Cross-Layer Design of Cluster Formation and Power Allocation in IR-UWB Sensor Networks

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Abstract— **Wireless sensor networks are usually deployed for specific purposes. A cross-layer design of networking algorithms adapted to the considered application can significantly improve overall performance metrics. In this paper, distributed signal detection in IR-UWB sensor networks with severe resource constraints is considered. The presented algorithms for power assignment aim at minimizing the energy necessary to meet an overall detection performance by exploiting dependencies between application and physical layer. To account for a limited transmission range of the sensor nodes, the approach is furthermore combined with an application-specific formation of node clusters which allows for a hierarchical transmission of the sensor decisions to a fusion center. Numerical results validate that this cross-layer approach leads to substantial energy savings compared to uniform power assignment.**

I. Introduction

Wireless sensor networks promise a large variety of applications like detection, tracking or monitoring of objects implemented in a distributed manner. Often the first step of sensing applications is the detection of a target. In distributed detection, the sensor nodes process their observations locally and make preliminary decisions about absence or presence of a target [1]. The local decisions are transmitted to a fusion center and combined to obtain a final detection result with high reliability.

As wireless sensor nodes are usually battery-operated, they are faced with severe resource constraints. Due to low transmission power, it becomes necessary to consider wireless channel conditions in order to optimally design the distributed detection system [2]. However, modern transceiver technology allows the control of transmission quality in communication networks by power assignment algorithms. In wireless sensor networks deployed for distributed detection, the power assignment eventually should be designed to minimize the necessary transmission power for maintaining a pre-specified value of the global probability of detection error. This can be achieved by a cross-layer approach for resource allocation which utilizes information from the detection application.

An important resource limitation of sensor nodes is a restricted maximum transmission range. In the parallel fusion network where all nodes directly transmit to the fusion center, this restriction leads to a severe limitation of the area that can be covered by the sensor network. One possibility to overcome this drawback is the formation of node clusters and a hierarchical transmission of node decisions. All leaf nodes in a cluster transmit their local decisions to the cluster head which combines these decisions with his own observation to a more reliable decision which is transmitted to the fusion center. At the fusion center, the final detection result is obtained by fusing the received cluster head decisions. The asymptotic behavior of a setup similar to the one considered here is analyzed in [3] and [4]. However, asymptotic results provide only limited information about practical sensor networks with realistic numbers of sensor nodes.

In the literature, several algorithms have been suggested for node clustering. The algorithms differ in their objectives, their complexity and the assumptions for the multiple access scheme. In [5] and [6] a TDMA scheme is assumed. In [7] two algorithms are presented, which are combined with an IR-UWB specific multiple access scheme. The objective of most algorithms is a minimization of the consumed energy. However, they are usually not adapted to a specific application which neglects the interdependencies between the overall performance metric and the consumed energy.

In this paper, we present a cross-layer design of wireless sensor networks which is adapted for distributed detection in hierachical networks. It consists of two parts. First we suggest an application specific cross-layer algorithm for node clustering. This algorithm for cluster head election and the formation of clusters includes application information in terms of individual sensor detection qualities. Based on the generated topology, we suggest a cross-layer approach for power allocation that depends both on individual sensor qualities as well as information from the generated topology. It aims at minimizing the necessary total transmission power while maintaining a predefined value of the global probability of detection error. As enabling technology for wireless sensor networks our approach is tailored for impulse radio ultra-wideband (IR-UWB) transceivers. These are well suited for wireless sensor nodes due to low power consumption, resilience against multipath fading, and low system complexity.

The remainder of the paper is organized as follows. In Section II, the problem of distributed detection in tree networks is stated. The cross-layer approach for node clustering is described in Section III and the cross-layer power allocation strategy is introduced in Section IV. Finally, numerical results and conclusions are presented in Section V.

