A Fast Energy-Aware Multi-Target Detection Technique using Binary Wireless Sensors

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***Abstract*—The paper proposes a fast multi-target detection technique based on simultaneous sensor data fusion for a binary wireless sensor network in a pre-deployed configuration. The synchronous binary sensors are circularly arranged in an area with the sink node on the central axis such that the line-of-sight communication dominates. All the binary sensors employed for detecting rapidly changing targets are similar, transmit simultaneously and operate on the same narrow frequency band without any specific ID assigned by a central control unit or the sink node, where the latter is affected by additive white Gaussian noise (AWGN). Each sensor is assumed to cover a previously known zone for target detection and it has no cooperation with other sensors. The proposed communication model including the channel estimation process and the devised distributed power allocation method, is mathematically described and the conducted simulations comprehensively confirm the good performance of the model with respect to the channel estimation and equalization errors at the transmitter and the AWGN power at the receiver.**

I. Introduction

Binary wireless sensors have potential applications in failure/threat detection and surveillance. The binary output of such sensors which is either 0 or 1 can be exploited for energy conservation in case of target absence. In other words, no signal is transmitted when there is no detected target. The binary wireless sensor networks (BWSNs) as a subgroup of wireless sensor networks (WSNs) are typically resource-limited in terms of energy and computational capacity. Therefore, similar to the WSNs, the signal processing algorithms for such systems should be specifically designed to meet their constraints. Among these constraints, the power consumption is the most stringent restriction which should be addressed as long as the main functionality of the system is not compromised. Since BWSNs use binary decision, they are good candidates for applications that involve threat or target detection. Sensor networks for surveillance applications, and in particular, for detection, are investigated in many papers covering a plethora of system designs with a wide class of objectives and constraints for specific applications. In [1], a distributed vector estimation for power-and bandwidth-constrained WSNs is considered, where the fusion center reconstructs the unknown vector by a linear estimation, and in [2], a computationally efficient localization scheme was proposed based on an iterative classification problem. The power allocation for sensor networks is also the topic of many papers, usually aiming at minimizing the detection error with respect to a global or local power budget [3], [4]. A WSN deployed for target detection might also be interpreted as a localization system, where the location of the sensors and their coverage areas are known. In some scenarios of target detection, the data from all sensors should be decoded instantly at the receiver side, i.e., in one single instant, the data from all sensors should be transmitted to the resource limited sink node which is typically equipped with a single omnidirectional antenna. In such scenarios, the alternative conventional routing and relaying schemes to gather the information at the sink node, result in relatively huge delays in the target detection and subsequently the tracking capability of the system as the data from each sensor should be combined with other sensors' data in some way and the location of sensors which detected a target should also be fused into the data being sent to the sink node during the relaying process. Apart from the fast detection and tracking capability, the short communication time in such target-detection wireless systems minimizes the usage of the occupied frequency band and thereby the interference with other wireless applications in the system. The other advantage of a short communication interval is that the channel characteristics remain approximately constant over one data-block length and therefore the detection improves as a result of more accurate channel estimation. This paper introduces a specific design of a WSN where the sensors are deployed in known positions, i.e., along the circumference of a circle, and the fusion center or the sink node reconstructs the binary

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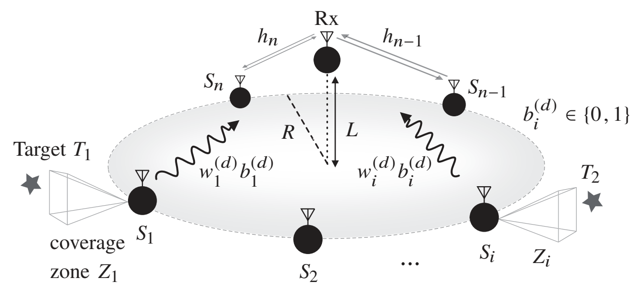

Fig. 1. A circular deployment of binary wireless sensors and the sink node somewhere on the 3D locus of points equidistant from the binary sensors to ensure a dominant line-of-sight propagation for all sensors.

