Channel Capacity Related Power Allocation for Ultra-Wide Bandwidth Sensor Networks with Application in Object Detection

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***Abstract*—This publication analyzes the power allocation problem for a distributed wireless sensor network which is based on ultra-wide bandwidth communication technology and is used to perform object detection. In the considered scenarios the presence or the absence of an object is observed by the sensors independently. Due to noisy communication channels, the interfered observations are fused into a reliable global decision in order to increase the overall detection probability. An approach based on information theory, that aims at maximization of channel capacity, is employed. It allows for analytically described allocation of total given power to the sensors and, thereby, optimizes the overall detection probability. Furthermore, we demonstrate the feasibility of object detection by using the introduced power allocation method in ultra-wide bandwidth signaling systems.**

***Index Terms*—Analytical power allocation, channel capacity, distributed target detection, impulse radio, information fusion, ultra-wide bandwidth signaling, wireless sensor networks.**

I. Introduction

In this report we analyze the problem of power allocation for a distributed wireless sensor network with sensor nodes (SN) based entirely on ultra-wide bandwidth (UWB) technology. This network is used to perform object detection where presence or absence of an object is observed by the sensors independently. UWB signals can be used for data communication between the SNs as well as for radar applications. The approach of misemploying the communication sensors as radar sensors, such that the data transmission is misused as a radar beam in order to detect a target object, helps realizing an energy-efficient radar system with compact and cheap SNs, which fulfills major requirements of wireless sensor networks. Hence, the integration of sensing functionality into common UWB sensors should be easy to implement without the usage of any additional hardware units. Since the compact and low complexity UWB sensors are limited in power and communication capabilities, the detection performance of a single sensor is restricted compared to that of a common complex radar system. To obtain an appropriate overall system performance we consider the case of distributed detection, where the local observations of the sensors are fused into a reliable global decision. Due to noisy communication channels and differences in distances between the object and the sensors, both, the observations and their transmissions are unequally interfered. One simple way to suppress interferences is to increase the power of each SN. But if the total power of the entire network is limited, then power allocation procedures are needed in order to increase the overall detection probability. In general, the mathematical function of the overall detection probability can not be analytically evaluated under a Bayesian-hypotheses-test criterion [1]. This limits the usability of this criterion for analytical optimization of power allocation. Bounds, such as the Bhattacharyya bound [2], are also difficult to use for optimizing multidimensional problems. Therefore, we employ an information theoretic approach [3] which is based on channel capacity maximization and, hereby, show the feasibility of object detection as well as a simple way for analytical suboptimization of power allocation in UWB signaling systems.

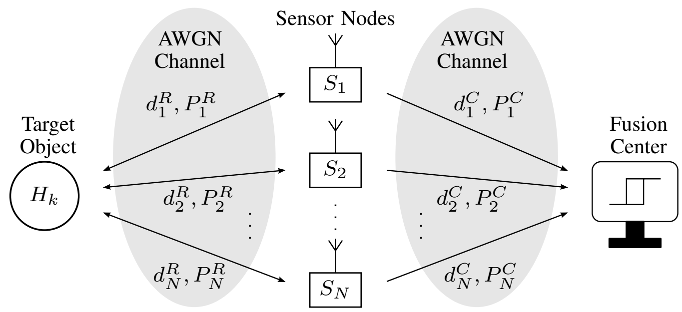

Fig. 1. System model of the distributed wireless sensor network.

The origin of research on distributed detection was based on the attempt to fuse signals of different radar devices [4]. Currently, distributed detection is usually discussed in the context of wireless sensor networks where the sensor unit of the nodes might be based on radar technology [5]–[7]. Other applications for UWB radar systems, which require or benefit from the detection and classification capabilities, are for example localization and tracking [8] or through-wall surveillance [9]. The physical layer design for an integrated UWB radar network that utilizes OFDM technology was analyzed in [10].

II. Overview and System Description

In the following parts of this paper we use the set of natural numbers $\mathbb{N}$ and the set of real numbers $\mathbb{R}$. Furthermore, the set $\mathbb{F}_N$ is a subset of the natural numbers and is defined as $\mathbb{F}_N := \{1, \ldots, N\}$ for any given number $N \in \mathbb{N}$.

