ADAPTIVE CONSENSUS-BASED DISTRIBUTED DETECTION IN WSN WITH UNRELIABLE LINKS

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ABSTRACT

Event detection is a crucial tasks in wireless sensor networks. The importance of a fast response makes distributed strategies, where nodes exchange information just with their one-hop neighbors to reach local decisions, more adequate than schemes where all nodes send observations to a central entity. Distributed detectors are usually based on average consensus, where all nodes iteratively communicate to asymptotically agree on a final result. In a realistic scenario, communications are subject to random failures, which impacts the performance of the consensus. We propose an alternative detector, which adapts to the statistical properties of the consensus and compensate deviations from the average. Simulation results show that this adaptive detector improves the performance and approximates to the one of the optimal detector.

***Index Terms*—** Distributed detection, average consensus, deflection coefficient

1. INTRODUCTION

The detection of an unexpected event is a determining task for multiple applications in wireless sensor networks (WSN). Detection of primary users by spectrum sensing in cognitive radios [1], intrusion detection [2], and catastrophe detection, such as fire [3] or landslide [4], are representative examples. Most of these applications require the detection process to be fast enough so that corresponding actions can be adopted in time. Hence, centralized schemes where nodes send their local observations to a central entity, which perform the optimal detection, are not the most appropriate strategies. In contrast, and for large scale networks, distributed approaches, where nodes exchange information just with their one-hop neighbors to make their final local decisions, provide the degree of flexibility and quickness that these applications demand. Further advantages of distributed detection are reduced communication bandwidth, increased reliability and reduced cost [5]. Distributed detection is usually solved by means of iterative consensus [6][7][8]. These schemes, where nodes exchange information until an agreement in a global common value is reached, rely on the fact that this common quantity is the average of the initial values of the nodes. In fact, and under certain conditions, this convergence to the average is guaranteed [9]. However, in a realistic scenario, where communications between nodes are subject to interferences and random link failures, the agreement value is a random variable different, in general, from the average. In this work, and starting from a consensus-based distributed implementation of the optimal detector for a known signal, we propose a variation of this detector, where the special features of the probabilistic consensus are considered. Our detector adapts itself to the statistical properties of the consensus in order to compensate its deviation from the average. We show how the adaptive detector increases the performance and approximates the one of the optimal detector. The paper is organized as follows: in Section 2 we provide some background and introduce the system models. In Section 3 we propose a consensus based distributed detector, and show how to refine it such that it adapts to statistical consensus properties. Section 4 presents some simulation results to verify the efficiency of our approach. Finally, conclusions are summarized in Section 5.

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2. BACKGROUND AND SYSTEM MODELS

We present some background necessary for the formulation of our proposal: the optimal detection of a known signal, and the concept of iterative consensus.

2.1. Optimal detection of a known signal

A WSN is deployed over the area of interest with the final aim of detecting an unexpected signal. The detection process can be cast as a binary decision problem, where the two alternative hypotheses, namely $\mathcal{H}_0$ and $\mathcal{H}_1$, denote respectively the absence or presence of the signal of interest, denoted by θ. This signal is perceived at each node i attenuated by a fading factor h_i, thus at the placement of each sensor i, the signal is received as $s_i = h_i\theta$. We denote by $\mathcal{E}$ the energy of the whole received signal, such that $\mathcal{E} = \|\mathbf{s}\|_2^2 = \sum_{i=1}^N s_i^2$. The signal $\mathbf{s}$ is corrupted by additive zero-mean Gaussian noise $\mathbf{w}$ with covariance matrix $\sigma^2\mathbf{I}$. If we denote by $\mathbf{y}$ the vector of observations, both hypotheses can be formulated as follows:

$$\begin{aligned}\mathcal{H}_0 &: \mathbf{y} = \mathbf{w} \\ \mathcal{H}_1 &: \mathbf{y} = \mathbf{h}\theta + \mathbf{w} = \mathbf{s} + \mathbf{w}\end{aligned} \tag{1}$$

If θ is known, the Neyman-Pearson theorem [10] provides the optimal decision criterion, where the likelihood ratio is compared with a threshold γ, previously computed to minimize a given false alarm probability P_{FA}. For the linear model in (1), the Neyman Pearson rule becomes:

$$T(\mathbf{y}) = \mathbf{y}^T\mathbf{s} = \sum_{i=1}^{N} y_i s_i \geq \gamma' \tag{2}$$

where $\gamma' = \sigma^2 \log\gamma + \frac{\mathbf{s}^T\mathbf{s}}{2}$. Since $T(\mathbf{y})$ is Gaussian, we have that the P_{FA} of the detector is given by:

$$P_{FA} = \Pr\left\{T(\mathbf{y}) > \gamma' |\, \mathcal{H}_0\right\} = Q\left(\frac{\gamma'}{\sqrt{\sigma^2}}\right) \tag{3}$$

The detection performance can also be characterized by the deflection coefficient [11]:

$$d^2 = \frac{\left(\mathbb{E}[T;\mathcal{H}_1] - \mathbb{E}[T;\mathcal{H}_0]\right)^2}{\text{var}[T;\mathcal{H}_0]} = \frac{1}{\sigma^2}\mathbf{s}^T\mathbf{s} = \frac{\mathcal{E}}{\sigma^2}$$

which gives an accurate insight about the performance of the detector even for non Gaussian scenarios [11]. The relationship between d^2 and P_{FA} can be found in [10].

2.2. Iterative consensus under unreliable links

At each time instant k, the network can be modeled as a random graph $\mathbf{G}(k) = (\mathbf{V}, \mathbf{E}(k))$, with a set $\mathbf{V}$ of N nodes and a set $\mathbf{E}(k)$ of links existing at time k. We denote by $\mathbf{A}(k)$ the $N \times N$ adjacency matrix, whose entry $[\mathbf{A}(k)]_{ij}$ is equal to 1 if $(i,j) \in \mathbf{E}(k)$ and 0 otherwise. Thus, this matrix is random and, in general, not symmetric. The random set of neighbors of a node i at time k is defined as $\mathbf{\Omega}_i(k) = \{j \in \mathbf{V} : (i,j) \in \mathbf{E}(k)\}$. The degree matrix $\mathbf{D}(k)$ is a diagonal matrix whose entries are $[\mathbf{D}]_{ii} = |\mathbf{\Omega}_i(k)|$, and the instantaneous Laplacian matrix is defined as $\mathbf{L}(k) = \mathbf{D}(k) - \mathbf{A}(k)$. If each node i of the network takes a random value $x_i(0)$, the distributed consensus problem consists of a succession of iterations, at each of which every node i refines its own state $x_i(k)$ by exchanging information only with those nodes belonging to $\mathbf{\Omega}_i(k)$. This procedure continues until all nodes agree asymptotically on a global common value, i.e. $\lim_{k\to\infty} \mathbf{x}[k] = \alpha\mathbf{1}$. Denoting by $\mathbf{W}(k)$ the matrix used by the nodes to mix their values at k, we have that:

$$\mathbf{x}(k) = \mathbf{W}(k)\ldots\mathbf{W}(0)\mathbf{x}(0) = \mathbf{M}(k)\mathbf{x}(0) \tag{4}$$

This expression asymptotically reaches consensus if $\lim_{k\to\infty}\mathbf{M}(k) = \mathbf{1}\mathbf{m}^T$. It occurs as long as every matrix $\mathbf{W}(k)$ is row stochastic, that is, $\mathbf{W}(k)\mathbf{1} = \mathbf{1}$, and the graph is connected on average [12]. In this case, $\alpha = \mathbf{m}^T\mathbf{x}(0)$. If every matrix $\mathbf{W}(k)$ is also column stochastic, that is, $\mathbf{1}^T\mathbf{W}(k) = \mathbf{1}^T$, then $\lim_{k\to\infty}\mathbf{M}(k) = \frac{1}{N}\mathbf{1}\mathbf{1}^T$, which ensures that the consensus value is the average of the initial values, hence $\alpha = \frac{1}{N}\sum_{i=1}^{N} x_i(0)$. However, in a real setting, each instantaneous topology defined by $\mathbf{A}(k)$ is also random, and so is its corresponding weight matrix $\mathbf{W}(k)$. This last condition can not be guaranteed, and $\mathbf{m} = [m_1 \ldots m_N]$ is a random vector, different, in general, from $\frac{1}{N}\mathbf{1}$. Close-form expressions for the first two moments of $\mathbf{m}$, namely its expectation $\boldsymbol{\mu}_m = [\mu_{m_1} \ldots \mu_{m_N}]$, and covariance matrix $\mathbf{C}_m$, with $\text{diag}(\mathbf{C}_m) = \left[\sigma^2_{m_1} \ldots \sigma^2_{m_N}\right]$, have been derived in [13], as a function of the weight matrices $\mathbf{W}(k)$. Furthermore, by applying a conjecture in [14], we can also conjecture that each component of $\mathbf{m}$ follows a log-normal distribution. Then, we say that the iterative consensus process presents no deviation from the average if the following two conditions hold:

$$\boldsymbol{\mu}_m = \frac{1}{N}\mathbf{1}, \quad \mathbf{C}_m = 0 \tag{5}$$

3. CONSENSUS BASED DISTRIBUTED DETECTION

In order to perform the detection task in a distributed fashion, every node must be able to compute $T(\mathbf{y})$ in (2) by just exchanging local information with their one hop neighbors. If each node i takes $x_i(0) = Ny_is_i$ as initial value and the dynamic system in (4) is applied, all nodes asymptotically reach consensus in the following random value:

$$T_c(\mathbf{y}, \mathbf{m}) = N\sum_{i=1}^{N} y_i s_i m_i = N\mathbf{y}^T\mathbf{\Delta}_m\mathbf{s} \tag{6}$$

where $\mathbf{\Delta}_m = \text{diag}(\mathbf{m})$. The performance of this detector is given by its deflection coefficient:

$$d_c^2 = \frac{1}{\sigma^2}\frac{\left(\mathbf{s}^T\mathbb{E}[\mathbf{\Delta}_m]\mathbf{s}\right)^2}{\mathbf{s}^T\mathbb{E}\left[\mathbf{\Delta}_m^2\right]\mathbf{s}} \tag{7}$$

It can be shown that this detector is, in general, suboptimal, and the optimality is achieved if and only if both conditions in (5) hold. In order to improve its performance, we propose a variation of this detector, whose design considers not only the signal to be detected, but also the properties of the consensus process, given by $\boldsymbol{\mu}_m$ and $\mathbf{C}_m$.

3.1. Adaptive distributed detector

The basis of the Neyman Pearson detector is to confront the observation $\mathbf{y}$ with the desired signal $\mathbf{s}$, such that the signal to noise ratio is maximized when $\mathbf{s}$ is present. However, if the detector is implemented in a distributed way by means of iterative consensus, the observation is not correlated with the original signal. Therefore, our proposal consists in choosing a different vector $\mathbf{r}$ to be confronted with the observations, such that it compensates the consensus error, and improves the final performance. Accordingly, each node i takes as initial value $x_i(0) = Ny_ir_i$, and asymptotically computes:

$$T_e(\mathbf{y}, \mathbf{m}, \mathbf{r}) = N\mathbf{y}^T\mathbf{\Delta}_m\mathbf{r} \tag{8}$$

for some vector $\mathbf{r}$. The moments of $T_e(\mathbf{y}, \mathbf{m}, \mathbf{r})$ are given by:

$$\begin{aligned} \mathbb{E}[T_e; \mathcal{H}_0] = 0, \;\; \mathbb{E}[T_e; \mathcal{H}_1] = N\mathbf{s}^T\mathbb{E}[\mathbf{\Delta}_m]\mathbf{r} \\ \text{var}\left(T_e; \mathcal{H}_0\right) = N^2\sigma^2\mathbf{r}^T\mathbb{E}\left[\mathbf{\Delta}_m^2\right]\mathbf{r} \end{aligned} \tag{9}$$

The deflection coefficient of $T_e(\mathbf{y}, \mathbf{m}, \mathbf{r})$ is given by:

$$d_e^2(\mathbf{r}) = \frac{1}{\sigma^2}\frac{\left(\mathbf{s}^T\mathbb{E}[\mathbf{\Delta}_m]\mathbf{r}\right)^2}{\mathbf{r}^T\mathbb{E}\left[\mathbf{\Delta}_m^2\right]\mathbf{r}} \tag{10}$$

If any one of the conditions in (5) is not satisfied, we have the following result:

Theorem 1. *There exists, at least, one N-dimensional vector $\mathbf{r}$ satisfying the energy constraint $\sum_{i=1}^N r_i^2 = \mathcal{E}$, such that, for $N >> \mathcal{E}$, the detector $T_e(\mathbf{y}, \mathbf{m}, \mathbf{r})$ outperforms the detector $T_c(\mathbf{y}, \mathbf{m})$ in terms of their deflection coefficients.*

Proof. If both conditions (5) are fulfilled, the detector in (6) is optimal $(i.e. d_c^2 = d^2)$ and cannot be improved. Therefore, it is enough to show that its performance can be improved as soon as any of the two conditions no longer holds. First, we consider the case when only the first condition in (5) is attained. Then, inequality $d_c^2 < d_e^2$ becomes:

$$\frac{\mathcal{E}^2}{\mathcal{E} + N^2\mathbf{s}^T\text{diag}(\mathbf{C}_m)\mathbf{s}} < \frac{(\mathbf{s}^T\mathbf{r})^2}{\mathcal{E} + N^2\mathbf{r}^T\text{diag}(\mathbf{C}_m)\mathbf{r}}$$

For $N >> \mathcal{E}$, and by rearranging terms, we have that:

$$\mathbf{r}^T\left[\text{diag}(\mathbf{C}_m) - \frac{1}{\mathcal{E}^2}\mathbf{s}\mathbf{s}^T\text{diag}(\mathbf{C}_m)\mathbf{s}\mathbf{s}^T\right]\mathbf{r}^T < 0 \tag{11}$$

A sufficient and necessary condition for this inequality to hold for some value of $\mathbf{r}$ is that $\lambda_{\text{min}}(\mathbf{U}) < 0$, where $\mathbf{U} = \text{diag}(\mathbf{C}_m) - \frac{1}{\mathcal{E}^2}\mathbf{s}\mathbf{s}^T\text{diag}(\mathbf{C}_m)\mathbf{s}\mathbf{s}^T$. The minimum eigenvalue of $\mathbf{U}$ is the minimum value of its Rayleigh quotient $\lambda_{\text{min}}(\mathbf{U}) = \min_{z, \|z\|=1} \mathbf{z}^T\mathbf{U}\mathbf{z}$, which vanishes for $\mathbf{z} = \frac{1}{\mathcal{E}}\mathbf{s}$. It implies that $\lambda_{\text{min}}(\mathbf{U}) \leq 0$. However, $\lambda_{\text{min}}(\mathbf{U}) = 0$ implies that $\det(\mathbf{U}) = 0$. If we apply the rule $\det(\mathbf{A} + \mathbf{b}\mathbf{c}^T) = \det(\mathbf{A})(1 + \mathbf{b}^T\mathbf{A}^{-1}\mathbf{c})$, we can express $\det(\mathbf{U})$ as follows:

$$\left(\sum_{i=1}^N \sigma_{m_i}^2\right)\left(1 - \frac{1}{\mathcal{E}^2}\sum_{i=1}^N s_i^2\sigma_{m_i}^2\sum_{i=1}^N s_i^2\sigma_{m_i}^{-2}\right)$$

Since we are considering that $\text{diag}(\mathbf{C}_m) \neq 0$, previous expression becomes zero only if $\sum_{i=1}^N s_i^2\sigma_{m_i}^2\sum_{i=1}^N s_i^2\sigma_{m_i}^{-2} = \mathcal{E}^2$, which holds only for the particular case that $\text{diag}(\mathbf{C}_m) = \sigma_m^2\mathbf{I}$ for any constant σ_m^2, that is, the variance of all the entries of $\mathbf{m}$ is the same. For any other case, $\lambda_{\text{min}}(\mathbf{U}) < 0$, hence expression (11) holds for some vector $\mathbf{r}$, and for this vector $d_c^2 < d_e^2$. