Robustness of the Counting Rule for Distributed Detection in Wireless Sensor Networks

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***Abstract*—We consider the problem of energy-efficient distributed detection to infer the presence of a target in a wireless sensor network and analyze its robustness to modeling uncertainties. The sensors make noisy observations of the target's signal power, which follows the isotropic power-attenuation model. Binary local decisions of the sensors are transmitted to a fusion center, where a global inference regarding the target's presence is made, based on the counting rule. We consider uncertain knowledge of: 1) the signal decay exponent of the wireless medium; 2) the power attenuation constant; and 3) the distance between the target and the sensors. For a given degree of uncertainty, we show that there exists a limit on the target's signal power below which the distributed detector fails to achieve the desired performance regardless of the number of sensors deployed. Simulation results are presented to determine the level of sensitivity of the detector to uncertainty in these parameters. The results throw light on the limits of robustness for distributed detection, akin to "SNR walls" for classical detection.**

***Index Terms*—Counting rule, distributed detection, energy efficiency, robust sensing, sensitivity.**

I. Introduction

DISTRIBUTED detection in wireless sensor networks (WSNs) has received significant attention both from theoretical and practical perspectives [1]–[3]. One of the key practical considerations for distributed detection is the energy efficiency of the network, since the WSNs normally operate in constrained settings (for example, low-cost and low-power sensors, limited communication bandwidth, etc.) [4]. Numerous methods to improve the energy efficiency of WSNs have been proposed. Examples include optimal sensor-selection schemes for distributed detection with minimum communication [5]–[9], energy-efficient routing protocols and passive clustering techniques to enhance the lifetimes of the energy-constrained sensors [10]–[13], distributed data compression and transmission [14], and collaborative signal processing [15]. Various sensor-transmission policies have also been devised wherein the local sensors transmit their observations, or local decisions, to a fusion center in an energy-efficient manner. Examples include censoring sensors [16], ordering sensor transmissions [17], [18], transmitting local sensor decisions in binary form to the fusion center [19]–[24] for efficient utilization of the network's communication bandwidth.

Another practical aspect in the operation of the WSNs is the sensitivity of the statistical inference procedures to uncertainties in modeling the environment in which the WSN operates. The inference schemes and their performances are characterized by many parameters, some of which are obtained via experimentation, while a few are obtained during the deployment stage of the WSN. For example, the signal-decay exponent of the wireless medium is generally obtained by using radiowave-propagation models to perform experiments in the environment in which the WSN is deployed and by using a variety of mathematical approximations [25]. Exact prediction of such parameters is possible only for very simple cases, such as the free space propagation model. In practice, experimental data is commonly affected by measurement errors due to miscalibration and lack of awareness of different errors to which instruments are subjected to [26]–[29]. Performance of signal-processing algorithms under modeling uncertainties has been widely studied [30]. It has been shown that modeling uncertainties deteriorate the performance of uncertainty-agnostic detectors (such as energy detectors and matched filters) and how accounting for these uncertainties improves their performance [31]–[34]. Therefore, it is important to analyze the performance of inference procedures, such as detection and estimation, via the use of WSNs in the presence of modeling uncertainties.

In this letter, we provide sensitivity analysis of the performance of an energy-efficient distributed detection scheme due to uncertainties in the system parameters associated with the hypothesis testing problem. As a concrete example, we consider the problem of distributed target detection in a WSN using the counting rule proposed in [19]. The setup comprises a large number of sensors deployed to detect the presence of a target in the ROI. The local-sensor decisions are transmitted to the fusion center in binary form (rather than unquantized data) to improve the utilization of the communication bandwidth of the WSN. At the fusion center, the number of local-sensor detections are counted and compared to a threshold to make a system-level inference. We consider uncertain knowledge of three parameters used to model the hypothesis testing problem: 1) the signal-decay exponent; 2) the attenuation constant of the medium; and 3) the distance between the target and the sensors. We show that, given the degree of uncertainty in these parameters, there exist limits on the target's signal power below which the