Distributed *target object* detection can be formally modeled by a binary hypothesis testing problem with hypotheses H_0 and H_1 indicating absence and presence of the object, respectively. At any instance of time a network of $N \in \mathbb{N}, N \geq 2$ independent and spatially distributed sensors obtains random observations $X_1, \ldots, X_N \in \mathbb{R}$ as shown in Fig. 1. In the case of energy detection X_n models the received signal at the receiver of the n^{th} sensor. If a target object is present, then the received energy is a part of the radiated energy of the same sensor which is reflected from the object's surface. We refer to this communication channel, between the sensors and the target object, as the *first* communication link and denote all dedicated parameters by an upper index R. The random observations $X_1, \ldots, X_N$ are assumed to be conditionally independent for each of the underlying hypotheses, i.e., the joint conditional probability density function of all the observations factorizes according to

$$f^R(X \mid H_k) \coloneqq \prod_{n=1}^{N} f_n^R(X_n \mid H_k),\ \forall k \in \{0,1\}, \tag{1}$$

where X denotes the sequence of random variables $X_1, \ldots, X_N$. In general, the observations are not identically distributed because the SNs have different distances d_n^R from the target object and their radiated powers P_n^R are also different. Therefore, the signal-to-noise ratio (SNR) varies between the SNs. Due to the distributed nature of the problem, the n^{th} sensor S_n performs independent measurements and processes its respective observation X_n by generating a local decision $U_n \coloneqq \theta_n(X_n), \forall n \in \mathbb{F}_N$, which depends only on its own observation and not on the observations of other SNs. After deciding locally each sensor transmits its decision to a fusion center located at a remote location. The communication between the SN and the fusion center is determined by the corresponding distance d_n^C as well as by the transmission power P_n^C of the same SN. We refer to this communication channel, between the SNs and the fusion center, as the *second* communication link and denote all dedicated parameters by an upper index C. Furthermore, we assume that both communication channels are non-fading channels without multipath propagation and that all data transmissions are affected only by additive white Gaussian noise (AWGN). We disregard time delays within all communication and assume synchronized data transmission. We use two distinct pulse-shift patterns for each SN to distinguish the first and the second communication link as described in [11]. Each pattern has to be suitably chosen in order to suppress inter-user interference at each receiver. Hence, the N received signals at the fusion center are uncorrelated and are assumed to be conditionally independent for each of the underlying hypotheses. These received random signals correspond to the local decisions $U_1, \ldots, U_N$ and are labeled by $\tilde{X}_1, \ldots, \tilde{X}_N \in \mathbb{R}$. Their joint conditional probability density function factorizes according to

$$f^C(\tilde{X} \mid H_k) \coloneqq \prod_{n=1}^{N} f_n^C(\tilde{X}_n \mid H_k),\ \forall k \in \{0,1\}, \tag{2}$$

where $\tilde{X}$ denotes the sequence of random variables $\tilde{X}_1, \ldots, \tilde{X}_N$. In general, these observations are – similar to the observations $X_1, \ldots, X_N$ – not identically distributed because of variation in distances d_n^C as well as that of the radiated powers P_n^C. Unlike the local decision rules the global decision rule $U_0 \coloneqq \theta_0(\tilde{X}_1, \ldots, \tilde{X}_N)$ depends on all observations in order to increase the overall detection probability.

All described assumptions are necessary in order to obtain an ideal framework for analyzing the problem of power allocation without studying problems of different detection methods in specific systems and their settings.