data of all sensors at the same time, thereby reducing the target detection delay to only one time-slot, which is the least possible delay. This fast detection technique can be used for studying the behavior of specific particles or substances undergoing experiments such as intense electromagnetic excitations, immense accelerations caused by chemical or nuclear reactions, accurate shockwave pattern acquisition, gunshot detection and periphery protection, rather than conventional target detection applications which might be conducted using other methods. For the mentioned applications, a very limited bandwidth which does not interact with the natural behavior of the phenomenon or the system is chosen and all sensors operate over this frequency. This also facilitates the replacement of sensors as they are all of the same type in terms of frequency and antenna pattern. Generally speaking, one way of achieving a fast transmission scheme in such BWSNs might be the assignment of different carrier frequencies to each sensor node as in frequency division multiplexing (FDM) which also play the role of a localization tag for pre-deployed sensor nodes. However, this is not always possible as sensors are typically of the same type and operate on the same frequency band. Furthermore, this approach occupies several times more bandwidth during the sensor transmission phase and therefore the interference with sources outside the network can result in false alarms. In this paper, we assume that all sensors use the same carrier frequency, but can transmit with different powers occasionally and the sink node at the receiver is a simple single antenna receiver. There is a wide variety of algorithms proposed for target detection or tracking using BWSNs. However, due to the high applicability of BWSNs, they are different in terms of their objectives and constraints. In [5], a distributed energy efficient algorithm for target tracking with BWSNs has been introduced, where the target location, velocity and trajectory are estimated in a distributed and asynchronous manner. In [6], a binary sensor model is proposed for tracking a moving object, where the binary information of each sensor is determined depending on whether the object is moving toward the sensor or away from it. In this work, the binary information of sensors is determined based on the target's presence or absence in the sensing range of each sensor and the objective is to simultaneously decode all sensors' data while the BWSN is subjected to the constraints summarized as follows. All sensors including the sink node, are similar, equipped with a single antenna for communication inside the BWSN, operate on the same narrow frequency band for both transmission and reception, and each sensor S_i covers a known zone for target detection denoted by Z_i, where depending on the BWSN deployment, Z_is may or may not be disjoint. The binary sensors are distributed over an area without any cooperation and there is no specific ID data or code assigned to them by a central unit in order to be sent within the data packets for distinguishing at the sink node. Also after obtaining the fastest data fusion solution as the first priority, an optimal power allocation scheme in terms of minimum power consumption subject to a uniform energy consumption distribution among the sensors is expected to be devised. The major contributions of this work are proposing an instantaneous multi-sensor data fusion technique for non-cooperative binary sensors and a new distributed power allocation technique based on energy consumption and an appropriate digital modulation.

