DISTRIBUTED TARGET DETECTION IN CENTRALIZED WIRELESS SENSOR NETWORKS WITH COMMUNICATION CONSTRAINTS

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ABSTRACT

Distributed inference is an important and challenging problem in wireless sensor networks (WSNs). In this paper we consider distributed detection of a target in centralized WSNs (i.e. WSNs with a fusion centre) subject to communication constraints. We focus on the parallel network topology, where the sensors can only exchange information with the fusion centre, and consider conditionally dependent observations. We develop two types of local decision rules for the sensors (binary and binary with abstention), based on the Neyman-Pearson criterion, and a fusion rule based on a support vector machine (SVM). Under these circumstances we show empirically that, even when individual sensors with very poor performance are used, both local configurations are able to provide very good detection rates as the number of nodes increases.

1. INTRODUCTION

Dense wireless sensor networks (WSNs) composed of a large number of sensors are becoming more and more popular for many applications thanks to the increasing availability of cheap, small and intelligent sensors [13]. Distributed or decentralized learning and inference is an important and challenging problem in WSNs that has attracted much attention from the signal processing and machine learning communities [7]. From a statistical signal processing point of view, inference problems can be classified into two broad categories: decision or detection problems, where the goal is discriminating between a finite number of hypothesis, and estimation tasks, where the goal is inferring an unknown signal.

We focus on distributed target detection in centralized WSNs with a fusion centre subject to communication constraints. Under this setting, the goal of the WSN is providing enough information to the fusion centre to discriminate between two hypothesis (absence or presence of a target) in an energy efficient way, i.e. transmitting only informative decisions from the sensors with a minimum number of bits/observation. The distributed detection problem in WSNs has been widely studied over the last two decades, with most work concentrating on the extension of classical results and methods from centralized detection to the distributed setting, particularly for conditionally independent observations [12, 4].

In this paper we consider the distributed learning model with abstention proposed in [6], where the fusion center queries the sensors about their measurements at a known location, and apply it to the distributed target detection problem, where the target's location is unknown. Note that this model is similar to the decentralized detection problem with censoring sensors, originally proposed by [8] and extended later on by several authors [3, 2]. However, our approach deviates from those approaches in four main issues: the empirical rather than theoretical view taken, the use of a physically-inspired model for the observations based on the free space propagation model, the simple and independent criterion adopted for the decision rule in each sensor, and, most notably, in the fact that we consider conditionally dependent observations.

The paper is organized as follows. In Section 2 we introduce the problem, briefly describing each of the stages that must be considered. Then, we develop the local decision rules for the sensors, based on the Neyman-Pearson (NP) criterion, in Section 3, and the fusion rule, based on a support vector machine (SVM), in Section 4. The good performance of the proposed scheme is demonstrated through simulations in Section 5, and the conclusions and future lines close the paper in Secion 6.

2. PROBLEM STATEMENT

In this paper we analyze the problem of distributed detection in *centralized* wireless sensor networks (WSNs). We consider a rectangular observation area, $A = X_1 \times X_2 = [-\Delta x_1,\ \Delta x_1] \times [-\Delta x_2,\ \Delta x_2]$, inside which N identical sensors are placed at fixed positions $\mathbf{x}_i = (x_{1,i},\ x_{2,i})$ ($1 \le i \le N$, $-\Delta x_1 \le x_{1,i} \le \Delta x_1$, $-\Delta x_2 \le x_{2,i} \le \Delta x_2$) and a single fusion centre is located at an arbitrary (but known) position, $(x_1^*,\ x_2^*)$. We focus on the *parallel network* configuration [11], where the sensors are only allowed to communicate with the fusion centre (either directly or through multiple hops), whereas local exchanges of information between them are forbidden. Each sensor takes samples from some physical magnitude ($y_i[k]$ for $1 \le k \le K$) at its own position, either periodically or when commanded by the fusion centre, and the goal of the WSN is detecting (and eventually even locating and tracking) a target entering its range.