A. Local detection rules

The local decision and detection rules θ_n are binary mappings of the kind $\theta_n \colon \mathbb{R} \to \{0,1\}, \forall n \in \mathbb{F}_N$. In this work hard-decision rules are used for performing local detection given by

$$\theta_n(X_n = x_n) = \begin{cases} 0 & \text{if } x_n < \tau_n, \\ 1 & \text{if } x_n \geq \tau_n, \end{cases} \quad \forall n \in \mathbb{F}_N, \tag{3}$$

where the thresholds $\tau_n \in \mathbb{R}$ are suitably chosen. The thresholds must be calculated separately for every SN in order to perform optimal detection. They depend on the prior probabilities of the hypotheses. These values can be calculated by a suboptimal approach which is described in Sec. III-A. In this way, every SN has a local probability of correct decision given by

$$\Pr(U_n = k \mid H_k) = \begin{cases} \Pr(X_n < \tau_n \mid H_k) \text{ if } k = 0, \\ \Pr(X_n \geq \tau_n \mid H_k) \text{ if } k = 1, \end{cases} \tag{4}$$

for all $n \in \mathbb{F}_N$.

B. Fusion of local decisions and global detection rule

Under the assumption of conditionally independent local decisions $U_1, \ldots, U_N$ at the SNs and independent noisy communication channels the optimal fusion rule at the fusion center, under the Bayesian-hypotheses-test criterion, is given by

$$U_0 = \theta_0(\tilde{X} = \tilde{x}) = \underset{k \in \{0,1\}}{\operatorname{argmax}} \big(\pi_k\, f^C(\tilde{x} \mid H_k)\big), \tag{5}$$

where $\pi_k \coloneqq \Pr(H_k)$ with $\pi_0 + \pi_1 = 1$ denotes the prior probability of hypothesis H_k. We use this formula to detect the target object. However, in order to optimize the allocation of the total power between the SNs we have to consider the overall detection probability. Therefore, we consider two disjoint regions $\mathcal{R}_0 \coloneqq \{\tilde{x} \in \mathbb{R}^N \mid \pi_0\, f^C(\tilde{x} \mid H_0) \geq \pi_1\, f^C(\tilde{x} \mid H_1)\}$ and $\mathcal{R}_1 \coloneqq \{\tilde{x} \in \mathbb{R}^N \setminus \mathcal{R}_0\}$. According to [1] the expected value of correct detection is given by

$$P_c \coloneqq \Pr(\tilde{x} \in \mathcal{R}_0, H_0) + \Pr(\tilde{x} \in \mathcal{R}_1, H_1), \tag{6}$$

which in general can not be analytically evaluated. Therefore, the previous formula can not be used to optimize the allocation of the total power analytically. Consequently, we choose a different approach for the optimization which is described in Sec. III-B.

C. Ultra-wide bandwidth sensor nodes

In Fig. 2 the system model of the considered impulse-radio UWB (IR-UWB) sensor nodes with pulse position modulation (PPM) is shown. The transmitter generates two streams of data symbols $s_n^C(t)$ and $s_n^R(t)$. The symbol stream s_n^C is

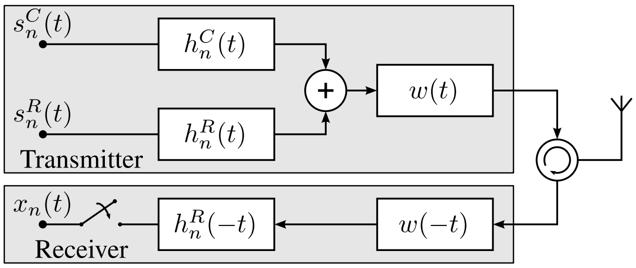

Fig. 2. System model of sensor node S_n with circulator and antenna.

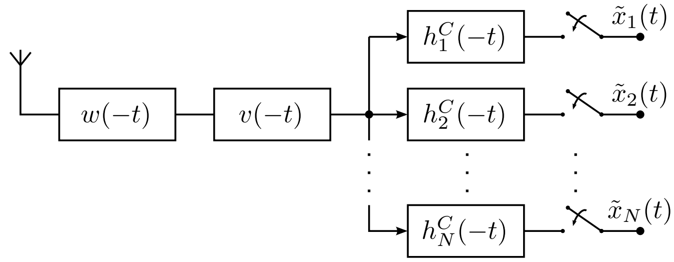

Fig. 3. System model of the fusion center.

used to establish the communication to the fusion center. This stream transmits the data symbols $u_n(i)$, which are generated for the time index i by the local decision algorithm defined in (3). The transmission power P_n^C of this stream is variable in order to adjust transmission power and to enable distributed power allocation.

