combines the received decisions and computes the final detection result. Since the transmission channels between the wireless sensors and the fusion center are subject to noise and interference, it is also necessary to consider the impact of wireless channel conditions on the overall detection performance [4].

Wireless sensor networks are usually designed to support multiple sensing tasks. Since the different tasks access the same limited resources, resource utilization in the network for a specified task should be optimized with respect to the corresponding performance metrics. In wireless sensor networks deployed for distributed detection applications, the power assignment eventually should be designed to optimize the overall sensor network detection performance in terms of the global probability of error.

In this paper, a cross-layer resource allocation algorithm is presented that is especially designed for distributed detection in wireless sensor networks with soft decision fusion. The special case of binary sensors and hard decision fusion was considered in [5]. The objective is to optimally distribute a total transmission power budget in order to minimize the global probability of detection error. The cross-layer resource allocation algorithm is based on a measure of individual sensor detection quality as well as location information. It leads to significant performance gains compared to uniform power assignment for a wide range of total transmission power. Although the approach is presented in a single hop scenario, it can be extended to hierarchical networks [6].

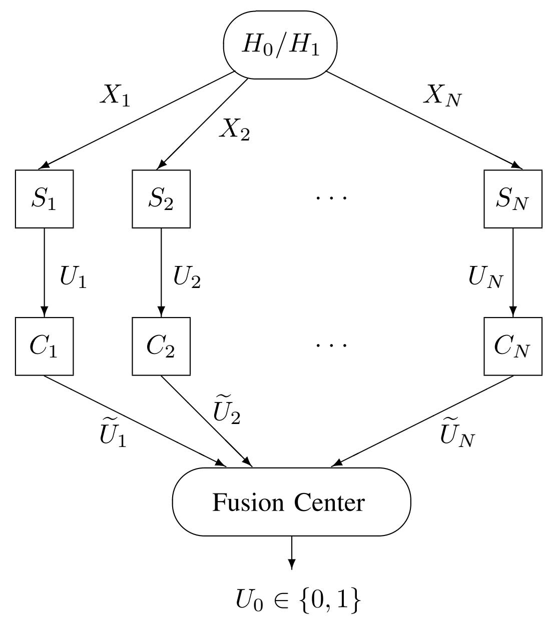

Fig. 1. Parallel fusion network with noisy channels.

As illustrative example, we consider impulse radio ultra-wideband (IR-UWB) sensor networks. IR-UWB transceivers are a promising candidate for wireless sensor nodes due to low power consumption, resilience against multipath fading, and low system complexity [7]. However, the cross-layer resource allocation strategy can also be applied to other wireless transmission technologies.

The remainder of this paper is organized as follows. In Section II, the problem of distributed detection in parallel fusion networks with soft decision fusion is stated. The cross-layer resource allocation strategy is introduced in Section III. The considered IR-UWB system model is described in Section IV. Finally, we present numerical results and conclusions in Section V.

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II. Distributed Detection

The problem of distributed detection in the parallel fusion network with noisy channels and soft decision fusion can be stated as follows (see Fig. 1) . We consider a binary hypothesis testing problem with hypotheses H_0 and H_1 indicating the state of the observed environment. The associated prior probabilities are $\pi_0 = P(H_0)$ and $\pi_1 = P(H_1)$. In order to detect the true state of nature, a network of N sensors $S_1, \ldots, S_N$ collects an array of random observations

$$(X_1, \ldots, X_N)' \in \mathcal{X}_1 \times \cdots \times \mathcal{X}_N \tag{1}$$

which are generated according to either H_0 or H_1. The random observations $X_1, \ldots, X_N$ are assumed to be conditionally independent across sensors given the underlying hypothesis. Because of the distributed nature of the problem, the sensors process their respective observations independently by forming local decisions $U_j = \delta_j(X_j)$ for $j = 1, \ldots, N$. Thus, the local decision U_j of sensor S_j only depends on its own observation X_j and not on the observations of the other sensors.