II. Proposed BWSN System Model

Figure 1 shows the deployment of the proposed BWSN model where the n binary sensors which detect the target(s) are placed on a supposed circle in the area of interest and the sink node is located anywhere on the vertical line crossing the center. The proposed communication scheme in this work is based on a combination of distributed beamforming (DBF), code division multiple access (CDMA) and superposition modulation (SM). Since the model in Figure 1 is basically a multiple-input single-output (MISO) scenario, the communication from the binary sensors to the sink node in instant $d \in \mathbb{N}$ can be modelled as $r_d = \mathbf{h}^T(\mathbf{w}_d \circledast \mathbf{b}_d) + n_d$ where scalars $r_d, n_d \in \mathbb{R}$ and vectors $\mathbf{h} := [h_1, h_2, \cdots, h_n]^T$, $\mathbf{w}_d := [w_1^{(d)}, w_2^{(d)}, \cdots, w_n^{(d)}]^T$, $\mathbf{b}_d := [b_1^{(d)}, b_2^{(d)}, \cdots, b_n^{(d)}]^T \in \mathbb{R}^n$ denote the received signal at the sink node, the additive white Gaussian noise (AWGN), the channel coefficients, the SM weights and the binary signal vector in instant d, respectively, and $\circledast$ indicates the Hadamard product. Also for the sake of compactness throughout this paper, we define the set $\mathbb{F}_i^j$ for any $i, j \in \mathbb{Z}, i \leq j$ as $\mathbb{F}_i^j := \{i, i+1, \cdots, j\}$. It is noteworthy that though the system model is the same as a conventional MISO, the configuration is quite different as the transmitter antennas are distributed and cannot cooperate with each other. If the channel state information (CSI) is not available at the transmitter side, at least n time-slots within a data block should be assigned to pilots for channel estimation at the receiver side. Apart from the long transmission time for pilots and channel occupation, the result of channel estimation and subsequently the data detection will not be accurate for two reasons. The first reason is that assuming the same transmission time for every symbol, the channel coherence degrades with the length of data block and this issue drastically affects the performance of channel estimation in a block fading model. The second reason is that the pilot symbols $\mathbf{p}_k$, $k \in \mathbb{F}_1^{m_p}$, where k denotes the time index and m_p is the number of pilot symbols, should at least have a linearly independent subset of size n such as $\{\mathbf{p}_{i_j} | \{i_j\}_{j=1}^n \subseteq \mathbb{F}_1^{m_p}\}$ within the data block of length n_d so that the channel estimation becomes reliable enough at the receiver side. This is not always practical as the binary sensors are distributed over an area without any cooperation and designing such pilots therefore needs to be pre-planned. Note that this requirement is mainly for the de-correlation of individual channel gains and distinguishing them at the receiver, but for de-noising the AWGN component, more pilots should be sent. This is of course when the least squares (LE) algorithm with enough bit-resolution is employed for the channel estimation at the sink node. If low-complexity adaptive filtering algorithms such as SM-NLMS and BEACON in [7] and SM-AP in [8], [9] with partial updates are performing the channel estimation, then the correlation of the pilots defined by the inner product $\mathbf{p}_i^T \mathbf{p}_j$ should be considered, as these values determine the extent of the linear dependency which strongly influences the performance of such adaptive filtering algorithms. Thus, in order to achieve the fastest convergence in such algorithms, orthogonal pilots should be employed, i.e., $\mathbf{p}_i^T\mathbf{p}_j = 0$ for appropriate i and j values ($i \neq j$). As a consequence of this part, for our proposed model, we use the CSI at the transmitter by sending a few pilot symbols from the sink node. Thus, due to the short communication time, the channel can be considered reciprocal for both transmission and reception. Denoting these scalar pilot symbols by p_k for $k \in \mathbb{F}_1^{m_p}$ and the corresponding received scalar signal at the binary sensor $S_i, i \in \mathbb{F}_1^n$, by $z_k^{(i)}$, the channel values can be simply estimated by LE at the binary sensors as $\forall i \in \mathbb{F}_1^n : \hat{h}_i = \sum_{k=1}^{m_p} z_k^{(i)} p_k / \sum_{k=1}^{m_p} p_k^2$ or just by averaging as $\hat{h}_i = \sum_{k=1}^{m_p} z_k^{(i)}/m_p$ when $p_k = 1$ for every $k \in \mathbb{F}_1^{m_p}$. This approach also comes with other advantages. In a resource constrained BWSN, the binary sensors involved in target detection can wait for transmission until they receive the incoming pilots from the sink node. This eliminates the inessential signal transmission and preserves energy for the sensors. In other words, the sink node reads the simultaneous sensors data whenever it requires. This *training-first* approach is also useful when energy is transferred to the sensors over this wireless link before they transmit data. In addition to the simple and accurate channel estimation and unconstrained pilot design, another advantage of this approach is the fact that the whole number of pilots transmitted from the sink node will be used to denoise the AWGN of binary sensors and not to decorrelate different channels. In spite of all these, as we will see in the following, the main reason for using CSI at the transmitter is to allow the incorporation of superposition modulation. Defining $\mathbf{w}_d := \beta \mathbf{v}_d^{\circlearrowleft} \oslash \hat{\mathbf{h}}$ where

$$\mathbf{v}_d^{\circlearrowleft} := [\rho^{\mathrm{mod}(d,n)}, \rho^{\mathrm{mod}(1+d,n)}, \cdots, \rho^{\mathrm{mod}(n-1+d,n)}]^T$$

is the cyclic amplitude allocation vector with $\rho \in \mathbb{F}_2^{\infty}$ in this paper, $\hat{\mathbf{h}} := [\hat{h}_1, \hat{h}_2, \cdots, \hat{h}_n]^T$ is the estimated channel vector with entries derived before as $\hat{h}_i$, $\oslash$ denotes the Hadamard matrix division, and β is a known parameter to all binary sensors and the sink node, which is used to avoid very high signal amplitudes as in zero-forcing channel equalization, the received signal at the sink node r_d can be expressed as follows

$$\begin{aligned} r_d &= \mathbf{h}^T(\beta \mathbf{v}_d^{\circlearrowleft} \oslash \hat{\mathbf{h}} \circledast \mathbf{b}_d) + n_d \\ &= \beta(\mathbf{h}^T \oslash \hat{\mathbf{h}}^T)(\mathbf{v}_d^{\circlearrowleft} \circledast \mathbf{b}_d) + n_d \qquad (1) \\ &\approx \beta[1, \ldots, 1]\mathbf{v}_d^{\circlearrowleft} \circledast \mathbf{b}_d + n_d \\ &= \beta \sum_{i=1}^{n} \rho^{\mathrm{mod}(i-1+d,n)} b_i^{(d)} + n_d \\ &= \beta\overline{(b_{t_{n-1}}^{(d)}, b_{t_{n-2}}^{(d)}, \ldots, b_{t_0}^{(d)})}_\rho + n_d \qquad (2) \end{aligned}$$

where for every $j \in \mathbb{F}_0^{n-1}$,

$$t_j := \arg_{i \in \mathbb{F}_1^n} [\mathrm{mod}(i-1+d,n) = j] \,.$$

In Equation (2), the number shown as $\overline{(b_{t_{n-1}}^{(d)}, b_{t_{n-2}}^{(d)}, \ldots, b_{t_0}^{(d)})}_\rho$ represents the decimal $\sum_{i=1}^{n} \rho^{\mathrm{mod}(i-1+d,n)} b_i^{(d)}$ in a base-ρ ($\rho \in \mathbb{F}_2^{\infty}$) system. The value of $\beta \leq 1$ is merely for practical purposes where the Hadamard division $\mathbf{v}_d^{\circlearrowleft} \oslash \hat{\mathbf{h}}$ returns high transmission amplitudes which cannot be achieved. In such cases, an appropriate $\beta < 1$ scales down the range as long as the signal-to-noise ratio (SNR) at the receiver is not drastically compromised. The value of $\sqrt{L^2 + R^2}$ with L and R defined in Figure 1 is the major factor for choosing β as $|h_i|^2$ for the line-of-sight (LOS) communication is proportional to $1/(\sqrt{L^2 + R^2})^{\gamma_{PL}}$, where γ_{PL} is the path-loss exponent.

A. *Differences with CDMA, DBF and SM*

In a CDMA system, several transmitters simultaneously share the same communication channel and frequency band using different codes. These codes are then used at the receiver side in order to exploit each user's data. Analogously, in a superposition modulation scheme, the serial binary input data is paralleled and the resultant data streams are mapped onto binary antipodal symbols using binary phase-shift keying (BPSK) modulation. These symbols are then weighted according to a defined mathematical model and finally add up to generate the output data symbol. The major difference between our proposed model for the BWSN and CDMA is the fact that the BWSN is very resource limited compared to the CDMA system, it is distributed, and there is no spreading sequence or spread spectrum involved here. On the other hand, the proposed BWSN model is not directly adaptable to the bijective SM modulation, as the former is a totally distributed model without any cooperated processing whereas the latter includes a summation module to perform the superposition of weighted symbols, as discussed in [10]. It is noteworthy that neglecting the summation module, the non-bijective mapping SM modulation is outside the scope of this paper as in this case, the targets detected by the sensors cannot be uniquely distinguished in one time slot. Another similar yet different technique is DBF. With the aid of BF, the SNR at the receiver can be maximized while the interference with other users at different locations is significantly suppressed. The term distributed here indicates that unlike the conventional arrays, the transmitter antenna arrays are not deployed in a uniformly-spaced manner such as in a linear array and there is no information about other antenna elements which are mounted on separate sensors at any sensor, though the sensors are still assumed to be synchronized. In sensor networking, DBF is sometimes modeled as a relay channel as discussed in [11], or is performed in a multi-hop communication system where there is also a direct channel between the source and destination. In the recent case, since the complete CSI knowledge is not available at each individual sensor, or there is no centralized control with access to complete CSI, a suboptimal solution is used for beamforming in order to avoid very high overhead [12]. In our BWSN model, rather than interference suppression via sidelobe reduction of array antennas, or serving the receivers at different locations with high SNRs which cannot be optimally implemented with DBF due to partial CSI knowledge, the purpose is to serve a pre-deployed receiver in order to construct a signal constellation by the superimposed waves. In other words, despite this (MISO) scenario in our model is often employed for spatial diversity, and the fact that the typical number of antenna requirement for a good error performance in spatial multiplexing is not met here, a spatial multiplexing scheme is performed.

B. A Discussion on Power Allocation

As discussed earlier, our BWSN model obeys the same rules governing the WSNs. Therefore, an efficient *distributed* power allocation plan should be devised capable of operating on individual binary sensors without accessing to any information from a centralized control unit. Considering the facts that the binary sensors have limited power and computational capacity, the detection data in the proposed model is carried on the signal amplitude, and the very fast target detection capability should not be compromised, the importance of the power allocation algorithm is more highlighted. To fulfill all these constraints, we proposed a cyclic power allocation algorithm which, by virtue of function mod$(.)$ in $\mathbf{v}_d^{\circlearrowleft}$, equally distributes the total energy among the sensors over every n sequential time slots. This approach exploits the only assumption we made for our model which is the synchronicity of the binary sensors for simultaneous transmissions. In addition, as discussed before, all sensors only transmit when they receive the pilots from the sink node and analogous to the on-off keying (OOK) digital modulation, although the transmission is implicitly requested by sending pilots from the sink node, the binary sensors with no detected targets still do not participate in transmission due to their zero amplitudes in vector $\mathbf{b}_d$, which in turn makes the power consumption plan more efficient. These new strategies for power allocation are accomplished by the devised $\mathbf{v}_d^{\circlearrowleft} \circledast \mathbf{b}_d$ and using CSI at the transmitter. Defining the final transmit amplitudes as random variables X_i, i.e.,

$$[X_1\, X_2\, \cdots\, X_n]^T := \beta \mathbf{v}_d^{\circlearrowleft} \oslash \hat{\mathbf{h}} \circledast \mathbf{b}_d,$$

denoting the temporal average by $\langle . \rangle$, the ensemble average by $E[.]$, the presence and absence of target T_i by $\exists T_i$ and $\nexists T_i$, respectively, and assuming $E[1/\hat{h}_i]$ and $Pr(\exists T_i)$ are independent of time which is indexed by d, the following relations hold for the average power consumption of the i^{th} sensor

$$\begin{aligned}
\langle E\left[X_i^2\right]\rangle &= \langle E\left[X_i^2|\exists T_i\right] Pr(\exists T_i)\rangle + \underbrace{\langle E\left[X_i^2|\nexists T_i\right]}_{=0} Pr(\nexists T_i)\rangle \\
&= \left\langle E\left[\beta \frac{\rho^{2\text{mod}(i-1+d,n)}}{\hat{h}_i}\right] Pr(\exists T_i)\right\rangle \\
&= \beta \left\langle \rho^{2\text{mod}(i-1+d,n)}\right\rangle E\left[\frac{1}{\hat{h}_i}\right] Pr(\exists T_i) \qquad (3) \\
&= \frac{\beta}{n}\left(\sum_{d=1}^{n} \rho^{2\text{mod}(i-1+d,n)}\right) E\left[\frac{1}{\hat{h}_i}\right] Pr(\exists T_i) \qquad (4) \\
&= \frac{\beta}{n}\frac{\rho^{2n}-1}{\rho^2-1} E\left[\frac{1}{\hat{h}_i}\right] Pr(\exists T_i), \qquad (5)
\end{aligned}$$

where Equation (4) is obtained from Equation (3) considering the periodic property mod$(i-1+d+n,n) =$ mod$(i-1+d,n)$. Note that as a result of OOK scheme at the transmitter, in relations above, the non-negative term $\langle E\left[X_i^2|\nexists T_i\right] Pr(\nexists T_i)\rangle$ is minimized to zero, which in turn satisfies a definite condition of minimizing the total average power, as $\langle E\left[X_i^2|\exists T_i\right] Pr(\exists T_i)\rangle$ and $\langle E\left[X_i^2|\nexists T_i\right] Pr(\nexists T_i)\rangle$ have mutually exclusive events. Thus, as shown by Equation (5), the deterministic term of average power, i.e., $\frac{\beta}{n}\frac{\rho^{2n}-1}{\rho^2-1}$, is independent of the sensor's index i, which means that the deterministic global power is equally distributed among all sensors and therefore, the lifetime of the network in terms of detection integrity is maximized.

III. Simulations

In this section, the performance of a BWSN with $n = 3$ binary sensors for target detection is analyzed where $\rho = 2$ and $\sigma_n^2 = 1$. Also as discussed before, $\beta < 1$ is only for practical implementation and in the simulations, we can set $\beta = 1$ if the same SNR range is considered. Figure 2 illustrates how the bits assigned to the in-phase quadrature (I-Q) signal constellation for decoding at the sink node shift over time in module $n = 3$. In conventional constellations, the decoding bits are assigned such that any two adjacent points have the minimum Hamming distance in order to improve the reliability via error correction algorithms. Here, since the uniform energy consumption distribution is one of the design constraints, and the whole vector $\mathbf{b}_d$ should be decoded in one time slot, the Hamming distance varies when all of the 2^n constellation points are considered for detecting n targets. Apart from these, in our BWSN, there is no cooperation between the sensors in order to perform any pre-coding before transmission. Note that in the basic model proposed here, the quadrature component is not used. Figure 3 depicts the cyclic amplitude allocation for this simulation. According to this figure, the amplitudes are assigned such that a Sudoku-like matrix forms. This matrix guarantees a bijective modulation scheme for uniquely detection of up to n targets, as well as a statistically uniform energy consumption for each sensor when the random variables $X_i, i \in \mathbb{F}_1^n$, associated with the appearance of each target T_i are i.i.d. The γ value in this figure is the threshold for a reliable decoding at the receiver. In other words, for transmission in any instant d, the minimum amplitude allocated to each sensor, i.e., $\rho^0 = 1$, should not fall behind this threshold. Figure 4 shows the actual probability that a target T_i exists at the detection range of sensor S_i, i.e., the probability of X_i which is denoted by $Pr_A^{T_i}$, for different values of noise power σ_n^2, where X_is are i.i.d with a uniform probability mass function (PMF). The uniform PMF can be seen from the fact that by averaging over 2×10^5 iterations, for each sensor and for any σ_n^2, we have $Pr_A^{T_i}(\sigma_n^2) \approx 0.5$. The performance evaluation in this section is based on this worst case scenario described in Figure 4. In fact, there is no a priori information about the targets at the sink node and a maximum likelihood detection is employed for evaluation. In order to show the effect of a channel estimation error

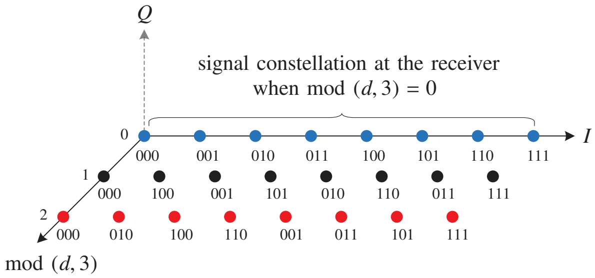

Fig. 2. Signal constellation over time (denoted by d) for three binary sensors detecting up to three uniquely identifiable targets. For all constellations, the binary digits from left to right are read as $b_3^{(d)}$, $b_2^{(d)}$ and $b_1^{(d)}$, respectively.

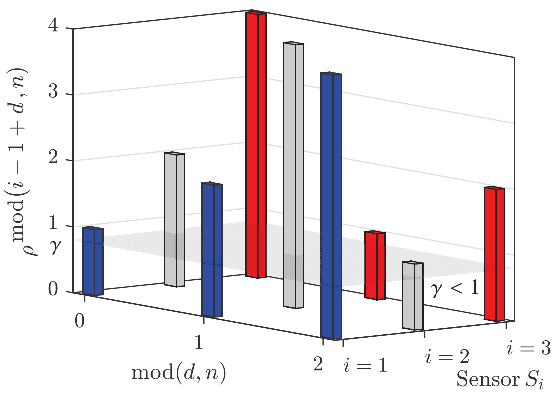

Fig. 3. An illustration of cyclic *amplitude* allocation for constellation shaping in a BWSN with $n=3$ binary sensors and $\rho=2$. The incorporation of channel equalization $\oslash\beta\hat{\mathbf{h}}$ is not shown here.

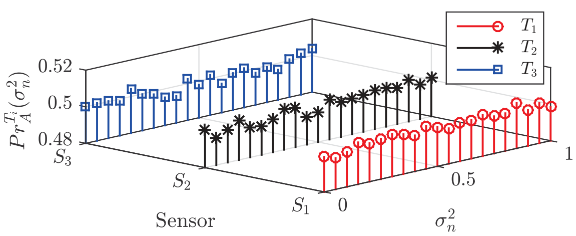

Fig. 4. $Pr_A^{T_i}(\sigma_n^2)$ denotes the actual probability that a target T_i exists at the detection range of sensor S_i for different values of noise power σ_n^2.

on the detection performance of the proposed model, the error of channel estimation should be first modeled and then incorporated into the term $\mathbf{h}^T\oslash\hat{\mathbf{h}}^T$ in Equation (1). For the sake of simplicity, we assume that all channel coefficients are the same, i.e., $\mathbf{h}=[h,h,\cdots,h]^T$, where $h\neq 0$. Thus, $\hat{\mathbf{h}}$ can be expressed as $\hat{\mathbf{h}}=\mathbf{h}+\mathbf{e}$ with $\mathbf{e}:=[e_1,e_2,\cdots,e_n]^T$ and therefore

$$\mathbf{h}^T\oslash\hat{\mathbf{h}}^T=\left[\frac{1}{1+e_1/h},\frac{1}{1+e_2/h},\cdots,\frac{1}{1+e_n/h}\right].$$

Casting the $\frac{e_i}{h}$ values into one vector, the normalized channel estimation error ($NCEE$) can be defined as $NCEE:=[\frac{e_1}{h},\frac{e_2}{h},\cdots,\frac{e_n}{h}]^T$. Considering the $NCEE$ as a random vector, its distribution depends on the channel estimation algorithm.

Here, due to the similarity of sensors and for simplicity, we assume $\frac{e_i}{h}$ are i.i.d., and therefore we re-define $NCEE$ as the random variable representing the distribution or value of each of them. In order to have a comprehensive performance evaluation, we model $NCEE$ as a normal distribution, a uniform distribution, and a constant deviation from the actual value h as follows. In Figure 5, the error free detection probability versus the noise power of the receiver σ_n^2 is shown, where the random vector $NCEE$ is normally distributed with mean zero and variance σ^2, denoted by $\mathcal{N}(0,\sigma^2)$. As expected, for the

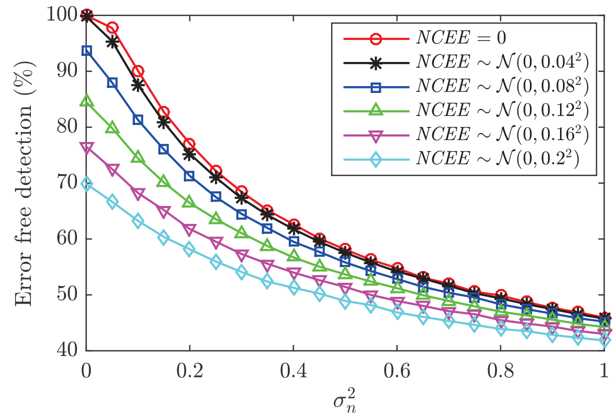

Fig. 5. The probability of error free detection versus the noise power σ_n^2 where NCEE is Gaussian distributed.

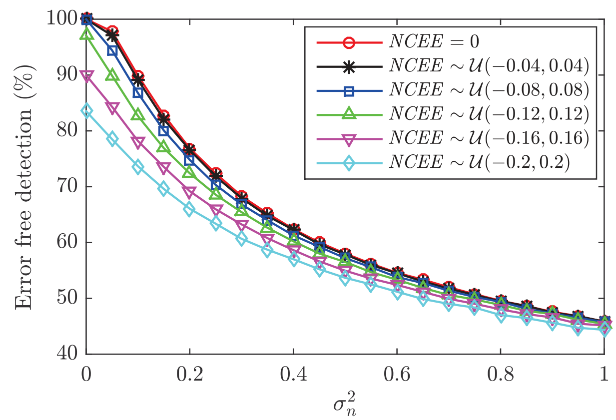

Fig. 6. The probability of error free detection versus the noise power σ_n^2 where NCEE is uniformly distributed.