The symbol stream s_n^R establishes the radiation to the target object and uses always the same data symbol. Its transmission power P_n^R is also variable. In order to increase the available power range at every SN, time-division multiple-access (TDMA) method is used to separate both streams into different time slots and to periodically share the same power amplifier.

In order to eliminate collisions due to multiple access, each user stream is assigned to a distinctive time-shift pattern after passing through the blocks $h_n^C(t)$ and $h_n^R(t)$. Their transfer functions are based on time-hopping sequences [11].

After superposition of both streams a monocyclic pulse shape filter $w(t)$ limits the bandwidth of the signal. This filter has to fulfill the Nyquist intersymbol interference (ISI) criterion in order to neglect the intersymbol interferences.

When this superposition is transmitted, a part of the radiated signal s_n^R will be reflected from the target surface back to the antenna. The received signal will pass through the matched-filter $w(-t)$ and will be decoded from its time-hopping sequence by $h_n^R(-t)$. The additive noise signal $b_n^R(t)$ will pass as well through both filters at the receiver. We denote the noise power by P_{noise}. If all receiver components are linear, then we can define the received power as

$$\tilde{P}_{n,k}^R := kP_n^R \tfrac{\alpha_n^R}{g^2(2d_n^R)}, \ \forall k \in \{0,1\}, \forall n \in \mathbb{F}_N, \tag{7}$$

where the transmitted power is weighted by the product of the factors $\alpha_n^R > 0$ and $g^{-2}(2d_n^R)$. The factor α_n^R includes the radar cross section, the influence of the antenna, the impacts of the filters, and all additional attenuation of the transmitted power. The path loss function g depends on the assumed communication channel and is usually an increasing function of the distance between transmitter and receiver. Here, the factor of two in the distance results from that back and forth transmission between the transceiver and the object. The factor k describes the absence or the presence of the target object. Therefore, the received power depends on the underlying hypothesis.

Due to the Gaussian distribution of the noise each sample is also a Gaussian random variable, which is conditionally distributed according to

$$f_n^R(X_n = x_n \mid H_k) := \tfrac{1}{\sqrt{2\pi P_{\text{noise}}}} \exp\left(-\tfrac{\left(x_n - \sqrt{\tilde{P}_{n,k}^R}\right)^2}{2P_{\text{noise}}}\right) \tag{8}$$

for all $n \in \mathbb{F}_N$ and $k \in \{0,1\}$. The local probabilities for false alarm as well as the local probabilities for correct decision (4) can be computed by the equations

$$\begin{aligned} \tilde{\pi}_{n,0} &:= \Pr(U_n = 1 \mid H_0) = \tfrac{1}{2}\operatorname{erfc}\left(\tfrac{\tau_n}{\sqrt{2P_{\text{noise}}}}\right) \quad \text{and} \\ \tilde{\pi}_{n,1} &:= \Pr(U_n = 1 \mid H_1) = 1 - \tfrac{1}{2}\operatorname{erfc}\left(\tfrac{\sqrt{\tilde{P}_{n,1}^R} - \tau_n}{\sqrt{2P_{\text{noise}}}}\right) \end{aligned} \tag{9}$$

for all $n \in \mathbb{F}_N$, respectively. Here, the mapping $\operatorname{erfc}(z)$ denotes the complementary error function of z.

D. Fusion center

After radiation of the stream s_n^C by the SN S_n, this signal is attenuated distance dependently and reaches the antenna at the fusion center as depicted in Fig. 3. The received signal is matched-filtered and decoded from its time-hopping sequence. As described in [11] we need a further filter, denoted by $v(t)$, in order to increase the Euclidian distance between both transmitted symbols. Thus, the received user power from the n^{th} SN is given by

$$\tilde{P}_n^C := P_n^C \tfrac{\alpha_n^C}{g^2(d_n^C)}, \ \forall n \in \mathbb{F}_N, \tag{10}$$

where we assume that the path loss function is the same as before. This power is independent of the underlying hypothesis because the data stream has the same power for both kinds of transmitted data symbols.