A. Local sensor decision rules

In the general case of M-ary quantization at the local sensors, the local sensor decision rules δ_j are mappings

$$\delta_j \colon \mathcal{X}_j \to \{1, \ldots, M\}, \quad j = 1, \ldots, N. \tag{2}$$

Warren and Willett have shown that the sensor decision rules leading to jointly optimal configurations under the Bayes criterion are monotone likelihood ratio partitions of the sensor observation spaces $\mathcal{X}_1, \ldots, \mathcal{X}_N$, provided that the observations are conditionally independent across sensors [8]. Hence, it is only necessary to consider sensor decision rules δ_j that can be parameterized by a set of real quantization thresholds $\tau_{j_1}, \ldots, \tau_{j_{M-1}}$, where $\tau_{j_0} = -\infty$, $\tau_{j_M} = \infty$, and $\tau_{j_k} \leq \tau_{j_{k+1}}$. In this way, each sensor S_j is characterized by the conditional probabilities

$$\alpha_{j_k} = P(U_j = k | H_0) = P(\tau_{j_{k-1}} < L_j \leq \tau_{j_k} | H_0), \tag{3}$$

$$\beta_{j_k} = P(U_j = k | H_1) = P(\tau_{j_{k-1}} < L_j \leq \tau_{j_k} | H_1), \tag{4}$$

where $L_j = \log(f_j(X_j|H_1)/f_j(X_j|H_0))$ is the local log-likelihood ratio of observation X_j. The probability vectors $\boldsymbol{\alpha}_j = (\alpha_{j_1}, \ldots, \alpha_{j_M})'$ and $\boldsymbol{\beta}_j = (\beta_{j_1}, \ldots, \beta_{j_M})'$ are computable given the local observation statistics $f_j(\cdot|H_k)$, $k = 0, 1$, and the quantization thresholds $\tau_{j_1}, \ldots, \tau_{j_{M-1}}$ for each $j = 1, \ldots, N$.

B. Transmission of local decisions

Upon local decision-making at the sensors, the vector of local decisions $\boldsymbol{U} = (U_1, \ldots, U_N)'$ is transmitted to the fusion center for decision combining. We model the communication link C_j between sensor S_j and the fusion center by a discrete noisy channel with transition matrix $\boldsymbol{T}_j$. The channel transition matrix $\boldsymbol{T}_j = (T_{kl}^{(j)})_{1 \leq k,l \leq M}$ is an $M \times M$ matrix with the klth entry defined as

$$T_{kl}^{(j)} = P(\widetilde{U}_j = k | U_j = l), \quad k, l \in \{1, \ldots, M\}, \tag{5}$$

where $\sum_{k=1}^{M} T_{kl}^{(j)} = 1$ for any $l \in \{1, \ldots, M\}$. Because of the noisy channels, the fusion center receives a vector of potentially distorted decisions $\widetilde{\boldsymbol{U}} = (\widetilde{U}_1, \ldots, \widetilde{U}_N)'$. The distribution of the distorted decisions $\widetilde{U}_j$ is determined by the conditional probabilities

$$\widetilde{\alpha}_{j_k} = P(\widetilde{U}_j = k | H_0) = \sum_{l=1}^{M} T_{kl}^{(j)} \alpha_{j_l}, \tag{6}$$

$$\widetilde{\beta}_{j_k} = P(\widetilde{U}_j = k | H_1) = \sum_{l=1}^{M} T_{kl}^{(j)} \beta_{j_l}. \tag{7}$$

Assuming knowledge of the channel transition matrices $\boldsymbol{T}_j$, we obtain the probability vectors $\widetilde{\boldsymbol{\alpha}}_j = (\widetilde{\alpha}_{j_1}, \ldots, \widetilde{\alpha}_{j_M})'$ and $\widetilde{\boldsymbol{\beta}}_j = (\widetilde{\beta}_{j_1}, \ldots, \widetilde{\beta}_{j_M})'$ characterizing the distribution of the received local decisions $\widetilde{U}_1, \ldots, \widetilde{U}_N$ under both hypotheses.

C. Optimal channel-aware fusion rule

At the fusion center, the received decisions are combined to yield the final detection result $U_0 = \delta_0(\widetilde{U}_1, \ldots, \widetilde{U}_N)$, where the fusion rule δ_0 is a binary-valued mapping

$$\delta_0 \colon \{1, \ldots, M\}^N \to \{0, 1\}. \tag{8}$$

The sensor network detection performance is measured in terms of the global probability of error

$$P_e = \pi_0 P_f + \pi_1 P_m, \tag{9}$$

which can be written as a weighted sum of the global probability of false alarm $P_f = P(U_0 = 1 | H_0)$ and the corresponding global probability of miss $P_m = P(U_0 = 0 | H_1)$.