Manuscript received April 2, 2018; revised May 19, 2018; accepted June 11, 2018. Date of publication June 25, 2018; date of current version July 4, 2018. This work was supported by ARO under Grant W911NF-14-1-0339. The associate editor coordinating the review of this manuscript and approving it for publication was Dr. Antonio Garcia Marques. *(Corresponding author: Kyatsandra G. Nagananda.)*

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Digital Object Identifier 10.1109/LSP.2018.2850529

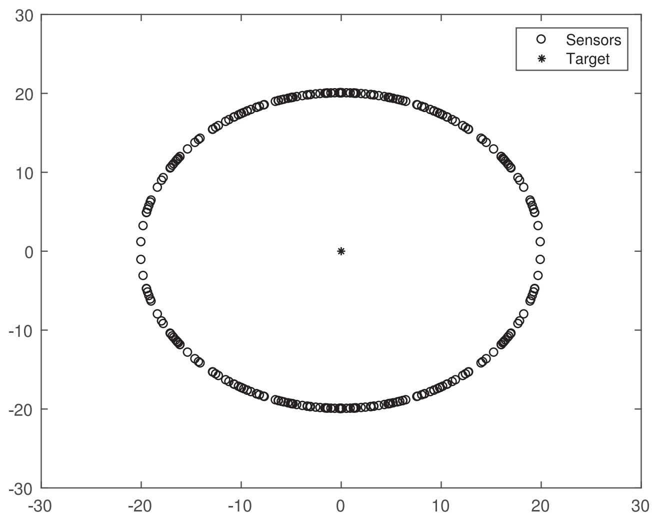

Fig. 1. Sensors deployed along the circumference of a circle.

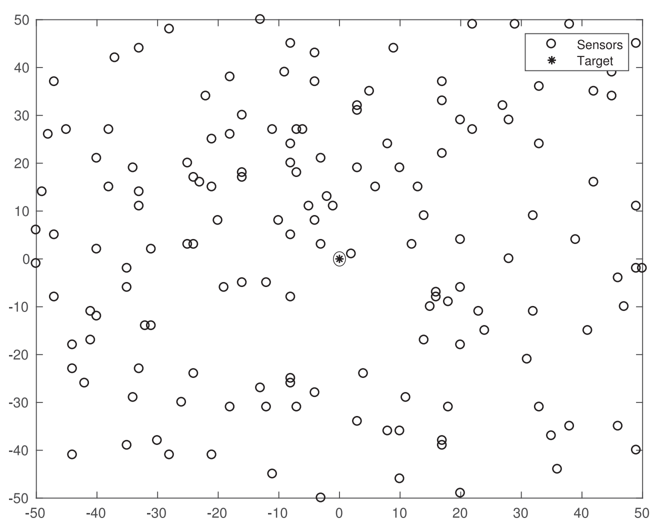

Fig. 2. Randomly deployed sensors.

counting-rule detector fails to achieve the desired performance, no matter how many sensors are deployed in the WSN. We consider two different sensor-deployment scenarios, and present simulation results to show the sensitivity of the counting rule to modeling uncertainties. Results show that the counting rule is most sensitive to uncertainty in the signal-decay exponent and is least sensitive to uncertainty in the power-attenuation constant. Our work is similar in spirit to the notion of "SNR walls" for signal detection [32], and complements the work on robustness of the counting rule presented in [35] and [36]. It also provides guidelines to analyze the robustness of various target-detection schemes in the existing literature; see, for example, [37]–[41].

II. System Model

Without loss of generality, the target (if present) is assumed to be located at the origin and N sensors are deployed in the region of interest (ROI), which is a square of area b^2 units. We consider two scenarios: (i) the sensors are deployed along the circumference of a circle of radius d units (see Fig. 1); and (ii) the sensors are randomly deployed in the ROI (see Fig. 2), where the ith sensor is located at a distance d_i from the target. The target's signal power is assumed to follow the isotropic power-attenuation model (see [22, Sec. 2]). The signal power at sensor i is given by

$$a_i^2 = \frac{P_0}{1+\alpha d_i^n},\ i = 1,\ldots,N \tag{1}$$

where P_0 is the target's signal power at distance zero, n is the signal decay exponent taking values between 2 and 3, and α is a constant (larger α implies faster power decay). The distance $d_i = \sqrt{x_i^2 + y_i^2}$, where (x_i, y_i) is the location of the ith sensor in the ROI. For scenario (i), $d_i = d$, for $i = 1,\ldots,N$. The ith sensor's observation is denoted by z_i.

