Power Allocation for Power-Limited Sensor Networks with Application in Object Classification

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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. The network has power-limited sensor nodes and it is used to classify target objects. In the considered scenarios, the absence, the presence, or the type of an object is observed by the sensors independently. Since the observations are transmitted over noisy communication channels, and are thus unreliable, the disturbed observations are fused into a reliable global decision in order to increase the overall classification probability. In [1] an information theoretic approach, that aims at maximization of the mutual information, has been employed. It enables the analytical allocation of the given total power to the sensor nodes so as to optimize the overall classification probability. We follow the same idea and improve on the results in [1] by a smart selection of the sensor nodes. Furthermore, we investigate the power constraint per sensor node and extend the results hereby.**

I. Introduction

In a recently accepted publication [1], the power allocation problem for a distributed wireless sensor network based entirely on ultra-wide bandwidth (UWB) technology has been investigated. In this essay we follow the same idea and we investigate the power allocation problem for a distributed wireless sensor network with power-limited sensor nodes (SN). The network is used to perform object classification, where the type 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, so that the data transmission is misused as a radar beam in order to classify a target object, helps in realizing an energy-efficient radar system with compact and cheap SNs. A further advantage of such radar systems is the fulfillment of major requirements of wireless sensor networks. This exploitation presupposes that the integration of sensing functionality into usual UWB sensors is implementable easily without the usage of any additional hardware units. Since the compact and low complexity UWB sensors are limited in power and communication capabilities, the classification 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 classification, where the local observations of the sensors are fused into a reliable global decision. The global decision about the object's type is obtained by a fusion center, which is located at a remote location. Due to noisy communication channels and differences in the distances between the target object, the SNs and the fusion center, both the observations and their transmissions are unequally disturbed. One simple way to suppress noise interference is to increase the power of each SN. But, if the total power of the entire network or the power-range of the SNs is limited, then power allocation procedures are needed in order to increase the overall classification probability. In general, for a Bayesian-hypotheses test-criterion the mathematical function of the overall classification probability cannot be analytically evaluated [2]. This limits the usability of this criterion for analytical optimization of the power allocation. Bounds, such as the Bhattacharyya bound [3], are also difficult to use for optimizing multidimensional problems. One simple however suboptimal analytical solution of the power allocation problem has been proposed by [1]. However, the power-limitation per SN has not been analyzed previously. In this publication, we investigate the power-limitation per SN and hereby we extend the results of [1]. Furthermore, we improve the results by a smart selection of the active SNs.

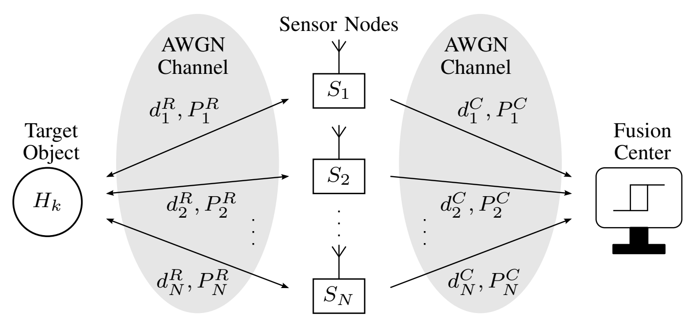

Fig. 1. System model of the distributed wireless sensor network.

The origin of the research on distributed detection has been 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]. In a recent publication [8], the power allocation problem is analyzed where a sensor network is used to detect target objects. Other applications for UWB radar systems, which require or benefit from the detection and classification capabilities, are for example localization and tracking [9] or through-wall surveillance [10]. The physical layer design for an integrated UWB radar network that utilizes OFDM technology was analyzed in [11].

In the next section, we give a superficial overview of the used system model which has been described in detail by [1]. After description of the system model, the power allocation procedure from [1] is explained briefly. In the same section, we extend the power allocation method without power-limited SNs into a power allocation method with individual power constraints per SNs. The investigation of the active sensor selection follows afterwards.