The optimal fusion rule under the minimum probability of error criterion can be performed by evaluating a log-likelihood ratio test of the form

$$\sum_{j=1}^{N} \mathcal{L}_j \underset{U_0 = 0}{\overset{U_0 = 1}{\gtrless}} \log\left(\frac{\pi_0}{\pi_1}\right) = \vartheta, \tag{10}$$

where $\mathcal{L}_j = \log(P(\widetilde{U}_j | H_1)/P(\widetilde{U}_j | H_0))$ is the log-likelihood ratio of receiving decision $\widetilde{U}_j$, and where ϑ is the fusion threshold.

D. Evaluation of global error probabilities

When using the optimal fusion rule according to (10), the global probability of false alarm P_f and the global probability of miss P_m are determined by the conditional tail probabilities

$$P_f = P\Big(\sum_{j=1}^{N} \mathcal{L}_j \geq \vartheta | H_0\Big) \tag{11}$$

and

$$P_m = P\Big(\sum_{j=1}^{N} \mathcal{L}_j < \vartheta | H_1\Big). \tag{12}$$

In order to evaluate the sensor network detection performance in terms of the global probability of error $P_e = \pi_0 P_f + \pi_1 P_m$, we employ an approach introduced in [9] which provides tight bounds on the global probability of false alarm (11) and the global probability of miss (12). Straightforward computation of (11) and (12) is in general not feasible.

III. Cross-Layer Resource Allocation Strategy

In the following, we propose a cross-layer resource allocation strategy based on a measure for the detection quality or discrimination power of the individual sensors. The resource allocation strategy consists of two steps. First, an application-specific choice of target signal-to-interference-and-noise ratios (SINRs) $\gamma_1, \ldots, \gamma_N$ allocated to the sensors $S_1, \ldots, S_N$ is determined. In a second step, a power assignment algorithm is executed that optimally allocates transmission power levels $p_1, \ldots, p_N$ to the sensors $S_1, \ldots, S_N$ in order to realize the determined SINR values.

A. Measures for individual sensor detection quality

A measure for the detection quality of each sensor is supposed to assess the discrimination power of the corresponding sensor with respect to the underlying binary hypothesis testing problem. From the fusion center's point of view, the sensor S_j is characterized by the probability vectors $\widetilde{\boldsymbol{\alpha}}_j$ and $\widetilde{\boldsymbol{\beta}}_j$ which determine the conditional distributions of the received decision from sensor S_j under hypothesis H_0 and H_1, respectively. A meaningful measure $Q(\widetilde{\boldsymbol{\alpha}}_j, \widetilde{\boldsymbol{\beta}}_j)$ for the effective detection quality of sensor S_j should therefore be based on some kind of distance between the probability vectors $\widetilde{\boldsymbol{\alpha}}_j$ and $\widetilde{\boldsymbol{\beta}}_j$. Examples of quality measures $Q(\widetilde{\boldsymbol{\alpha}}_j, \widetilde{\boldsymbol{\beta}}_j)$ based on the distance between probability vectors are given in Table I.

TABLE I
Quality measures

Kullback-Leibler distance	$Q(\widetilde{\boldsymbol{\alpha}}_j, \widetilde{\boldsymbol{\beta}}_j) = \sum_{k=1}^{M} \widetilde{\alpha}_{j_k} \log\left(\frac{\widetilde{\alpha}_{j_k}}{\widetilde{\beta}_{j_k}}\right)$
Variational distance	$Q(\widetilde{\boldsymbol{\alpha}}_j, \widetilde{\boldsymbol{\beta}}_j) = \sum_{k=1}^{M} \lvert\widetilde{\alpha}_{j_k} - \widetilde{\beta}_{j_k}\rvert$
Chernoff distance	$Q(\widetilde{\boldsymbol{\alpha}}_j, \widetilde{\boldsymbol{\beta}}_j) = \max_{0 \le t \le 1} - \log \sum_{k=1}^{M} \widetilde{\alpha}_{j_k}^{t} \widetilde{\beta}_{j_k}^{1-t}$

As is well known from information theory [10], the Kullback-Leibler and Chernoff distances occur as asymptotic error exponents in Neyman-Pearson and Bayesian hypothesis testing, respectively. Accordingly, it might be reasonable to measure the detection quality of a sensor in terms of these distances, as they indicate the contribution of a sensor to the overall discrimination distance at the fusion center.