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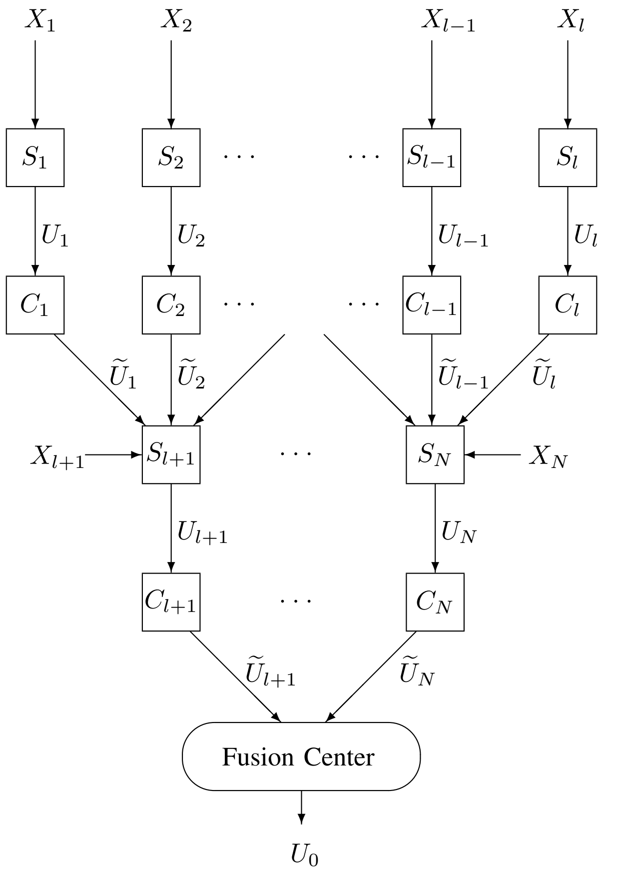

Fig. 1. Tree network with noisy channels. Sensors $S_1, \dots, S_l$ are leaf nodes, sensors $S_{l+1}, \dots, S_N$ are cluster heads.

II. Distributed Detection in Tree Networks

The problem of distributed detection in tree networks can be stated as follows (see Fig. 1). We consider a binary hypothesis testing problem with hypotheses H_0, H_1 indicating the state of the observed environment and associated prior probabilities $\pi_0 = P(H_0)$, $\pi_1 = P(H_1)$. In order to detect the true state of nature, a network of N sensors $S_1, \dots, S_N$ collects an array of random observations $(X_1, \dots, X_N)' \in \mathcal{X}_1 \times \cdots \times \mathcal{X}_N$ which is generated according to either H_0 or H_1. The random observations $X_1, \dots, X_N$ are assumed to be conditionally independent across sensors given the underlying hypothesis and distributed according to

$$H_0\colon X_j \sim \mathcal{N}(0, \sigma_j^2), \quad H_1\colon X_j \sim \mathcal{N}(\mu_j, \sigma_j^2), \tag{1}$$

$j = 1, \dots, N$. 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. The local observation signal-to-noise ratio (SNR) at sensor S_j is given by

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

A. Leaf node decision rules

As depicted in Fig. 1, the leaf nodes $S_1, \dots, S_l$ of the tree network process their respective observations $X_1, \dots, X_l$ independently by forming local decisions

$$U_j = \delta_j(X_j), \quad j = 1, \dots, l. \tag{3}$$

In the case of binary quantization, the leaf node decision rules are mappings $\delta_j\colon \mathcal{X}_j \to \{0, 1\}$. Sensor decision rules leading to optimal configurations are monotone likelihood ratio quantizers provided that the observations are conditionally independent across sensors [8]. Thus, for the leaf nodes $S_1, \dots, S_l$, we consider decision rules δ_j that can be parameterized by real quantization thresholds θ_j. In this way, each local decision U_j of a leaf node is characterized by the following local false alarm and miss probabilities

$$P_{f_j} = P(U_j = 1 | H_0) = P(L_j \geq \theta_j | H_0), \tag{4}$$
$$P_{m_j} = P(U_j = 0 | H_1) = P(L_j < \theta_j | H_1), \tag{5}$$

where L_j is the local log-likelihood ratio of observation X_j.

B. Transmission of local decisions

The leaf nodes $S_1, \dots, S_l$ transmit their decisions $U_1, \dots, U_l$ to their associated cluster heads and the cluster heads $S_{l+1}, \dots, S_N$ transmit their decisions $U_{l+1}, \dots, U_N$ to the fusion center. Due to noisy channels, the cluster heads receive decisions $\widetilde{U}_1, \dots, \widetilde{U}_l$ and the fusion center receives decisions $\widetilde{U}_{l+1}, \dots, \widetilde{U}_N$ that are potentially corrupted. We model the communication channels $C_1, \dots, C_N$ of both the leaf nodes and the cluster heads by binary symmetric channels with bit-error probabilities $\varepsilon_1, \dots, \varepsilon_N$, i.e.