From a mathematical point of view we can model this problem as a hypothesis test with with two possible situations: the noise or negative hypothesis (H_{-1}), where no target is present inside A, and the target or positive hypothesis (H_1), where one or more targets are located inside A. Under the *negative hypothesis* the sensor's measurements are simply independent identically distributed white Gaussian noise (WGN) samples, i.e. $y_i[k] = w_i[k]$ with $w_i[k] \sim N(0, \sigma_w^2)$ and $N(0, \sigma_w^2)$ denoting a univariate Gaussian PDF with zero mean and variance σ_w^2. Under the *positive hypothesis*, the sensor's measurements are the sum of the signal received from the target, $z_i[k]$, plus WGN, i.e. $y_i[k] = z_i[k] + w_i[k]$.

Regarding the physical magnitude, here we consider cheap sensors which are only able to measure a received signal's strength (RSS). Thus, $z_i[k] = \sqrt{P(d_i[k])}$, where $P(d_i[k])$ is the instantaneous power of the signal received by the i-th sensor at the k-th sampling instant.[1] Assuming the free space propagation model [9],

$$P(d_i[k]) = P(d_0)\left(\frac{d_i[k]}{d_0}\right)^{-\eta}, \tag{1}$$

where $d_i[k] = \|\mathbf{x}_i - \widetilde{\mathbf{x}}[k]\|_2$ is the Euclidean distance between the i-th sensor and the target, located at $\widetilde{\mathbf{x}}[k]$, $P(d_0)$ is the received power at a reference distance d_0 (usually $d_0 = 1$ m.), and η is the propagation constant (typically $2 \le \eta \le 4$).

Given the strict energy and bandwidth constraints characteristic of WSNs, the sensors cannot transmit their observations directly to the fusion centre. Therefore, each sensor applies an independent local decision rule on each new observation,

$$\lambda_i[k] = \Lambda_i(y_i[k];\ \boldsymbol{\theta}_i),$$

[1] In fact, the measurements at each sensor will be $y_i^2[k] = (z_i[k] + w_i[k])^2$. However, we can work equivalently with $y_i[k]$ instead of $y_i^2[k]$.

where Λ_i is the quantization or decision rule used by the i-th sensor, $\boldsymbol{\theta}_i$ its parameters, and $\lambda_i[k] \in \{\alpha_1, \ldots, \alpha_Q\}$ its result for the k-th sample, which can only take Q different quantized values. We assume that all the sensors use the same decision rule and, following the approach proposed in [6, 7], consider two types of decision rules based on thresholds on the RSS: binary and binary with abstention.[2]

After quantization every sensor transmits $\lambda_i[k]$ to the fusion centre, either directly or following some routing protocol through the network. Here we consider error-free communication channels, with each sensor transmitting at most one bit per observation. Finally, the fusion centre receives all the information from the sensors and takes a global decision about the presence or absence of a target by applying some global detection or fusion rule:

$$\hat{H}[k] = \Gamma(\boldsymbol{\lambda}[k];\ \boldsymbol{\phi}),$$

where $\hat{H}[k] \in \{H_{-1},\ H_1\}$ corresponds to the decision of the fusion centre (i.e. the estimated hypothesis) at the k-th time instant, $\boldsymbol{\lambda}[k] = [\lambda_1[k], \ldots, \lambda_N[k]]^\top$ are the quantized decisions from all the sensors, and $\boldsymbol{\phi}$ denotes the parameters of the fusion rule. In this paper we assume no computational or energy constraints for the fusion centre. Moreover, we also assume that a network training or calibration stage can be performed prior to its operative stage. Hence, we consider a support vector machine (SVM) based fusion rule.