B. Application-specific choice of target SINRs

The probability vectors $\widetilde{\boldsymbol{\alpha}}_j$ and $\widetilde{\boldsymbol{\beta}}_j$ are obtained according to (6) and (7) as

$$\widetilde{\boldsymbol{\alpha}}_j = \boldsymbol{T}_j \boldsymbol{\alpha}_j, \quad \widetilde{\boldsymbol{\beta}}_j = \boldsymbol{T}_j \boldsymbol{\beta}_j, \tag{13}$$

where $\boldsymbol{T}_j$ is the channel transition matrix of the discrete noisy channel C_j, and $\boldsymbol{\alpha}_j$, $\boldsymbol{\beta}_j$ are the probability vectors describing the conditional distributions of the local sensor decisions before transmission to the fusion center. Consequently, $\widetilde{\boldsymbol{\alpha}}_j$ and $\widetilde{\boldsymbol{\beta}}_j$ are functions of the values of the matrix $\boldsymbol{T}_j$. The channel quality and thus the entries of the matrix $\boldsymbol{T}_j$ depend on the SINR γ_j associated with channel C_j, i.e., $\boldsymbol{T}_j = \boldsymbol{T}_j(\gamma_j)$. Therefore, we obtain $\widetilde{\boldsymbol{\alpha}}_j = \widetilde{\boldsymbol{\alpha}}_j(\gamma_j)$ and $\widetilde{\boldsymbol{\beta}}_j = \widetilde{\boldsymbol{\beta}}_j(\gamma_j)$ and eventually $Q(\widetilde{\boldsymbol{\alpha}}_j, \widetilde{\boldsymbol{\beta}}_j)$ as functions of the target SINR γ_j.

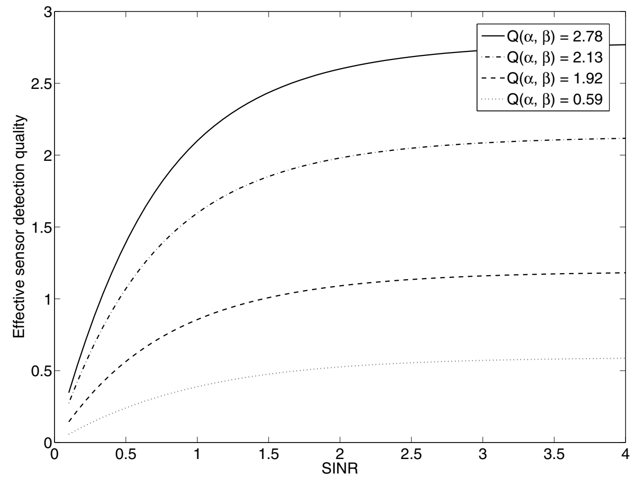

Fig. 2. Effective sensor detection quality $Q(\widetilde{\boldsymbol{\alpha}}_j, \widetilde{\boldsymbol{\beta}}_j)$ as a function of the SINR γ_j for different values of the initial sensor detection quality $Q(\boldsymbol{\alpha}_j, \boldsymbol{\beta}_j)$.

Fig. 2 shows the effective sensor detection quality $Q(\widetilde{\boldsymbol{\alpha}}_j, \widetilde{\boldsymbol{\beta}}_j)$ measured in terms of the Kullback-Leibler distance as a function of the target SINR γ_j of channel C_j for different values of the initial sensor detection quality $Q(\boldsymbol{\alpha}_j, \boldsymbol{\beta}_j)$. It can be observed that for high values of γ_j, the effective quality approaches the initial quality. In this case, increasing γ_j does not result in an improved effective sensor quality. The value of γ_j, from which on the effective sensor quality $Q(\widetilde{\boldsymbol{\alpha}}_j, \widetilde{\boldsymbol{\beta}}_j)$ is not further improved significantly, increases with the initial sensor quality $Q(\boldsymbol{\alpha}_j, \boldsymbol{\beta}_j)$. It is therefore advantageous to assign higher values of target SINR to sensors with high initial quality than to ones with low initial quality.

We employ a sensitivity analysis of the effective sensor detection quality and assign the target SINR for which the slope of the effective sensor quality $Q(\widetilde{\boldsymbol{\alpha}}_j, \widetilde{\boldsymbol{\beta}}_j)$ with respect to γ_j falls under a predetermined threshold ϱ. Fig. 3 illustrates this procedure. The threshold value ϱ can be used as a trade-off parameter to balance total transmission power $p_{\text{tot}} = \sum_{j=1}^{N} p_j$ and global probability of error P_e.

To account for signal attenuation in the SINR assignment we also consider location information. Wireless sensors near to the fusion center are favored because in this case a high SINR can be realized by comparatively low transmission power. We use a weighting factor given by the inverse distance d_j of sensor S_j to the fusion center normalized by the maximal distance $d_{\max}$. Eventually, we determine the designated target SINR γ_j of sensor S_j according to

$$\gamma_j = \left(\frac{d_j}{d_{\max}}\right)^{-\beta} \cdot \left(\frac{\partial Q(\widetilde{\boldsymbol{\alpha}}_j, \widetilde{\boldsymbol{\beta}}_j)}{\partial \gamma_j}\right)^{-1} (\varrho). \tag{14}$$

The exponent β is chosen corresponding to a pathloss model.

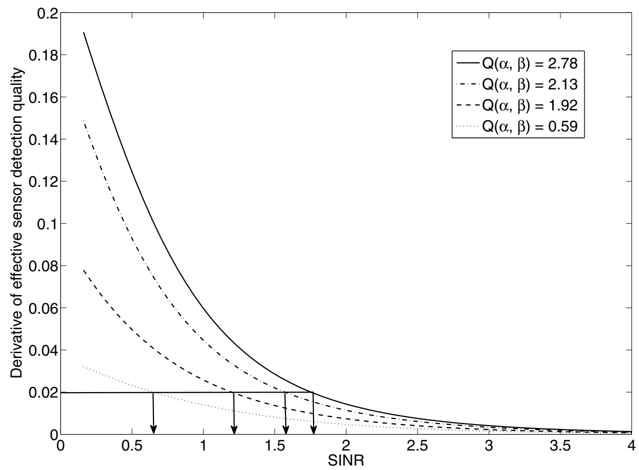

Fig. 3. Derivative $\partial Q(\widetilde{\boldsymbol{\alpha}}_j, \widetilde{\boldsymbol{\beta}}_j)/\partial\gamma_j$ of the effective sensor detection quality with respect to the SINR γ_j. The threshold ϱ is chosen to be equal to 0.02.

The actual power assignment is obtained by using the target SINRs (14) in order to compute the transmission power levels p_j of the sensor nodes according to a specified power assignment algorithm as described in the following section.

IV. Power Assignment in IR-UWB Networks

Due to low power consumption and low transceiver complexity, IR-UWB is a promising candidate as an air interface for wireless sensor nodes. Therefore, we assume each sensor node to be equipped with an IR-UWB transceiver unit. In particular, we consider IR-UWB with pulse position modulation with modulation index α and pseudo random time hopping codes as multiple access scheme as described in [11]. The transmitted signal from sensor S_j can then be written as

$$s_j(t) = A_j \sum_{i=-\infty}^{\infty} w(t - iT_f - c_i^{(j)} T_c - \alpha d^{(j)}_{\lfloor i/N_j \rfloor}), \qquad (15)$$

where T_f denotes the length of a time frame in which one impulse of form $w(t)$ is transmitted. In the frame, the impulse is delayed by an integer multiple of the chip length T_c according to the time hopping code $c_i^{(j)}$. Each data bit $d^{(j)}$ belonging to the local decision U_j of sensor S_j is transmitted by a number of N_j equally modulated pulses with amplitude A_j.