Given z_i, the ith sensor seeks to resolve the following hypotheses: $H_0 : z_i = w_i$ and $H_1 : z_i = a_i + w_i$, where $w_i \sim \mathcal{N}(0,1)$. We assume that all the local sensors use the same threshold τ to make a local decision. The sensor-level false alarm and detection probabilities are given by $p_{\text{fa}} = Q(\tau)$ and $p_{d_i} = Q(\tau - \sqrt{\frac{P_0}{1+\alpha d_i^n}})$, respectively, where $Q(\cdot)$ is the complementary distribution function of the standard Gaussian distribution. A local sensor transmits its decision in binary form ($I_i \in \{0,1\}$; $I_i = 1$ if there is a detection, otherwise $I_i = 0$) to the fusion center, where the number of detections made by the local sensors are counted and compared to a threshold T. The performance of this counting-rule detector is characterized in [22] (also see [19]–[23]). The system-level false-alarm probability is given by

$$P_{\text{fa}} \approx Q\left(\frac{T - Np_{\text{fa}}}{\sqrt{Np_{\text{fa}}(1-p_{\text{fa}})}}\right). \tag{2}$$

The following notation is introduced before providing an expression for the system-level detection probability P_{d} [22, Sec. 4.2]:

$$\gamma = Q\left(\tau - \sqrt{\frac{P_0}{1+\alpha\left(\frac{\sqrt{2}b}{2}\right)^n}}\right) \tag{3}$$

$$\bar{p}_{\text{d}} = \frac{2\pi}{b^2}\int_0^{b/2} Q\left(\tau - \sqrt{\frac{P_0}{1+\alpha r^n}}\right) r dr + \left(1 - \frac{\pi}{4}\right)\gamma \tag{4}$$

$$\bar{\sigma}^2 = \frac{2\pi}{b^2}\int_0^{b/2}\left(1 - Q\left(\tau - \sqrt{\frac{P_0}{1+\alpha r^n}}\right)\right) \times Q\left(\tau - \sqrt{\frac{P_0}{1+\alpha r^n}}\right) r dr + \left(1-\frac{\pi}{4}\right)\gamma(1-\gamma) \tag{5}$$

where $r = \sqrt{x^2 + y^2}$. Finally, the system-level P_d is given by

$$P_d = Q\left(\frac{T - N\bar{p}_d}{\sqrt{N\bar{\sigma}^2}}\right). \tag{6}$$

By setting $p_{d_i} = p_d$ in the Chair–Varshney fusion rule [42], we obtain the optimal counting rule [22, Sec. 4.5]. In practice, the parameters n and α pertaining to the wireless medium are obtained by performing experiments before the WSN is deployed, while the distances d_is can be inferred after deployment, though they are generally unknown to the WSN. In this letter, we assume uncertain knowledge of n, α, and d_is and analyze the sensitivity of the counting rule.

III. Sensitivity to Uncertain Parameters

In this section, we analyze the behavior of the counting rule by taking into account the modeling uncertainties associated with parameters n, α, and d_i. We first consider uncertainty in the signal decay exponent n. We say that the counting-rule detector is robust to uncertainties in the signal-decay exponent n if it achieves the desired system-level performance by satisfying the following conditions:

$$\sup_n P_{\text{fa}}(N, n) \le P_{\text{fa}}^* \tag{7}$$

$$\inf_n P_d(N, n) \ge P_d^* \tag{8}$$

for some $0 \le P_{\text{fa}}^* \le 1$ and $0 \le P_d^* \le 1$. We say that the counting rule is nonrobust for a given value of P_0 if it cannot achieve the desired performance, i.e., the (P_d, P_{fa})-pair, where $0 \le P_{\text{fa}} \le 1/2$, $1/2 \le P_d \le 1$ even when the number of sensors N is arbitrarily large. Simulation results show that there exists a threshold value P_0' such that the counting rule is nonrobust for all $P_0 < P_0'$. Similar definitions of robustness and detector "breakdown" hold for uncertainties in α and d_is. For simplicity, the sensitivity analysis is performed by considering the uncertainties in n, α, and d_is independently; the case where the uncertainties are jointly analyzed is complicated and is relegated to future work.

For convenience of analysis, we characterize the degree of uncertainty in terms of a single parameter $\phi > 0$, i.e., we let $n = \phi n$. Using simple modifications to (2) and (6), it can be shown that the number of sensors N required to achieve the desired (P_d, P_{fa})-pair robustly [in the sense of (7) and (8)] in the presence of uncertainty in n for the scenario where the sensors are deployed along the circumference of the circle of radius d is

$$N = \left[\frac{Q^{-1}(P_d)\sqrt{p_d'(1-p_d')} - Q^{-1}(P_{\text{fa}})\sqrt{p_{\text{fa}}(1-p_{\text{fa}})}}{p_{\text{fa}} - p_d'}\right]^2 \tag{9}$$

where $p_d' = Q(\tau - \sqrt{\frac{P_0}{1+\alpha d_i^{\phi n}}})$. In the next section, we will show that (9) in fact reveals a limit on the target's signal power, below which it becomes impossible to achieve the desired (P_d, P_{fa}) and at the same time fails to satisfy the robustness conditions in (7) and (8). Essentially, this establishes the limits of robustness of the counting rule. For the scenario where the sensors are randomly distributed in the ROI, we get

$$N = \left[\frac{Q^{-1}(P_d)\sqrt{\bar{\sigma}^2} - Q^{-1}(P_{\text{fa}})\sqrt{p_{\text{fa}}(1-p_{\text{fa}})}}{p_{\text{fa}} - \bar{p}_d'}\right]^2 \tag{10}$$

where

$$\bar{p}_d' = \frac{2\pi}{b^2}\int_0^{b/2} Q\left(\tau - \sqrt{\frac{P_0}{1+\alpha r^{\phi n}}}\right) r dr \tag{11}$$

$$\bar{\sigma}^2 = \frac{2\pi}{b^2}\int_0^{b/2}\left(1 - Q\left(\tau - \sqrt{\frac{P_0}{1+\alpha r^{\phi n}}}\right)\right) \times Q\left(\tau - \sqrt{\frac{P_0}{1+\alpha r^{\phi n}}}\right) r dr. \tag{12}$$

To analyze the performance of the counting rule in the presence of uncertainties in the attenuation constant α we let $\alpha = \omega\alpha$, where the parameter $\omega > 0$ quantifies the degree of uncertainty. In this case, the expression for the number of sensors N needed to achieve the system-level (P_d, P_{fa})-pair robustly is similar to those in (9) [for scenario (i)] and (10) [for scenario (ii)], but with the following differences:

$$p_d' = Q\left(\tau - \sqrt{\frac{P_0}{1+\omega\alpha d_i^n}}\right) \tag{13}$$

$$\bar{p}_d' = \frac{2\pi}{b^2}\int_0^{b/2} Q\left(\tau - \sqrt{\frac{P_0}{1+\omega\alpha r^n}}\right) r dr \tag{14}$$

$$\bar{\sigma}^2 = \frac{2\pi}{b^2}\int_0^{b/2}\left(1 - Q\left(\tau - \sqrt{\frac{P_0}{1+\omega\alpha r^n}}\right)\right) \times Q\left(\tau - \sqrt{\frac{P_0}{1+\omega\alpha r^n}}\right) r dr. \tag{15}$$