3. LOCAL DETECTION RULES FOR THE SENSORS

3.1 Binary Detection Rule

The simplest local decision rule is the binary detection: only two levels are used for quantizing the output of each sensor (i.e. $Q = 2$) and the decision rule is simply given by

$$\lambda_i[k] = \Lambda_b(y_i[k];\ \gamma) = \begin{cases} -1, & |y_i[k]| < \gamma; \\ +1, & |y_i[k]| > \gamma; \end{cases} \tag{2}$$

where $\lambda_i[k] = -1$ corresponds to a negative decision (i.e. target absence or H_{-1}) and $\lambda_i[k] = +1$ to a positive decision (i.e. target presence or H_1), and its only parameter is the threshold, $\gamma = \gamma_{fa}$, which is obtained using the Neyman-Pearson criterion for a fixed false alarm rate, P_{fa}. Under the null hypothesis, the PDF for the observations of each sensor is

$$p(y_i[k]|H_{-1}) \sim N(0, \sigma_w^2),$$

and the false alarm probability is given by[3]

$$P_{fa} = 2\int_{\sqrt{\gamma_{fa}}}^{\infty} p(y_i[k]|H_{-1})\ \mathrm{d}y_i[k]. \tag{3}$$

Since $p(y_i[k]|H_{-1})$ is Gaussian, this integral can be easily solved, obtaining a closed-form expression for the threshold:

$$\gamma = \gamma_{fa} = 2\sigma_w^2 \left[\mathrm{erfc}^{-1}(P_{fa})\right]^2, \tag{4}$$

where $\mathrm{erfc}^{-1}(x)$ denotes the inverse of the complementary error function, defined as [1]

$$\mathrm{erfc}(x) = \frac{2}{\sqrt{\pi}} \int_x^{\infty} \exp(-t^2)\ \mathrm{d}t,$$

An interesting analysis for this decision rule can be provided by noting that, according to the propagation model given by (1), the noise free observations, $z_i[k]$, only depend on the distance between the sensors and the target. Hence, equating (1) to the false alarm threshold, γ_{fa}, we can easily obtain the *detection radius*,

$$r_d = d_0 \left(\frac{\gamma_{fa}}{P(d_0)}\right)^{-1/\eta}. \tag{5}$$

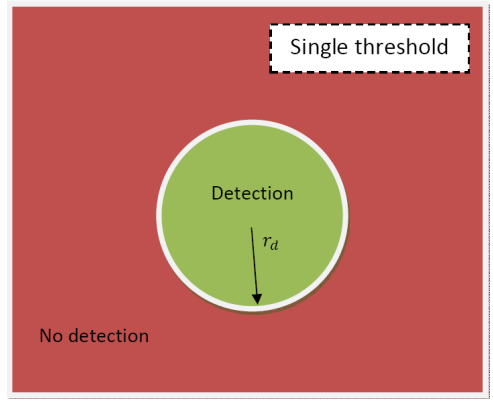

Figure 1: Detection range for the binary local decision rule.

Figure 1 shows the detection circle for a sensor placed at the origin. On the one hand, the sensor should detect any target located inside the circle (since the RSS is greater than the detection threshold), with those targets not detected corresponding to misdetections due to noise. On the other hand, outside this circle no target should be detected (since the RSS is lower than the detection threshold), with detections corresponding to false alarms caused again by noise.

Finally, note that the observations under hypothesis H_{-1} are conditionally independent [12], i.e.

$$p(\mathbf{y}[k]|H_{-1}) = \prod_{i=1}^{N} p(y_i[k]|H_{-1}),$$

meaning that the false alarm thresholds can be set independently for each sensor and the binary decision rule given by (2) is optimal from the point of view of obtaining the desired false alarm rate. Note also that, for an error-free channel and the binary decision rule, only positive decisions shall be transmitted: negative decisions are uninformative and spend valuable network energy. The presence of errors in the communications channel (e.g. the possibility of missing a transmitted message from a sensor) introduces uncertainty in the negative decisions. However, if the error rate is not too large, the energy saving obtained from not transmitting the negative decisions compensates for this uncertainty.