A. Signal-to-interference-and-noise ratio

According to [12], in a multi-user scenario the SINR γ_j of sensor S_j can be written as

$$\gamma_j = N_j \frac{g_j p_j}{\sigma^2 \sum_{k \neq j} g_k p_k + \frac{1}{T_f}\eta}, \qquad (16)$$

with p_j denoting the transmission power of sensor node S_j. The parameter σ^2 depends on the correlation properties of the employed pulse form $w(t)$. The path gain between sensor S_j and the fusion center is denoted by g_j. The transmitted signal is subject to additive white Gaussian noise with energy η.

B. Power assignment

A feasible power assignment to the given SINR requirements $\gamma_1, \ldots, \gamma_N$ determined by (14) can be obtained using a special case of the dimensionality reduction procedure presented in [12]. If a feasible solution exists, the power of node S_j can be computed very efficiently by

$$p_j = \frac{\frac{\eta}{T_f \sigma^2}}{g_j \left(\frac{N_j}{\sigma^2 \gamma_j} + 1\right)\left(1 - \sum_{k=1}^{N} \frac{1}{\frac{N_k}{\sigma^2 \gamma_k} + 1}\right)}. \qquad (17)$$

The fulfilled SINR requirements $\gamma_1, \ldots, \gamma_N$ can be used subsequently to compute the corresponding bit-error rates.

C. Bit error rates and channel transition matrices

Using the standard Gaussian approximation for multiple access interference, the bit error rate ε_j of sensor node S_j can be expressed as

$$\varepsilon_j = \tfrac{1}{2}\mathrm{erfc}(\sqrt{\gamma_j}). \qquad (18)$$

If we assume $M = 2^b$ possible values for the local decision U_j, we have to transmit b bits for each local decision. Assuming consecutive and independent transmission of the bits, this results for, e.g., $b = 2$ in the channel transition matrix

$$\boldsymbol{T}_j = \begin{pmatrix} (1-\varepsilon_j)^2 & \varepsilon_j(1-\varepsilon_j) & \varepsilon_j(1-\varepsilon_j) & \varepsilon_j^2 \\ \varepsilon_j(1-\varepsilon_j) & (1-\varepsilon_j)^2 & \varepsilon_j^2 & \varepsilon_j(1-\varepsilon_j) \\ \varepsilon_j(1-\varepsilon_j) & \varepsilon_j^2 & (1-\varepsilon_j)^2 & \varepsilon_j(1-\varepsilon_j) \\ \varepsilon_j^2 & \varepsilon_j(1-\varepsilon_j) & \varepsilon_j(1-\varepsilon_j) & (1-\varepsilon_j)^2 \end{pmatrix}$$

for the discrete noisy channel C_j. Via equations (16) and (18), the channel transition matrix $\boldsymbol{T}_j$ becomes a function of the assigned transmission power p_j for $j = 1, \ldots, N$.

V. Numerical Results and Conclusions

In this section, we investigate the performance of the cross-layer resource allocation strategy from Section III compared to uniform power assignment by simulations. The scenario is generated by randomly deploying sensor nodes uniformly in a rectangular area A. The fusion center is supposed to be located in the middle of the scenario. The involved parameters are summarized in Table II.

TABLE II
Parameters used in the simulation

parameter	value
N	40
A	100 m × 100 m
β	2
σ^2	$1.9966 \cdot 10^{-3}$
N_j	10
T_c	2 ns
T_f	100 ns
η	10^{-11} J

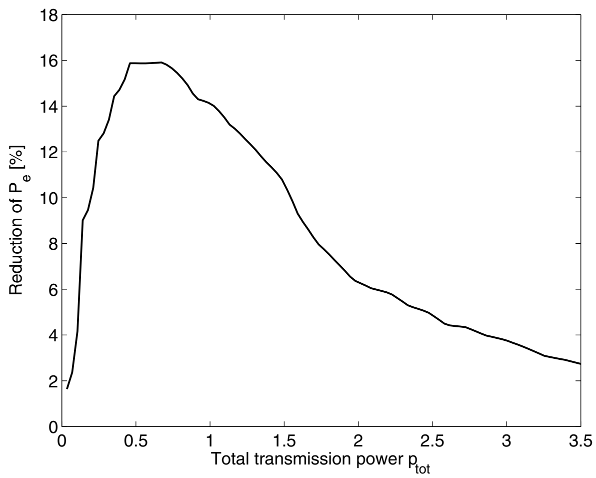

Fig. 4. Relative performance gain of the cross-layer resource allocation strategy in terms of reduction of the global probability of error P_e for the Kullback-Leibler distance as quality measure Q.