II. Overview and System Description

Throughout this paper we denote the set of natural, real, and complex numbers by $\mathbb{N}$, $\mathbb{R}$, and $\mathbb{C}$, respectively. Note that the set of natural numbers does not include the element zero. Furthermore, we use the subset $\mathbb{F}_N \subseteq \mathbb{N}$ which is defined as $\mathbb{F}_N := \{1, \ldots, N\}$ for any given natural number N. The mathematical operations $|z|$ and $|\mathbf{z}|$ denote the absolute value of a real or complex-valued number z and the Euclidian length of a real or complex vector $\mathbf{z}$, respectively.

Distributed *target object* classification can be formally modeled by a multiple hypotheses testing problem with hypotheses $H_k \forall k \in \mathbb{F}_K$ for a specified number $K \in \mathbb{N}, K \geq 2$ of different objects. We assume that all objects have the same size, shape, alignment, and position. They only differ in material and are classified by their complex-valued reflection coefficients $r_k \in \mathbb{C}$, which are ordered in a strictly increasing manner $0 \leq |r_1| < \cdots < |r_K| \leq 1$. Therefore, the reflection coefficients are the only recognition features in this work.

At any instance of time a network of $N \in \mathbb{N}$ independent and spatially distributed sensors, as shown in Fig. 1, obtains random observations. If a target object is present, then the received energy at the SN S_n is a part of its own radiated energy which is reflected from the object's surface and is weighted by its reflection coefficient. The corresponding random observations are assumed to be conditionally independent for each of the underlying hypotheses. We refer to this communication channel, between the sensors and the target object, as the *first* communication link and denote all dedicated parameters by the superscript R.

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 by generating a local decision, 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 the superscript C. Furthermore, we assume that both communication channels are non-fading channels and that all data transmissions are affected only by additive white Gaussian noise (AWGN). We disregard time delays within all transmissions and assume synchronized data communication. We use two distinct pulse-shift patterns for each SN in order to distinguish its first and second communication link from the communication links of other SNs as described in [12]. 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 at the SNs and are also 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 depends on all observations in order to increase the overall classification probability.

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

A. Fusion of local decisions and global classification rule

In this work hard-decision rules are used for performing the local decisions and classifying the target objects. The thresholds $\tau_{n,k} \in \mathbb{R}, \forall n \in \mathbb{F}_N, \forall k \in \mathbb{F}_K$ are suitably chosen and they must be calculated separately for every SN in order to perform optimal classification. They depend on the prior probabilities of the hypotheses. Their values can be calculated by a suboptimal approach, which is described in [1].

The optimal fusion rule at the fusion center is given by applying the Bayesian-hypotheses test-criterion [2]. It enables the fusion of the local decisions to a global decision. The Bayesian-hypotheses test-criterion presupposes that the prior probabilities $\pi_k := \Pr(H_k)$ with $\sum_{k=1}^{K} \pi_k = 1$ of the hypotheses H_k are known. We use this criterion to classify the target object. However, in order to optimize the allocation of the total power to the SNs, the corresponding overall classification probability is needed. But, the classification probability cannot be analytically evaluated in general. Consequently, we have chosen a different approach for the optimization in [1], which is based on maximization of the information flow between the target object and the fusion center.

B. Ultra-wide bandwidth sensor nodes

We consider impulse-radio UWB (IR-UWB) sensor nodes with pulse position modulation (PPM). Each transmitter generates two streams of data symbols $s_n^C(t)$ and $s_n^R(t)$.

The symbol stream s_n^C is used to transmit the local decisions to the fusion center. We assume that K different modulation symbols are available in order to assign each of them to one type of the target objects. 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 which are based on time-hopping sequences [12].

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 avoid 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. The additive noise signal will pass as well through the filters at the receiver. We denote the corresponding noise power by P_{noise}. If all receiver components are linear, then we can describe the received power by

$$\tilde{P}_{n|k}^R := P_n^R \frac{\alpha_n^R \, |r_k|^2}{g^2(2d_n^R)}, \ \forall k \in \mathbb{F}_K, \forall n \in \mathbb{F}_N, \tag{1}$$

where the transmitted power is weighted by the product of the factors $\alpha_n^R > 0$, $|r_k|^2$, 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. Due to the reflection coefficient r_k of the target object the received power depends on the underlying hypothesis. The path loss function g depends on the assumed multipath propagation 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.