Last, for the uncertainty in the knowledge of the distance d_i between the ith sensor and the target, we let $d_i = \rho d_i$, where the uncertainty is quantified by $\rho > 0$. Here again, the number of sensors N required to attain the desired system-level (P_d, P_{fa})-pair robustly is the same as in (9) [for scenario (i)] and (10) [for scenario (ii)] with

$$p_d' = Q\left(\tau - \sqrt{\frac{P_0}{1+\alpha\rho^n d^n}}\right) \tag{16}$$

$$\bar{p}_d' = \frac{2\pi}{b^2}\int_0^{b/2} Q\left(\tau - \sqrt{\frac{P_0}{1+\alpha\rho^n r^n}}\right) r dr \tag{17}$$

$$\bar{\sigma}^2 = \frac{2\pi}{b^2}\int_0^{b/2}\left(1 - Q\left(\tau - \sqrt{\frac{P_0}{1+\alpha\rho^n r^n}}\right)\right) \times Q\left(\tau - \sqrt{\frac{P_0}{1+\alpha\rho^n r^n}}\right) r dr. \tag{18}$$

IV. Experimental Results and Discussion

In this section, we evaluate the formulas derived in the previous section to show how the robustness of the detector breaks down due to modeling uncertainties. We note that the results demonstrate the robustness of the system-level (P_d, P_{fa}) performance and not of the local sensor-level (p_{d_i}, p_{fa}) performance. This distinguishes our results from the SNR walls of [32], which was for centralized detection.

For scenario (i), the target is located at the origin in the ROI, which is a square of area 50 units, and the sensors are deployed along the circumference of the circle of radius $d = 20$ units. We consider the local sensor-level $p_{\text{fa}} = 0.2$, while the desired system-level performance is $(P_{\text{d}}, P_{\text{fa}}) = (0.9, 01)$. Similar to [22], we let the signal-decay exponent $n = 2$ and the attenuation constant $\alpha = 200$. We express the degree of uncertainty in n, α, and d on the decibel scale. We consider three uncertainty values for each parameter; specifically, when we deal with uncertainty in the signal-decay exponent n, we let $\phi = 0.2$ dB, ϕ= 2 dB, and ϕ= 5 dB. Similarly for ω and ρ when dealing with uncertainties in α and d, respectively.

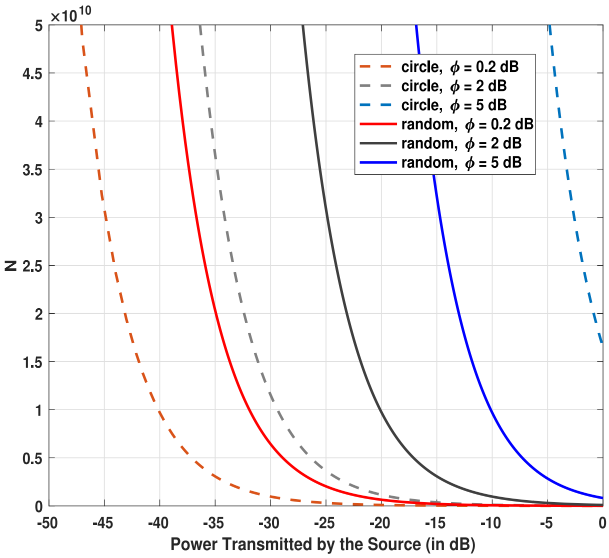

Fig. 3. Robustness to uncertainty in n when the sensors are along the circumference of a circle and when they are randomly deployed in the ROI.