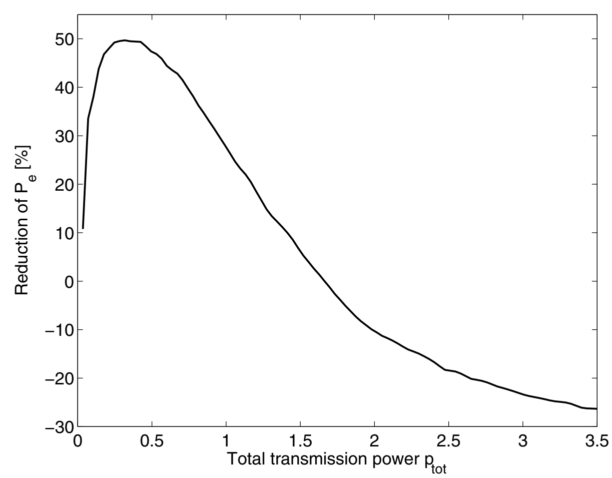

Fig. 5. Relative performance gain of the cross-layer resource allocation strategy in terms of reduction of the global probability of error P_e for the Chernoff distance as quality measure Q.

As an example, we consider the problem of detecting the presence or absence of a deterministic signal in Gaussian noise, i.e., we assume that the observations $X_1, \ldots, X_N$ at the local sensors are conditionally independent distributed according to

$$H_0\colon X_j \sim \mathcal{N}(0, \sigma_j^2), \quad H_1\colon X_j \sim \mathcal{N}(\mu_j, \sigma_j^2), \tag{19}$$

$j = 1, \ldots, N$. The variance σ_j^2 describes Gaussian background noise and the mean μ_j indicates the deterministic signal component under hypothesis H_1 at sensor S_j. At sensor S_j, the local observation signal-to-noise ratio (SNR) is given by

$$\mathrm{SNR}_j = 10 \log_{10} \left(\frac{\mu_j^2}{\sigma_j^2} \right) \quad [\mathrm{dB}]. \tag{20}$$

The log-likelihood ratio L_j of the observation X_j is again a Gaussian random variable which is conditionally distributed according to

$$H_0\colon L_j \sim \mathcal{N}\Big(-\frac{\mu_j^2}{2\sigma_j^2}, \frac{\mu_j^2}{\sigma_j^2} \Big), \quad H_1\colon L_j \sim \mathcal{N}\Big(\frac{\mu_j^2}{2\sigma_j^2}, \frac{\mu_j^2}{\sigma_j^2} \Big). \tag{21}$$

In the simulation, we assume the local observation signal-to-noise ratios $\mathrm{SNR}_1, \ldots, \mathrm{SNR}_N$ to be independent and identically uniformly distributed between 0 and 10 dB. The quantization thresholds for the log-likelihood ratio L_j are heuristically chosen to be $\tau_{j_1} = -1$, $\tau_{j_2} = 0$, and $\tau_{j_3} = 1$ for all sensors $S_1, \ldots, S_N$.

Fig. 4 depicts the simulation results for the Kullback-Leibler distance. The suggested strategy reduces the global probability of error P_e up to 16 % compared to uniform power assignment. For high values of the total transmission power p_{tot}, the performance gain decreases due to a lower relative influence of channel errors on the overall detection performance.

Fig. 5 depicts the simulation results for the Chernoff distance. Obviously, the reduction of the global probability of error P_e is significantly higher compared to the Kullback-Leibler distance. The reduction amounts to 50 % compared to uniform power assignment. Interestingly, for higher values of the total transmission power p_{tot}, the performance gain becomes negative. This might be caused by an inefficient use of the total power budget, i.e., a dispensable power allocation to higher quality sensors and a deficient power allocation to lower quality sensors.

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