C. Fusion center

After radiation of the stream s_n^C by the SN S_n, the signal is attenuated depending on the distance and it reaches the antenna at the fusion center. The received signal is matched-filtered and decoded from its time-hopping sequence.

In case of additive zero-mean noise and due to the assumptions of $w(t)$ the received power from the n^{th} SN is given by

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

where we assume that the path loss function is the same as for the first communication link. The power $\tilde{P}_n^C$ is independent of the underlying hypothesis because the data stream s_n^C has the same power for all kinds of transmitted data symbols.

The additive noise signal 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 at the fusion center is equal to P_{noise} as well.

III. Suboptimal Allocation of the Total Power

In [1], we have shown a suboptimal approach which has been based on maximization of the information flow. The corresponding allocation method assigns the given total power P_{tot} to the SNs by separating the power allocation problem from the object classification procedure. The following question arises thereby: *why is the limitation of the total transmission power reasonable?* We motivate this case of power-limitation in the next section and conclude the corresponding results from [1] afterwards.

A. Limitation of transmission power

We assume that both the radar and the communication signal use the same bandwidth and are uncorrelated to each other, due to separation of the sensing task and the communication task into different time slots (see Section II-B). In this case and for each new classification process, the limitation of the total transmission power P_{tot} is an upper bound for the sum

$$\sum_{n=1}^{N} \underbrace{\underbrace{P_n^R}_{\text{Radar sensing}} + \underbrace{P_n^C}_{\text{Data communication}}}_{\text{Transmission power of one sensor for a single observation}} \leq P_{\text{tot}} \ . \tag{3}$$

The proposed allocation method in [1], which will be described briefly in the next section, is based on the restriction (3). Previously, we discuss some special cases of the power constraint.

In real applications the transmission power of each SN is also limited. Consider the case in which all SNs have the same power-limitation P_{max} with $\frac{P_{\text{tot}}}{N} \leq P_{\text{max}} < P_{\text{tot}}$. If the power regulation, which is described in the next section, wants to allocate a higher power to $P_n^R > P_n^C$ of the n^{th} SN than its limitation, then we set the transmission power P_n^R equal to its highest possible limitation given by P_{max}, recalculate P_n^C which is given in terms of $P_n^R = P_{\text{max}}$, discard this n^{th} SN from the list of unallocated SNs, decrease the given total transmission power P_{tot} by $P_{\text{max}} + P_n^C(P_{\text{max}})$, and reallocate the remaining total power $P_{\text{tot}} - P_{\text{max}} - P_n^C(P_{\text{max}})$ recursively to the remaining SNs by the same procedure described in the next section. In a case, where the power P_n^C instead of $P_n^R > P_n^C$ will be regulated higher than P_{max}, we can reverse the roles of both transmission powers and repeat this reallocation method until no more SNs are left which exceed their power-limitation. Therefore, the described limitation of the total transmission power is the generalized case which includes the limitation of the transmission power of each SN.

Note that this procedure is applicable for individual power constraints per node as well. Furthermore, note that in each iteration more than one node can be discarded from the list of unallocated SNs in order to decrease the computation complexity.

B. Power allocation procedure

The suboptimal solution of the power allocation problem has been described in [1] by the formulaes

$$P_n^R = P_{\text{noise}} \frac{g^2(2d_n^R)}{\alpha_n^R} \frac{4}{(|r_K|-|r_1|)^2} \cdot \max\big(0, \ \tfrac{\lambda}{\beta_n} - 1\big) \tag{4}$$

and

$$P_n^C = P_{\text{noise}} \frac{g^2(d_n^C)}{\alpha_n^C} \frac{K}{K-1} \cdot \max\big(0, \ \tfrac{\lambda}{\beta_n} - 1\big) \tag{5}$$

for all $n \in \mathbb{F}_N$, where the factor β_n is defined by

$$\beta_n := \frac{g^2(2d_n^R)}{\alpha_n^R} \frac{4}{(|r_K|-|r_1|)^2} + \frac{g^2(d_n^C)}{\alpha_n^C} \frac{K}{K-1}. \qquad (6)$$