The additive noise signal $b_n^C(t)$ will also pass through all the filters. We assume that the noise spectral density at the fusion center is the same as at the SNs. Due to similarity in architecture of the fusion center and the SNs the noise power of each stream is equal to P_{noise}.

Due to the Gaussian distribution of noise each sample is also a Gaussian random variable, which is conditionally distributed according to

$$\begin{aligned} f_n^C(\tilde{X}_n = \tilde{x}_n \mid H_k) := &\tfrac{\tilde{\pi}_{n,k}}{\sqrt{2\pi P_{\text{noise}}}} \exp\left(-\tfrac{\left(\tilde{x}_n - \sqrt{\tilde{P}_n^C}\right)^2}{2P_{\text{noise}}}\right) \\ &+ \tfrac{1-\tilde{\pi}_{n,k}}{\sqrt{2\pi P_{\text{noise}}}} \exp\left(-\tfrac{\left(\tilde{x}_n + \sqrt{\tilde{P}_n^C}\right)^2}{2P_{\text{noise}}}\right) \end{aligned} \tag{11}$$

for all $k \in \{0,1\}$ and for all $n \in \mathbb{F}_N$.

Because of the convex superposition of Gaussian distributions it is difficult to use (11) with the properties of (2) to optimize the distributed power allocation. Bounds, such as the Bhattacharyya bound [2], are also difficult to use due to multidimensional nature of (2). Therefore, we propose an applicable technique which is motivated by concepts of information theory and is described in the next section.

III. Suboptimal Allocation of Power

In this section we motivate and present an approach to suboptimally allocate transmission power to the radar and the communication task. The objective is to maximize the overall detection probability, given a limited total transmission power P_{tot} that can be arbitrarily allocated to the radar task as well as to the communication task. A direct solution to this problem does not exist, since there are no analytical expressions for the overall detection probability (6) available. Instead, we independently maximize the mutual information of both communication channels by maximizing the corresponding channel capacities in order to determine the power allocation. The motivation for this approach is the fact that for an error-free data communication at a certain data rate a specific SNR is required. The existence of a unique channel-code sequence is hereby an essential assumption [3]. This means that theoretically it is possible to transmit the observation of the target object almost without error up to nearly a limit of the channel capacity. In this case we can separate the problem of power allocation from object detection because data communication does not affect the detection of the target object.

Note that this theoretical concept can not be realized in practice. However, we apply this concept as a heuristical method in this work.

A. Threshold calculation

For the optimization of the thresholds in Sec. II-A, in order to increase the overall detection probability, the analytic solution of (6) is needed. Due to the fact that this explicit form for the overall detection probability is unknown and due to the separation of the data communication from the detection task we can propose the following simple approach to calculate the thresholds.

We increase the probability of correct decision of each SN independently to achieve suboptimal values for the thresholds; Thus, the overall detection probability is increased, too. According to equations (4) and (9) the local probability of correct decision is given by

$$\begin{aligned}\sum\nolimits_{k=1}^{2} \Pr(H_k)\Pr(U_n = k \mid H_k) \\ = \tfrac{1}{2}\left[1 + \pi_1 \operatorname{erf}\left(\frac{\sqrt{\tilde{P}_{n,1}^R} - \tau_n}{\sqrt{2P_{\text{noise}}}}\right) + \pi_0 \operatorname{erf}\left(\frac{\tau_n}{\sqrt{2P_{\text{noise}}}}\right)\right],\end{aligned} \tag{12}$$

which has to be maximized. Here, the mapping $\operatorname{erf}(z)$ denotes the error function of z. Its solution can be explicitly found by using differential calculus and this is identical to that which is obtained by using the Bayesian-hypotheses-test criterion. This is given by

$$\tau_n = \sqrt{\tilde{P}_{n,1}^R} \cdot \left[\tfrac{1}{2} - \tfrac{P_{\text{noise}}}{\tilde{P}_{n,1}^R} \ln\left(\tfrac{\pi_1}{\pi_0}\right)\right], \ \forall n \in \mathbb{F}_N. \tag{13}$$

B. Channel capacity-based power allocation

For the minimization of error rate we set the bit-error probabilities of both communication channels equal. This leads to same error probabilities on both sides for higher SNR values. The expected bit-error probability of the first link is the one for unipolar data transmission and that of the second link is the one for bipolar data transmission. Hence, for higher SNR values the equation

$$\tfrac{1}{2}\operatorname{erfc}\left(\sqrt{\tfrac{\tilde{P}_{n,1}^R}{8P_{\text{noise}}}}\right) = \tfrac{1}{2}\operatorname{erfc}\left(\sqrt{\tfrac{\tilde{P}_n^C}{2P_{\text{noise}}}}\right), \ \forall n \in \mathbb{F}_N, \tag{14}$$

has to be solved in order to find the relationship between the powers. After calculation and usage of the equations (7) and (10) we obtain the analytical result

$$P_n^C = P_n^R \cdot \tfrac{\alpha_n^R}{4\alpha_n^C} \tfrac{g^2(d_n^C)}{g^2(2d_n^R)}, \ \forall n \in \mathbb{F}_N. \tag{15}$$

In the next step we increase the overall mutual information of the first link by maximization of the cumulative channel capacity subject to the total given power of the sensor network. Then the optimization problem is given by

$$\underset{P_1^R,\dots,P_N^R}{\text{maximize}} \quad \sum\nolimits_{n=1}^{N} \tfrac{1}{2}\log\left[1 + \tfrac{P_n^R \alpha_n^R}{4P_{\text{noise}} g^2(2d_n^R)}\right] \tag{16}$$

subject to $\sum_{n=1}^{N} P_n^C + P_n^R \le P_{\text{tot}}$. It has to be considered that the sum of concave functions is also concave and that the arguments of the logarithms are linear functions of the powers. The domain of the constraints is a closed convex set and, therefore, only one global maximum of the problem exists. This maximum can be explicitly found by using the method of Lagrange multipliers which is equivalent to the water-filling power allocation result [3]. This result is given by

$$P_n^R = P_{\text{noise}} \tfrac{4g^2(2d_n^R)}{\alpha_n^R} \cdot \max\left(0, \ \tfrac{\lambda}{\beta_n} - 1\right), \ \forall n \in \mathbb{F}_N, \tag{17}$$

where the factor β_n is defined by $\beta_n := \frac{4g^2(2d_n^R)}{\alpha_n^R} + \frac{g^2(d_n^C)}{\alpha_n^C}$. For the following equations we assume that the quantities given by β_n are ordered in an increasing manner. Then the constant λ is a value specified by

$$\beta_{\tilde{N}} \le \lambda \le \tfrac{1}{\tilde{N}}\left[\tfrac{P_{\text{tot}}}{P_{\text{noise}}} + \sum\nolimits_{n=1}^{\tilde{N}} \beta_n\right], \tag{18}$$

where the index $\tilde{N}$ with $1 \le \tilde{N} \le N$ is the largest integer number for which the inequality $\sum_{n=1}^{\tilde{N}}(\beta_{\tilde{N}} - \beta_n) \le \frac{P_{\text{tot}}}{P_{\text{noise}}}$ holds. From (15) and (17) the allocated power for the second channel is determined as

$$P_n^C = P_{\text{noise}} \tfrac{g^2(d_n^C)}{\alpha_n^C} \cdot \max\left(0, \ \tfrac{\lambda}{\beta_n} - 1\right). \tag{19}$$

This allocation has the following interpretation. The SN S_n with the lowest β_n gets the largest part of the total power because its communication channels are possibly the best due to the low distances. Therefore, the observation of the target object is less interfered by noise and consequently results in better data communication. SNs with higher distances get smaller parts of the total power and some of them do not get

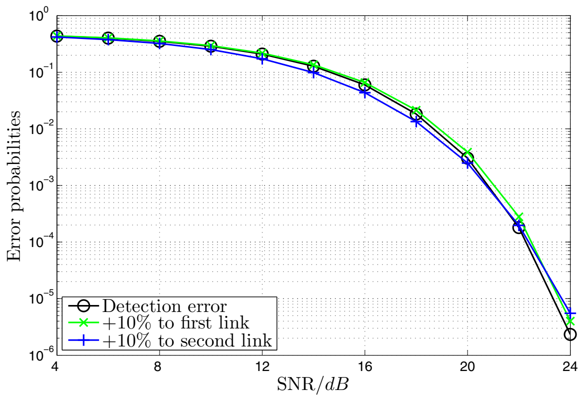

Fig. 4. Verification of proposed power allocation between the two communication links of a single sensor node network.

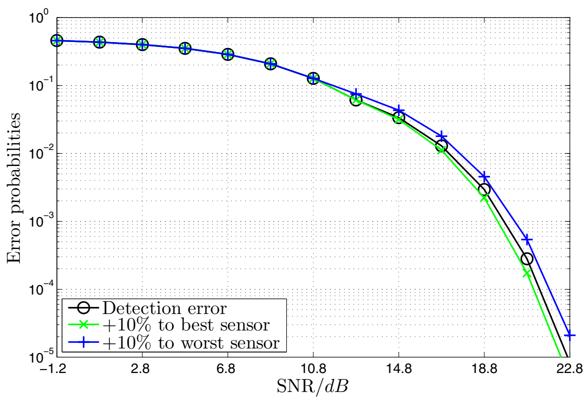

Fig. 5. Verification of proposed power allocation between two sensor nodes.

any power at all. They participate neither in the data communication nor in the detection of the target object. Their information reliability is too poor to be considered for data fusion. More and more SNs will become active by increasing the total power. Then the overall detection probability increases because more correct information is provided by the observations.

IV. Numerical Results and Conclusions

In this section we present some numerical results obtained by applying the proposed optimization method from Sec. III. As observation model we use the constant signal in Gaussian noise as described in Sec. II with equal prior probabilities $\pi_0 = \pi_1 = \frac{1}{2}$. Furthermore, the path-loss function is modeled by line-of-sight propagation.

The verification of the proposed power allocation between both communication links of one SN is shown in Fig. 4. The overall error probability of detection increases for higher SNR values for the case where the power of one link is reduced by 10% and at the same time the power of the other link is stepped up by this 10%. This is due to the assumptions of equation (14). This result shows that the proposed power allocation between both communication links is optimal for higher SNR values.

In Fig. 5 another verification of the power allocation between two SNs is shown. The overall error probability of detection decreases if we decrease the power of the SN,

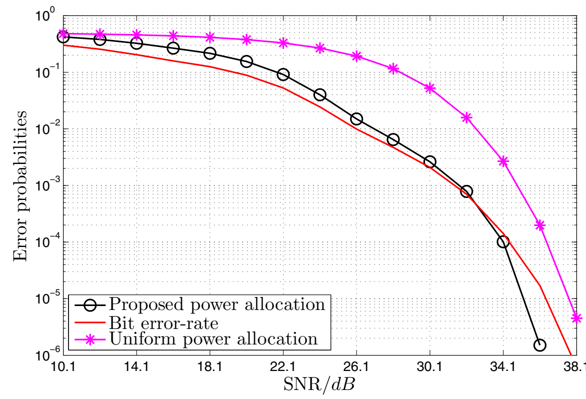

Fig. 6. Comparison of proposed power allocation to a uniform power allocation in a network of ten sensor nodes.

which has the smallest part of the total power, by 10% and allocate this amount of power to the other SN. This result shows that the proposed power allocation between the SNs is only suboptimal.

As shown in Fig. 6 the proposed method yields a better detection probability in comparison to a uniform power allocation, where a network of ten SNs is used. In particular, it is shown that the same overall detection probability can be achieved with much lower transmission energy by using an efficient power allocation method. Furthermore, the bit-error probability of the SN with the highest part of the total power is also shown. The detection accuracy is better than the best bit-error probability for higher SNR values, which affirms the gain of data fusion and illustrates the feasibility of object detection in this kind of sensor networks.

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