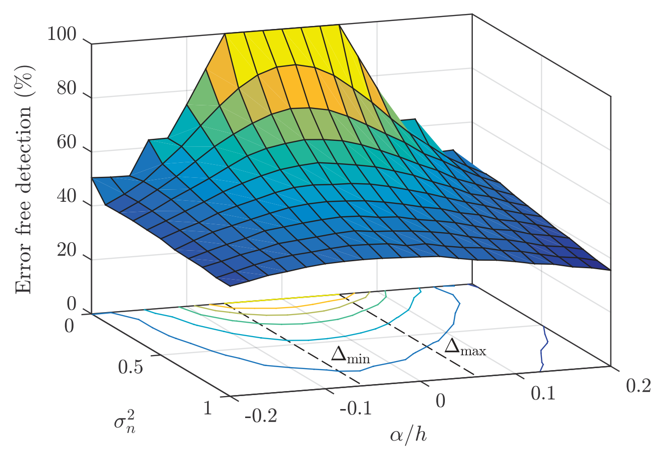

Fig. 7. The probability of error free detection versus the noise power σ_n^2 and the exact value of $NCEE$. Here, $\Delta_{\min}=-0.06$ and $\Delta_{\max}=0.06$.

zero value of σ_n^2 and $NCEE = 0$, the performance is error free and by increasing the noise power or the variance of $NCEE$, the performance degrades correspondingly. In Figure 6, the same evaluation is conducted, but where $NCEE$ is uniformly distributed in the interval $(a, b),\ a, b \in \mathbb{R}$, denoted by $\mathcal{U}(a, b)$. The reason for considering a uniform distribution is the fact that with such a distribution, each entry of $NCEE$ is upper bounded by b and lower bounded by a. This is contrary to any Gaussian distribution with a non-zero variance, which was explored in Figure 5. The degradation trend of the system's performance in Figure 6 is similar to that of Figure 5, except that for a uniform distribution $\mathcal{U}(-\sigma, \sigma)$, the amount of degradation is typically less than that of an equivalent normal distribution $\mathcal{N}(0, \sigma^2)$, which is due to the bounded error characteristic in $\mathcal{U}(-\sigma, \sigma)$. In Figure 7, the probability of error free detection is plotted in three dimensions as a function of σ_n^2 and $\frac{\alpha}{h}$, where α is the value of all individual channel estimation errors, i.e., $\mathbf{e} = [\alpha, \alpha, \cdots \alpha]^T$. In fact, the surface in Figure 7 demonstrates the conjoint effect of the noise power and the actual value of $NCEE$, which is $\frac{\alpha}{h}$ here, on the system's reliability. The important conclusion drawn from this figure is the fact that neglecting the effect of noise power, i.e., for $\sigma_n^2 = 0$, the communication is error free for $NCEE$ between $\Delta_{\min} = -0.06$ and $\Delta_{\max} = 0.06$. In other words, for a reliable target detection, the $NCEE$ deviation of the proposed model with $n = 3, \rho = 2$ and $e_i = \alpha$ for every $i \in \mathbb{F}_1^n$, should not exceed 6%. In Figure 6, the performance of the curve associated with the case $NCEE \sim \mathcal{U}(-0.04, 0.04)$ compared to the case $NCEE = 0$ justifies this result, considering the fact that $0.04 \in (\Delta_{\min}, \Delta_{\max})$.

IV. Conclusion

A fast multi-target detection technique for a binary wireless sensor network was proposed where the binary sensors in the detection area are arranged on a circle with the single antenna sink node on the central axis equidistant to the sensors such that the dominant LOS communication is guaranteed. As in a resource-constrained WSN, an efficient distributed power allocation algorithm was proposed for the BWSN model and it was shown that at any instant, the data of the whole n sensors observing n targets can be simultaneously decoded at the sink node, despite all sensors transmit at the same time and on the same narrow frequency band, and have no cooperation with each other. The most important achievement of this fast detection scheme is that all data for one time-slot is live, and there is no computationally costly coding or decoding scheme involved to achieve that, which in turn accelerates the decoding at the fusion center. As a result, the phenomenon can be tracked accurately as there is no data loss induced by sensors transmitting in different time slots. The appropriate channel estimation scheme was proposed and the effects of the normalized channel estimation error in conjunction with the AWGN of the receiver on the detection performance was investigated in detail by the conducted simulations. Due to the simultaneous detection in one time slot, the proposed model minimizes the multi-target detection time in a pre-deployed distributed BWSN subject to the single narrow band frequency constraint and uniform energy consumption distribution.

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