The derived allocation method is equivalent to the water-filling power allocation procedure [13]. The results depend on the water-filling level λ, which is a value specified by the inequality

$$\beta_{\tilde{N}} < \lambda \leq \frac{1}{\tilde{N}} \left[\frac{P_{\text{tot}}}{P_{\text{noise}}} + \sum_{n=1}^{\tilde{N}} \beta_n \right]. \qquad (7)$$

In practice, the water-filling level is chosen as large as possible in order to exploit the given total transmission power. For the determination of the water-filling level as well as for the choice of the number $\tilde{N}$ it is important to arrange the factors β_n in an increasing manner. The number $\tilde{N}$ with $1 \leq \tilde{N} \leq N$ is a suitably chosen integer value for which the inequality

$$\sum_{n=1}^{\tilde{N}} (\beta_{\tilde{N}} - \beta_n) < \frac{P_{\text{tot}}}{P_{\text{noise}}} \qquad (8)$$

holds. By substitution of (4) in (5) we get the communication power in terms of the sensing power, which is given as

$$P_n^C(P_n^R) = P_n^R \cdot \frac{\alpha_n^R}{\alpha_n^C} \frac{g^2(d_n^C)}{g^2(2d_n^R)} \frac{K}{K-1} \frac{(|r_K|-|r_1|)^2}{4}, \ \forall n \in \mathbb{F}_N. \quad (9)$$

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 any power at all. The last ones participate neither in the data communication nor in the classification 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 classification probability increases because more correct information is provided by the observations. Therefore, the classification probability strongly depends on the number $\tilde{N}$ of active SNs. The wrong choice of the number $\tilde{N}$ has a considerable impact on the results. In [1] we have shown some promising results, where the number of active SNs has been chosen as large as possible. In this paper, we propose the allocation of the total power to a number of SNs that is as low as possible. Hereby, we improve our old results and we show a better classification performance in Section IV.

C. Computational effort

In order to calculate the transmission powers (4) and (5) the computation of β_n, λ, and $\tilde{N}$ is necessary. The parameters K, N, P_{tot}, P_{noise}, r_k, α_n^R, and α_n^C are fixed system parameters which are known to the computation unit. The distances d_n^R and d_n^C depend on the position of the target object and are therefore unknown. They can be estimated for example by a tracking algorithm. If these values are also determined, then the equations (4)–(9) can be calculated with little effort, because of simple mathematical operations such as summation and multiplication. The only difficulty is the evaluation of the path loss function g, which can include complex mathematical operations. Its complexity depends on the underlying multipath channel.

However, the computation effort of the equations (4)–(9) is less complex than the evaluation of the classification algorithm such as the Bayesian-hypotheses test-criterion. If one can find simpler classification algorithms (see, for example [14]), then the assessment of the calculation effort becomes important and it should be considered in detail. In generell, the computational effort is strongly dependent on the number $\tilde{N}$ of active SNs. Therefore, a reduction of the active SNs to a minimum number helps in decreasing computational complexities and is consequently very important. Hence, the above described selection of the SNs is necessary to achieve this purpose.

IV. Numerical Results

In this section we present some simulation results obtained by applying the proposed power optimization method from Section III. We simulate target objects with equal probabilities of occurrence $\pi_k = \frac{1}{K} \ \forall k \in \mathbb{F}_K$ and corresponding reflection coefficients chosen as $|r_k| = \frac{k-1}{K-1} \ \forall k \in \mathbb{F}_K$. Thereby, we always use a sensor network of ten SNs, which has a total power-limitation of P_{tot} as described in previous sections. Furthermore, the path loss function is always modeled as line-of-sight propagation. The ratio $\text{SNR} = 10dB \log\left(\frac{P_{\text{tot}}}{P_{\text{noise}}}\right)$, instead of *received* SNRs, is depicted on the abscissa of all figures. The probability of classification error is obtained by averaging over all failed classifications for the occurrence of the K different objects at each SNR value. In the first two figures we allow the occurrence of three different types of target objects. In contrast, the occurrence of more object types is considered in the last figure.

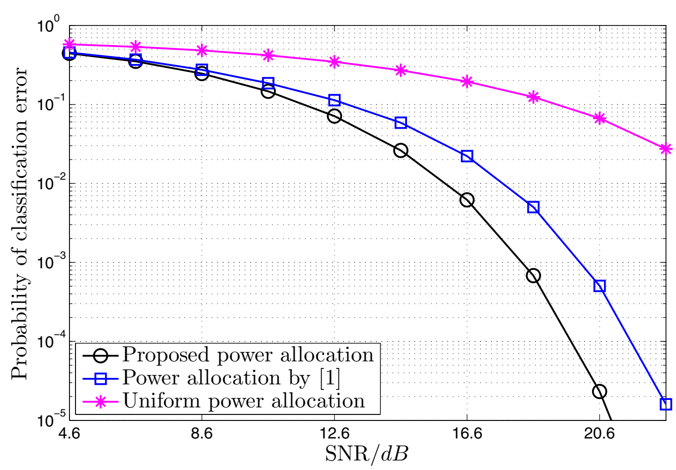

Fig. 2. Comparison of the proposed power allocation and a uniform power allocation in a network without power-limitation of the sensor nodes.

In Fig. 2, we consider a network, where the SNs do not have any power constraints. As shown, the proposed method yields a better classification probability in comparison to a uniform power allocation method. In particular, it is shown that the same overall classification probability can be achieved with much lower transmission power, especially for low SNR values, by using an efficient power allocation method. The larger the number of SNs is, the more important a smart power allocation procedure becomes. Furthermore, the achievable classification probability by using the method from [1] is also shown. Using the minimum possible number of SNs leads the proposed method to an improved classification accuracy in comparison to the usage of the maximum possible number of SNs for the classification process.

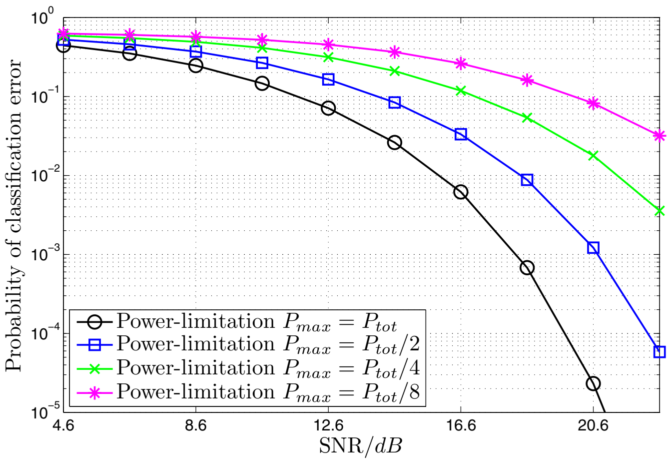

Fig. 3. Comparison of proposed power allocation with and without power-limited sensor nodes.

The comparison of a network without power-limitation of the SNs to the same network with different power constraints per SN is shown in Fig. 3. The limitation $P_{\max} < P_{\text{tot}}$ of the transmission powers reduces the overall classification performance as expected. The lower the power-limitation $P_{\max}$ is, the worse the classification probabilities are.

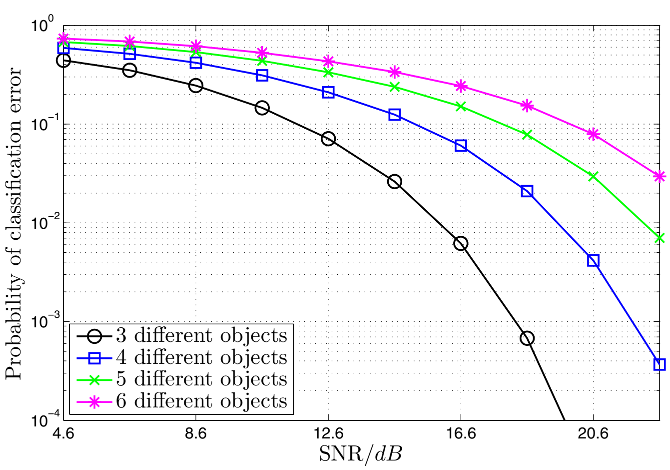

Fig. 4. Comparison of different number of object types.

In Fig. 4, we consider again a network without power constraints per SNs, but with different number of object types. The different number of object types are chosen as $K \in \{3, 4, 5, 6\}$. As expected, the overall classification probability decreases quickly by increasing the number of different object types. There are three reasons for this deterioration that rises by increasing the number of different object types. First, the reflection coefficients are artificially placed closer to each other. Second, the probability of occurrence is smaller for each of the target objects. Third, the number of possibilities is larger in misclassifying the target object.

V. Conclusion

The goal of the power allocation is to maximize the classification probability in a distributed wireless sensor network, which is based on ultra-wide bandwidth communication technology. A two-stage decision process is used for the object classification procedure, which has been initially proposed in [1]. We have shown that the proposed allocation procedure works in networks with and without consideration of the transmission-power limitation per sensor node. Numerical results illustrate the performance of the described extension as well as the achieved classification probability. Furthermore, the new approach for sensor node selection improves the former results. This selection method allows us to decrease the number of active sensor nodes. It subsequently increases the classification performance while the computation complexity is decreased simultaneously.

References

[1] G. Alirezaei and R. Mathar, "Channel capacity related power allocation for distributed sensor networks with application in object classification," in *2013 International Conference on Computing, Networking and Communications, Wireless Ad Hoc and Sensor Networks Symposium (ICNC'13 - WAHS)*, San Diego, USA, Jan. 2013, pp. 1–5.

[2] R. O. Duda, P. E. Hart, and D. G. Stork, *Pattern Classification*, 2nd ed. John Wiley & Sons, Inc, 2000.

[3] A. Lapidoth, *A Foundation in Digital Communication*. Cambridge University Press, 2009.

[4] R. Srinivasan, "Distributed radar detection theory," *IEE Proceedings-F*, vol. 133, no. 1, pp. 55–60, Feb 1986.

[5] A. L. Hume and C. J. Baker, "Netted radar sensing," in *Proc. IEEE Int. Radar Conf.*, 2001, pp. 23–26.

[6] L. Pescosolido, S. Barbarossa, and G. Scutari, "Radar sensor networks with distributed detection capabilities," in *Proc. IEEE Int. Radar Conf.*, May 2008, pp. 1–6.

[7] Y. Yang, R. S. Blum, and B. M. Sadler, "A distributed and energy-efficient framework for Neyman-Pearson detection of fluctuating signals in large-scale sensor networks," *IEEE J. Sel. Areas Commun.*, vol. 28, pp. 1149–1158, Sep 2010.

[8] G. Alirezaei, "Channel capacity related power allocation for ultra-wide bandwidth sensor networks with application in object detection," in *Ultra-Wideband (ICUWB), 2012 IEEE International Conference on*, Syracuse, NY, Sep. 2012, pp. 115–119.

[9] S. Gezici, Z. Tian, G. B. Giannakis, H. Kobayashi, A. F. Molisch, H. V. Poor, and Z. Sahinoglu, "Localization via ultra-wideband radios: A look at positioning aspects for future sensor networks," *IEEE Signal Process. Mag.*, vol. 22, pp. 70–84, Jul 2005.

[10] C. Debes, J. Riedler, A. M. Zoubir, and M. G. Amin, "Adaptive target detection with application to through-the-wall radar imaging," *IEEE Trans. Signal Process.*, vol. 58, no. 11, pp. 5572–5583, 2010.

[11] S. C. Surender and R. M. Narayanan, "UWB noise-OFDM netted radar: Physical layer design and analysis," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 47, no. 2, pp. 1380–1400, 2011.

[12] M. Z. Win and R. A. Scholtz, "Ultra-wide bandwidth time-hopping spread-spectrum impulse radio for wireless multiple-access communications," *IEEE Trans. Commun.*, vol. 48, no. 4, pp. 679–691, 2000.

[13] T. M. Cover and J. A. Thomas, *Elements of Information Theory*, 2nd ed. John Wiley & Sons, Inc, 2006.

[14] P. K. Varshney, *Distributed Detection and Data Fusion*. New York: Springer, 1997.