3.2 Binary Detection Rule with Abstention

A slightly more complex local decision rule is the binary detection with abstention: three levels are used for quantizing the output of each sensor (i.e. $Q = 3$) using a decision rule given by

$$\lambda_i[k] = \Lambda_a(y_i[k];\ \gamma_\ell,\ \gamma_h) = \begin{cases} -1, & |y_i[k]| < \gamma_\ell; \\ 0, & \gamma_\ell < |y_i[k]| < \gamma_h; \\ +1, & |y_i[k]| > \gamma_h; \end{cases} \tag{6}$$

where $\lambda_i[k] = -1$ and $\lambda_i[k] = +1$ are associated again to the noise and target hypotheses, H_{-1} and H_1 respectively, whereas $\lambda_i[k] = 0$ corresponds to a new local hypothesis, H_0, which denotes uncertainty about the presence or absence of a target.

In this case the decision rule has two parameters, the low level threshold, γ_ℓ, used to take a negative decision, and the high level threshold, γ_h, used to take a positive decision. Both are obtained

[2]Note that this is equivalent to imposing communication constraints on the network, as sensors are limited to transmitting at most a single bit per channel use and on average they transmit even less.

[3]We consider the threshold, γ_{fa}, over the instantaneous power received, $y_i^2[k]$. Thus, in (3) we have to use $\sqrt{\gamma_{fa}}$ instead.

again using the Neyman-Pearson criterion for fixed false alarm and no detection rates, P_{fa} and P_{nd} respectively. The false alarm threshold, γ_{fa}, is still given by (4), whereas we require the PDF of the observations under the target hypothesis, H_1, in order to obtain the no detection threshold, P_{nd}. When the position of the target is known (i.e. given $d_i[k]$ or equivalently $\widetilde{\mathbf{x}}$) the PDF of the observations is simply a Gaussian,

$$p(y_i[k]|\widetilde{\mathbf{x}},H_1) \sim N(\sqrt{P(d_i[k])},\sigma_w^2).$$

Note that, in this situation the observations are still conditionally independent, i.e.

$$p(\mathbf{y}[k]|\widetilde{\mathbf{x}},H_1) = \prod_{i=1}^{N} p(y_i[k]|\widetilde{\mathbf{x}},H_1),$$

since the only randomness comes from the noise, which is independent for each sensor. However, when the target's position is unknown this is no longer true, since the target's position, $\widetilde{\mathbf{x}}$, becomes a random variable. This means that the distance between the target and the observations, $d_i[k]$, and the RSS, $z_i[k]$, become random signals, and the PDF of each observation is now given by

$$\begin{aligned} p(y_i[k]|H_1) &= \int_A p(y_i[k]|\widetilde{\mathbf{x}},H_1)p(\widetilde{\mathbf{x}}|H_1)\,\mathrm{d}\widetilde{\mathbf{x}} \\ &= \frac{1}{4\Delta x_1 \Delta x_2}\int_A p(y_i[k]|\widetilde{\mathbf{x}},H_1)\,\mathrm{d}\widetilde{\mathbf{x}}, \end{aligned} \tag{7}$$

where, in order to obtain the last expression in (7), we have assumed a uniform distribution for $\widetilde{\mathbf{x}}$ inside the observation area,

$$p(\widetilde{\mathbf{x}}|H_1) = \begin{cases} \frac{1}{4\Delta x_1 \Delta x_2}, & \widetilde{\mathbf{x}} \in A; \\ 0, & \widetilde{\mathbf{x}} \notin A. \end{cases}$$

Unfortunately, a closed-form expression for the integral in (7) cannot be obtained due to the strongly nonlinear dependence of $d_i[k]$ on $\widetilde{\mathbf{x}}$. However, we only require $p(\widetilde{\mathbf{x}}|H_1)$ to obtain the no detection threshold through the following integral,

$$P_{nd} = \frac{1}{4\Delta x_1 \Delta x_2}\int_{-\sqrt{\gamma_{nd}}}^{\sqrt{\gamma_{nd}}}\int_A p(y_i[k]|\widetilde{\mathbf{x}},H_1)\,\mathrm{d}\widetilde{\mathbf{x}}\,\mathrm{d}y_i[k], \tag{8}$$

which only needs to be solved once for a particular value of γ_{nd}. Hence, we can take an empirical approach to this problem. First of all, we generate a large number of samples for $\widetilde{\mathbf{x}}$ and approximate $p(y_i[k]|\widetilde{\mathbf{x}},H_1)$ using impulses centered on the samples obtained,

$$p(y_i[k]|\widetilde{\mathbf{x}},H_1) \approx \frac{1}{M}\sum_{j=1}^{M} p(y_i[k]|\widetilde{\mathbf{x}}_j,H_1)\delta(\widetilde{\mathbf{x}}-\widetilde{\mathbf{x}}_j), \tag{9}$$

where M is the number of samples used for potential target's locations, $\widetilde{\mathbf{x}}_j$ ($1 \le j \le M$) indicates the precise positions obtained, and $\delta(\cdot)$ denotes Dirac's delta. Then, substituting (9) in (8) we obtain an approximation for the no detection probability, $P_{nd} \approx J(\gamma_{nd})$, where

$$J(\gamma_{nd}) = \frac{1}{2M}\sum_{j=1}^{M}\left[\mathrm{erf}\left(\frac{\sqrt{\gamma_{nd}}+\widetilde{\mathbf{x}}_j}{\sqrt{2\sigma_w^2}}\right)+\mathrm{erf}\left(\frac{\sqrt{\gamma_{nd}}-\widetilde{\mathbf{x}}_j}{\sqrt{2\sigma_w^2}}\right)\right], \tag{10}$$

and erf is the error function [1],

$$\mathrm{erf}(x) = \frac{2}{\sqrt{\pi}}\int_0^x \exp(-t^2)\,\mathrm{d}t = 1-\mathrm{erfc}(x).$$

Thus, the no detection threshold can be formally expressed as $\gamma_{nd} = J^{-1}(P_{nd})$. Finally, although (10) cannot be inverted to obtain an analytical expression for γ_{nd}, we notice that it is a strictly increasing function of γ_{nd}, which implies that this threshold is unique and can be easily determined by a simple one-dimensional grid search.

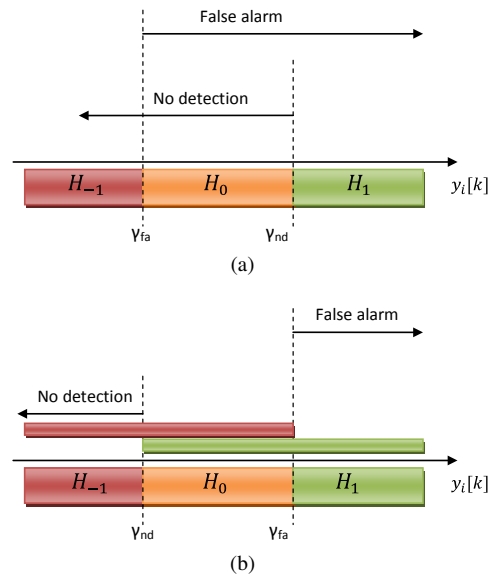

Figure 2: Thresholds for the binary detection rule with abstention. (a) $\gamma_{fa} < \gamma_{nd}$. (b) $\gamma_{fa} > \gamma_{nd}$.

Note that, since γ_{fa} and γ_{nd} have been obtained independently, in principle we cannot determine which one is lower *a priori*. Therefore, the final thresholds for the decision rule are established as

$$\begin{aligned} \gamma_\ell &= \min(\gamma_{fa},\ \gamma_{nd}), \\ \gamma_h &= \max(\gamma_{fa},\ \gamma_{nd}). \end{aligned}$$

According to the threshold selection and the decision rule, two possibilities exist for the uncertainty region, as shown in Figure 2:

1. $\gamma_{fa} < \gamma_{nd}$, as illustrated in Figure 2(a), meaning that $\gamma_\ell = \gamma_{fa}$, $\gamma_h = \gamma_{nd}$ and the uncertainty region corresponds to observations classified as target presence (i.e. H_1) by the low level threshold and as target absence (i.e. H_{-1}) by the high level threshold.
2. $\gamma_{fa} > \gamma_{nd}$, as illustrated in Figure 2(b), meaning that $\gamma_\ell = \gamma_{nd}$, $\gamma_h = \gamma_{fa}$ and the uncertainty region corresponds to observations classified as target absence (i.e. H_{-1}) by the low level threshold and as target presence (i.e. H_1) by the high level threshold.