$$\varepsilon_j = P(\widetilde{U}_j = 1 | U_j = 0) = P(\widetilde{U}_j = 0 | U_j = 1) \tag{6}$$

for $j = 1, \dots, N$. The modified error probabilities $\widetilde{P}_{f_j} = P(\widetilde{U}_j = 1 | H_0)$ and $\widetilde{P}_{m_j} = P(\widetilde{U}_j = 0 | H_1)$ are given as

$$\begin{aligned} \widetilde{P}_{f_j} &= P_{f_j} + \varepsilon_j (1 - 2P_{f_j}), \\ \widetilde{P}_{m_j} &= P_{m_j} + \varepsilon_j (1 - 2P_{m_j}). \end{aligned} \tag{7}$$

Based on the modified error probabilities (7), we define the weight of sensor S_j as

$$\widetilde{\lambda}_j = \log \left(\frac{(1 - \widetilde{P}_{f_j})(1 - \widetilde{P}_{m_j})}{\widetilde{P}_{f_j} \widetilde{P}_{m_j}} \right), \quad j = 1, \dots, N. \tag{8}$$

C. Cluster head decision rules

The cluster heads $S_{l+1}, \dots, S_N$ process their observations $X_{l+1}, \dots, X_N$ with respect to the received local decisions $\widetilde{U}_1, \dots, \widetilde{U}_l$ from the leaf nodes. E.g., if the cluster head S_{l+1} receives the subset $\widetilde{U}_1, \dots, \widetilde{U}_k$ of local decisions from the leaf nodes, it makes a decision

$$U_{l+1} = \delta_{l+1}(X_{l+1}, \widetilde{U}_1, \dots, \widetilde{U}_k), \tag{9}$$

where the cluster head decision rule δ_{l+1} is a mapping $\delta_{l+1}\colon \mathcal{X}_{l+1} \times \{0, 1\}^k \to \{0, 1\}$.

The cluster heads perform binary quantization of their local log-likelihood ratios $L_{l+1}, \dots, L_N$, where the applied decision thresholds depend on the values of the received decisions from the leaf nodes [9].

D. Optimal channel-aware fusion rule

At the fusion center, the received decisions $\widetilde{U}_{l+1}, \ldots, \widetilde{U}_N$ from the cluster heads $S_{l+1}, \ldots, S_N$ are combined to yield the final decision $U_0 = \delta_0(\widetilde{U}_{l+1}, \ldots, \widetilde{U}_N)$, where the fusion rule δ_0 is a Boolean function $\delta_0\colon \{0,1\}^{N-l} \rightarrow \{0,1\}$. The sensor network detection performance is measured in terms of the global probability of error $P_e = \pi_0 P_f + \pi_1 P_m$, which is 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 channel-aware fusion rule can be implemented by a linear threshold test [9]

$$\sum_{j=l+1}^{N} \widetilde{\lambda}_j \widetilde{U}_j \underset{U_0=0}{\overset{U_0=1}{\gtrless}} \vartheta \tag{10}$$

with decision threshold

$$\vartheta = \log\left(\frac{\pi_0}{\pi_1} \prod_{j=l+1}^{N} \frac{1-\widetilde{P}_{f_j}}{\widetilde{P}_{m_j}}\right). \tag{11}$$

III. Application-Specific Node Clustering

In this section, we present a cross-layer algorithm that performs the clustering of the sensor network into a tree structure as considered in the previous section. It is based on both location information of the nodes and on information from the application layer in terms of the local observation SNRs (2). The algorithm selects the non-empty set of cluster heads $\mathcal{M} = \{l+1, \ldots, N\}$ among the set of all nodes $\mathcal{N} = \{1, \ldots, N\}$. The remaining nodes form the set of leaf nodes $\mathcal{L} = \mathcal{N} \setminus \mathcal{M}$. Every leaf node is associated to exactly one cluster head by the mapping

$$c\colon \mathcal{L} \rightarrow \mathcal{M}. \tag{12}$$

The set of nodes that transmit to the same cluster head $m \in \mathcal{M}$ is denoted by $\mathcal{C}_m$. A formal description of the algorithm is given in Algorithm 1. It starts with an initialization of the already introduced sets $\mathcal{M}, \mathcal{L}$ and $\mathcal{N}$. Initially, set $\mathcal{H}$ is empty, and $\mathcal{D}$ contains all nodes. For each node $j \in \mathcal{N}$ an application-specific metric $\mu(j)$ is computed by