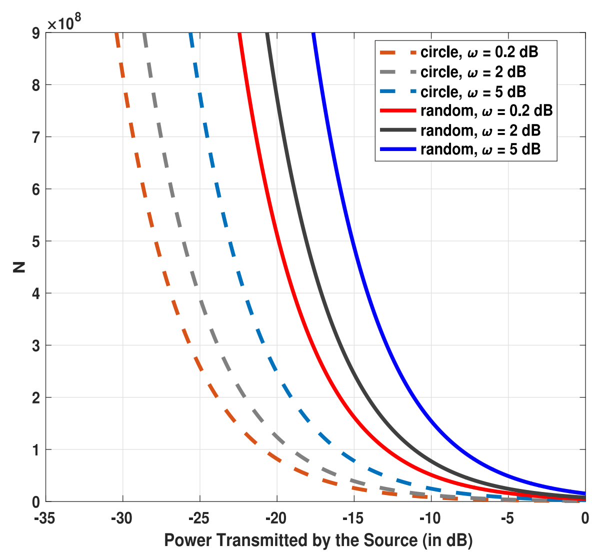

Fig. 4. Robustness to uncertainty in α when the sensors are along the circumference of a circle and when they are randomly deployed in the ROI.

In Fig. 3, we plot the number of sensors N required to robustly achieve the desired $(P_{\mathrm{d}}, P_{\mathrm{fa}})$-pair for various values of the target's signal power when there is uncertainty in the signal-decay exponent n. We show the results for the scenario where the sensors are along the circumference of a circle and when the sensors are randomly deployed in the ROI. The following is the interpretation of this plot: Given the target's signal power, we can infer the number of sensors required to achieve the desired $(P_{\mathrm{d}}, P_{\mathrm{fa}})$-pair robustly under the given degree of uncertainty. If the target's signal power is reduced below this level keeping the degree of uncertainty constant, then no matter how many more sensors are added to the network, it becomes impossible to achieve this performance robustly. In other words, the increasing trend in Fig. 3 establishes the limits of robustness of the counting rule due to uncertainty in n, beyond which the detector breaks down. From Fig. 3, it can be seen that this limit is demonstrated by a wall-type behavior, which indicates how

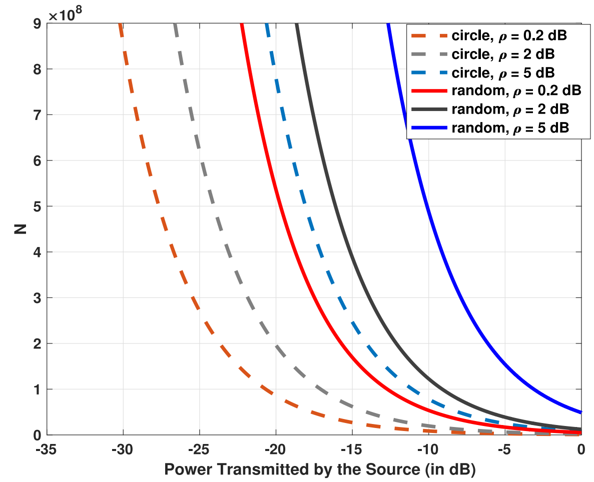

Fig. 5. Robustness to uncertainty in d_i when the sensors are along the circumference of a circle and when they are randomly deployed in the ROI.

the robustness breaks down in spite of using an arbitrarily large number of sensors. A similar behavior can be observed for uncertainties in α and d, as shown in Figs. 4 and 5, respectively. By comparing Figs. 3–5, it can also be seen that for a given degree of uncertainty, the counting rule is most sensitive to uncertainty in n and is least sensitive to uncertainty in α, both when the sensors are placed along the circumference of a circle and when they are randomly deployed.

V. Concluding Remarks

We studied the limits of robustness of the counting-rule detector to uncertainties in modeling parameters, such as the signal-decay exponent, the power-attenuation constant, and the distance between the target and the sensors. We considered two sensor-deployment scenarios and showed that among the three parameters considered the counting rule is most sensitive to uncertainties in the signal-decay exponent, while it is least sensitive to the power-attenuation constant. Beyond studying the impact of modeling uncertainties on the performance of distributed detection in WSNs, our results show the broader applicability of the notion of performance limits in detection problems originally studied in [32], where SNR walls for energy detectors were considered. Note that, the received-signal strength is a function of the distance of the sensor from the source. When the noise variance varies across the sensors, it is possible to have a sensitivity analysis for different local p_{fa}, however, this is outside the scope of the present letter and is relegated to future work.

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