In both cases there is no consensus between the two criteria (i.e. we cannot guarantee simultaneously the desired false alarm and no detection rates), so the sensor refrains from taking any final decision (either positive or negative) and returns an abstention.

We remark that a similar analysis to the binary decision rule can also be performed in terms of the detection and abstention radius, as shown in Figure 3. Here the inner radius, r_{int}, is obtained using γ_ℓ in (5) instead of γ_{fa}, whereas the outer radius, r_{ext}, is obtained using γ_h. Finally, we also notice that the results of the binary decision rule with abstention can also be communicated to the fusion centre using at most a single bit per observation [6, 7]: both positive and negative decisions are transmitted, whereas those sensors which abstain remain silent. Alternatively, note that in fact it may be more efficient to allow those sensors that abstain to transmit instead of those with negative decisions.

4. GLOBAL SVM-BASED FUSION RULE

In this section we briefly describe the global detection or fusion rule, which is based on a support vector machine (SVM). In using an SVM-based fusion rule we are making two assumptions:

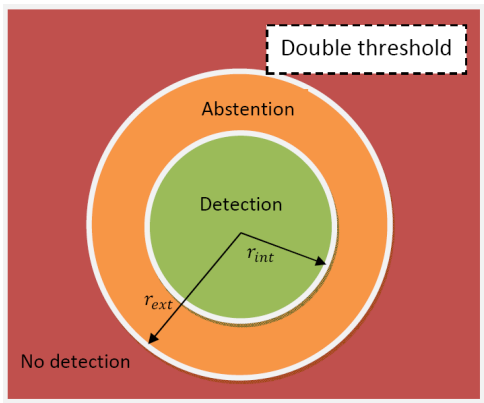

Figure 3: Detection and abstention ranges for the binary local decision rule with abstention.

1. The fusion centre is not constrained in energy or computational power, as training and evaluating the SVM is much more resource consuming than the simple local decision rules considered for the sensors.
2. A training stage (i.e. network calibration) can be performed using labelled inputs.

Under these circumstances, the SVM is known to provide a very good performance for a wide range of detection problems [10]. Hence, using the SVM as the global detector amounts to considering a very powerful "black box" fusion rule, assumed to be able to extract all the information contained in the inputs, so that we can concentrate on studying the performance of the local decision rules.

There are two critical stages in working with an SVM: selecting the kernel and training it. Regarding the first isssue, we only consider a linear kernel, since the dimension of the input space is large enough to allow us to perform the separation between the two hypothesis, as will be shown in Section 5. With respect to the second issue, the SVM training stage (i.e. the obtention of both the hyperparameters and the support vectors), it is performed using the LIB-SVM package [5] with a balanced data set consisting of 480 samples corresponding to the negative hypothesis (i.e. noise only measurements in the sensors) and 480 samples corresponding to the positive hypothesis (i.e. signal plus noise). For this second case we consider targets moving through the network following 6 prespecified trajectories (as part of the calibration stage) composed of a fixed number of samples (20), as shown in Figure 4.

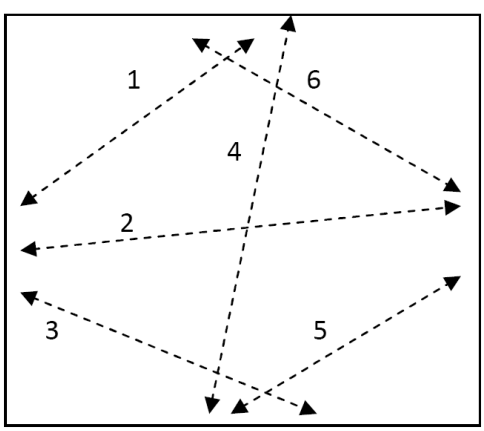

Figure 4: Trajectories used for training the SVM.

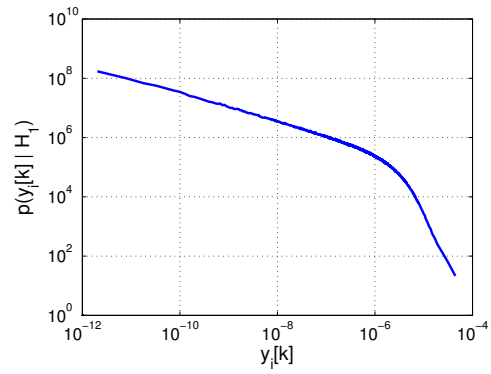

Figure 5: Empirical approximation to $p(y_i[k]|H_1)$ using (9) with $M = 10^6$ samples.

5. RESULTS

In this section we present empirical results obtained through simulations considering a 40000 m^2 observation area with $\Delta x_1 = \Delta x_2 = 100$ m., i.e. $A = [-100, 100] \times [-100, 100]$. Inside this area, a variable number of sensors, $N \in \{10,\ 50,\ 100,\ 300,\ 500,\ 1000\}$, are uniformly distributed. Note that the first case ($N = 10$) corresponds to a very sparse sensor placement (with only 0.00025 sensors/m^2), whereas the last situation ($N = 1000$) corresponds to a much denser WSN (with 0.025 sensors/m^2), allowing us to study the performance of the proposed local and global decision rules as the number of sensors increases. A target may be located inside the observation area or not. When a target is present, we assume that it transmits an RF signal with $P(d_0) = 1$ mW at $d_0 = 1$ m and that the propagation constant is $\eta = 2$. In both cases the noise power is $\sigma_w^2 = 10^{-6}$.

We are interested in analyzing the global performance when we combine cheap sensors with poor individual performance. Hence, we set $P_{fa} = P_{nd} \in \{0.1,\ 0.2,\ 0.3,\ 0.4\}$ and obtain the thresholds for both decision rules. On the one hand, the false alarm threshold, γ_{fa}, is straightforward to obtain from (4) for the different values of P_{fa}. On the other hand, for the no detection threshold, γ_{nd}, we need to obtain first an approximation for $p(y_i[k]|H_1)$, which does not depend on the number of sensors. Figure 5 shows the empirical approximation to this PDF obtained using $N = 300$ sensors and $M = 10^6$ uniformly distributed sample positions (i.e. $N \times M = 3 \times 10^8$ distances), which clearly shows the exponential decay in the PDF. Using this approximation we may obtain the thresholds and radius for the binary detection with abstention rule, as shown in Table 1. Note that in all cases $\gamma_\ell = \gamma_{nd}$ and $\gamma_h = \gamma_{fa}$, implying that $r_{ext} = r_d$. In fact, this will be the usual situation, as illustrated in Figure 6, since the thresholds only cross for $P_{fa} = P_{nd} \approx 0.47$.

Once the thresholds for the local decision rules have been established we generate the synthetic data and use them to train the SVM as indicated in Section 4. After the training stage, Figure 7 shows graphically a typical situation where a target (black square) is present on the bottom left portion of the observation area (normalized to $[-1, 1] \times [-1, 1]$) and sensors are represented by circles. Finally, Table 2 shows the performance results in terms of precision (percentage of correct decisions), sensitivity (percentage of correct positive decisions) and specificity (percentage of correct negative

Table 1: Thresholds and radius for binary detection with abstention.

P_{fa}	γ_ℓ	γ_h	r_{int}	r_{ext}
0.1	0.02×10^{-6}	2.71×10^{-6}	19.2	223.0
0.2	0.08×10^{-6}	1.64×10^{-6}	24.7	110.5
0.3	0.19×10^{-6}	1.07×10^{-6}	30.5	72.7
0.4	0.35×10^{-6}	0.71×10^{-6}	37.6	53.4

decisions) as a function of the false alarm probability, whereas in Table 3 we provide the same results as a function of the number of sensors. Note that good results are obtained in all cases, both for the binary local decision rule and the decision rule with abstention, especially as the number of sensors grows, even for very poor false alarm and no detection probabilities for the individual sensors.

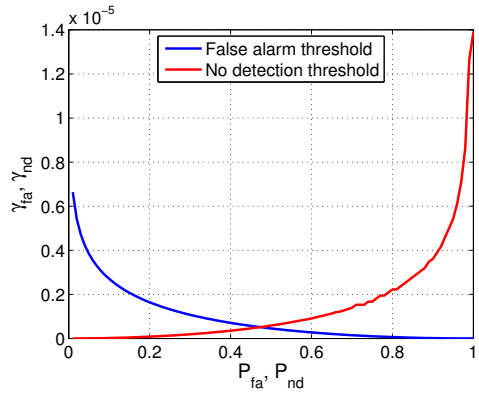

Figure 6: False alarm and no detection thresholds.

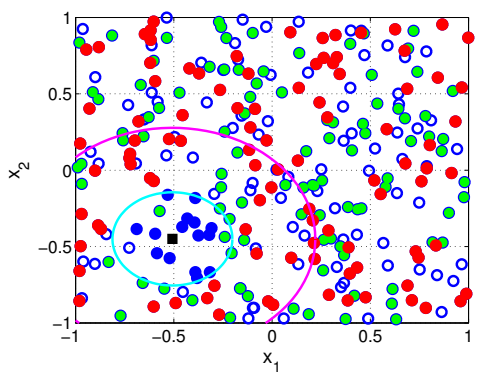

Figure 7: Example of network state at a given instant for one target (black square) and $N = 300$ sensors (circles) with $P_{fa} = P_{nd} = 0.3$: internal radius (cyan line), external radius (magenta line), correct detections (filled blue circles), no detections (unfilled blue circles), abstentions (green circles) and false alarms (red circles).

Table 2: Performance as a function of P_{fa} for $N = 1000$ in terms of precision (P), sensitivity (S) and specificity (E).

	Abstention			No Abstention		
P_{fa}	P	S	E	P	S	E
0.1	0.9525	0.9458	0.9592	0.9748	0.9683	0.9812
0.2	0.9406	0.9421	0.9392	0.9658	0.9612	0.9704
0.3	0.9254	0.9192	0.9317	0.9371	0.9354	0.9387
0.4	0.9021	0.8967	0.9075	0.9096	0.9071	0.9121

Table 3: Performance as a function N for $P_{fa} = 0.1$ in terms of precision (P), sensitivity (S) and specificity (E).

	Abstention			No Abstention		
N	P	S	E	P	S	E
100	0.7106	0.6704	0.7508	0.7375	0.7133	0.7617
300	0.8650	0.8596	0.8704	0.8858	0.8754	0.8962
500	0.8967	0.8821	0.9112	0.9235	0.9187	0.9283
1000	0.9525	0.9458	0.9592	0.9748	0.9683	0.9812

6. CONCLUSIONS AND FUTURE LINES

In this paper we have considered distributed detection in centralized wireless sensor networks, where the sensors cannot exchange information locally and are only allowed to transmit up to one bit per observation to the fusion centre. We have described two simple local decision rules (binary and binary with abstention) that can be applied independently for each observation of each sensor, showing empirically their good performance asymptotically (i.e. as the number of sensors increases) in combination with an SVM-based fusion rule, even for correlated measurements and poor performance of the individual sensors. Future work lines include providing a detailed theoretical analysis of the proposed scenario, extending it to location and tracking problems and considering the effect of transmission errors on the global performance of the network.

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