$$\mu(j) = \big((\frac{1}{|\mathcal{T}_j|} \sum_{i \in \mathcal{T}_j} d_{ji}) \cdot d_j^{\text{FC}}\big)^{-1} \cdot \text{SNR}_j, \tag{13}$$

where d_{ji} is the distance between nodes S_j and S_i and d_j^{FC} denotes the distance of S_j to the fusion center. Set $\mathcal{T}_j$ includes all nodes inside the maximum transmission range d_{tr} of node S_j. The metric aims to minimize the necessary transmission power by privileging cluster configurations with low distances between transmitters and receivers. Furthermore, nodes with a high local observation SNR are favored to become cluster head, because it was observed in [10], that it is advantageous for hierarchical detection networks to order sensors from least reliable to most reliable detection quality.

In the main loop of the algorithm the element of $\mathcal{D}$ with maximum metric is chosen as cluster head. Afterwards, all neighboring nodes inside the maximum transmission range d_{tr} of the new cluster head being in $\mathcal{D}$ are deleted from $\mathcal{D}$. If $\mathcal{D}$ is nonempty the process returns to the beginning of the loop and selects the next cluster head. After the loop is finished and the cluster heads have been selected, all leaf nodes associate themselves to the spatially nearest cluster head.

Algorithm 1 Cross-layer algorithm for node clustering

Initialize:
$d_{ij} \leftarrow \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}; \quad i, j \in \mathcal{N}$
$(\mathcal{M} = \mathcal{H}) \leftarrow \emptyset;$
$(\mathcal{D} = \mathcal{L}) \leftarrow \mathcal{N};$
$\mathcal{T}_j \leftarrow \{S_i \in \mathcal{N} | d_{ji} \leq d_{\text{tr}}\}; \quad j \in \mathcal{N}$
$\mu(j) \leftarrow ((\frac{1}{|\mathcal{T}_j|} \sum_{i \in \mathcal{T}_j} d_{ji}) \cdot d_j^{\text{FC}})^{-1} \cdot (\text{SNR}_j); \quad j \in \mathcal{N}$
while $\mathcal{D} \neq \emptyset$ **do**
  $k = \arg\max_{j \in \mathcal{D}} \mu(j);$
  $\mathcal{M} \leftarrow \mathcal{M} \cup k;$
  $\mathcal{L} \leftarrow \mathcal{L} \setminus k;$
  $\mathcal{H} \leftarrow \{j \in \mathcal{D} | d_{kj} < d_{\text{tr}}\};$
  $\mathcal{D} \leftarrow \mathcal{D} \setminus \mathcal{H};$
end while
$\mathcal{C}_m \leftarrow \{j \in \mathcal{L} | d_{jm} < d_{jn},\ n \in \mathcal{M} \setminus m\}; \quad m \in \mathcal{M};$

IV. Cross-Layer Resource Allocation

A. Determination of target SINRs

In the following, we propose a cross-layer power assignment strategy for the tree network generated by the algorithm in the previous section. It is based on an application-specific choice of the target signal-to-interference-and-noise ratios (SINRs) γ_j of the communication link between node S_j and its receiver, formally defined in the following subsection. The objective is to minimize the total transmission power while maintaining a bound for the global probability of detection error P_e. Fig. 2 shows the effective sensor weight $\widetilde{\lambda}$ dependent on the target SINR γ for different initial sensor weights λ. It can be observed that for high values of γ the effective sensor quality approaches the initial sensor quality. In this case, increasing γ does not result in an improved effective sensor quality. The value of γ from which on the effective sensor quality $\widetilde{\lambda}$ is not further improved significantly, increases with the initial sensor quality λ. It is therefore advantageous to assign higher values of SINR to sensors with high initial quality than to ones with low initial quality. We employ a sensitivity analysis of the effective sensor weight and assign the SINR for which the slope of the effective sensor weight $\widetilde{\lambda}$ with respect to γ 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. In order to favor nodes near to their cluster head or near to the fusion center, respectively, we use a weighting factor given by the inverse distance d_j of sensor S_j to its receiver normalized by the maximal distance

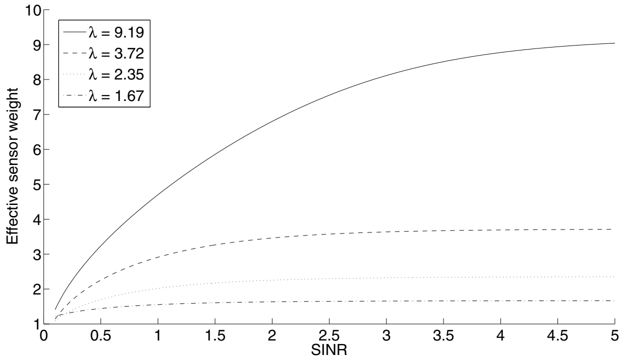

Fig. 2. Effective sensor quality $\widetilde{\lambda}$ as function of the SINR γ for different values of the initial sensor quality λ.

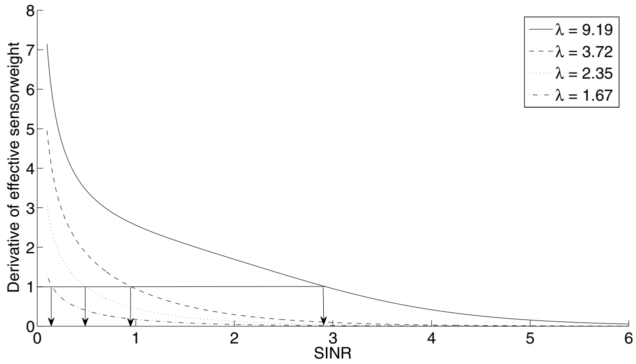

Fig. 3. Derivative $\partial\widetilde{\lambda}/\partial\gamma$ of the effective sensor quality $\widetilde{\lambda}$ with respect to the SINR γ. Here, threshold ϱ is chosen to be equal to 1.

$d_{\max}$ in the corresponding step. Eventually, we determine the designated target SINR γ_j of S_j according to

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

The exponent β is chosen corresponding to a pathloss model. Given γ_j, the bit-error rate ε_j of the jth channel C_j according to (6) can be computed by

$$\varepsilon_j = \frac{1}{2}\mathrm{erfc}(\sqrt{\gamma_j}). \tag{15}$$

The SINR levels can be realized by appropriate power assignment as described in the following.

B. Achieving target SINRs by power assignment

As transmission scheme of the transceiver nodes we assume IR-UWB as described by Scholtz et al. [11]. In this scheme in each frame of length T_f one ultra short pulse with shape $w(t)$ is transmitted. Data bits are assumed to be coded by binary pulse position modulation (PPM) with modulation index α. Multiple access to the channel is realized by pseudo random time hopping codes c_i which reduce the probability of repeated collisions of pulses from two transmitters at a receiver position. Inside a frame the pulse is delayed by an integer multiple of the chip length T_c given by the hopping code. The resulting transmitted signal $s_j(t)$ of node S_j then reads as

$$s_j(t) = A_j \sum_{i=-\infty}^{\infty} w(t - iT_f - c_i^{(j)}T_c - \alpha d^{(j)}_{\lfloor i/N_j \rfloor}). \tag{16}$$

Here $d^{(j)}$ are the local detection results of node S_j, which are transmitted by a number of N_j subsequent equally modulated impulses of amplitude A_j.

The SINR builds the basis for the described resource allocation strategy. For the link between node S_j and its receiver S_{m_j} it can be written as

$$\gamma_j = \frac{g_{jm_j}p_j}{\sigma^2 \sum_{k\neq j} g_{km_j}p_k + \frac{\eta_{m_j}}{T_f}}, \tag{17}$$

where σ^2 is a parameter depending on the correlation properties of the employed impulse form, p_j denotes the transmission power of S_j, g_{jm_j} is the path gain between sensor node S_j and its receiver S_{m_j} and η_{m_j}/T_f is an additional noise term.

The goal of the considered power assignment strategy is to find the minimal transmission power levels for all transceivers such that the individual SINR requirements according to (14) are met for all nodes.

For both steps, transmission from leaf nodes to cluster heads and transmission from cluster heads to the fusion center a vector $\boldsymbol{p}$ with the optimal transmission power levels of the transmitting nodes as elements can be computed by

$$\boldsymbol{p} = [\boldsymbol{I} - \boldsymbol{\Gamma}\boldsymbol{N}^{-1}\boldsymbol{B}]^{-1}\boldsymbol{\tau}. \tag{18}$$

The diagonal matrices $\boldsymbol{\Gamma}$ and $\boldsymbol{N}$ contain the target SINRs γ_j and the number of pulse repetitions N_j for one data bit as entries. The entries b_{ij} of matrix $\boldsymbol{B}$ read as

$$b_{ij} = \begin{cases} \sigma^2 g_{jm_i}/g_{im_i}, & i \neq j \\ 0, & i = j \end{cases}.$$

The elements τ_j of the positive vector $\boldsymbol{\tau}$ are given by $\tau_j = (\eta_{m_j}\gamma_j)/(T_f N_j g_{jm_j})$. To decrease the computational effort of the power assignment to the leaf nodes an efficient reformulation of (18) can be used [7]. The power assignment to the cluster heads in the second step further simplifies to

$$p_j = \frac{\frac{\eta}{T_f\sigma^2}}{g_j\left(\frac{N_j}{\sigma^2\gamma_j}+1\right)\left(1 - \sum_{k\in\mathcal{M}} \frac{1}{\frac{N_k}{\sigma^2\gamma_k}+1}\right)}, \quad j \in \mathcal{M}. \tag{19}$$

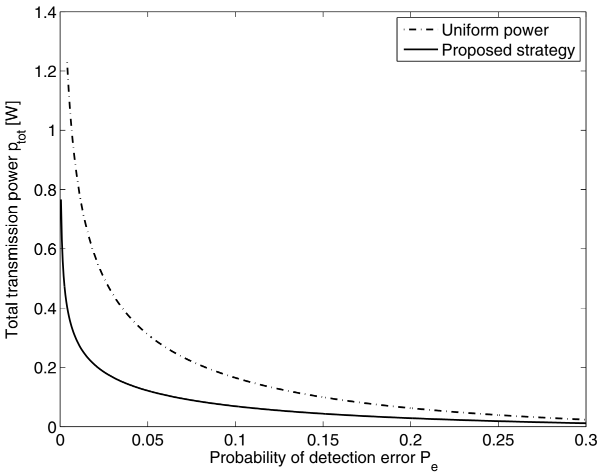

Fig. 4. Necessary total transmission power p_{tot} to maintain a pre-specified level of detection error P_e at the fusion center for both the cross-layer strategy and for uniform power assignment.

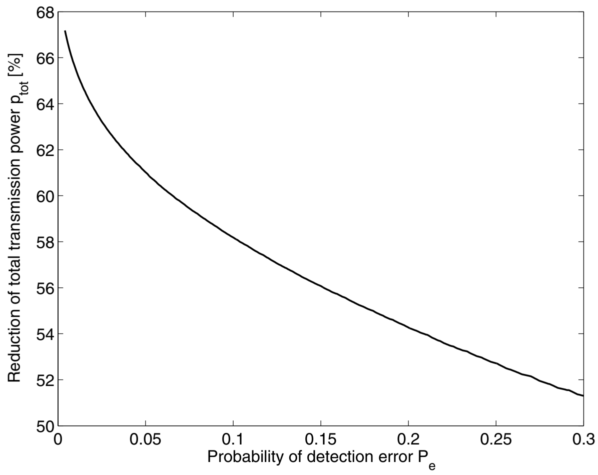

Fig. 5. Reduction of total transmission power p_{tot} of the cross-layer strategy to maintain a pre-specified level of probability of detection error P_e compared to uniform power assignment.

V. Numerical Results and Conclusions

In this section, we investigate the performance of our cross-layer approach from Section III and Section IV by simulations. The scenario is generated by randomly deploying $N = 40$ sensor nodes uniformly in a rectangular area A. The fusion center is supposed to be located in the middle of the scenario. As path loss model we assume signal attenuation according to $d^{-\beta}$. The involved parameters for the scenario and the employed IR-UWB transceivers are summarized in Table I.

In the simulation, we assume the local observation signal-to-noise ratios $\text{SNR}_1, \ldots, \text{SNR}_N$ to be independent and identically uniformly distributed between 0 and 10 dB.

Fig. 4 and Fig. 5 depict the simulation results. From Fig. 4 it can be observed that to maintain a pre-specified value of the global probability of detection error, for all values of P_e a significantly higher total transmission power is necessary for uniform power assignment compared to the cross-layer approach. Fig. 5 quantifies the relative reduction of total transmission power. By utilizing the proposed strategy the transmission power can be reduced up to almost 70%.

TABLE I
PARAMETERS USED IN THE SIMULATION.

parameter	value
N	40
A	100 m $\times$ 100 m
d_{tr}	30 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

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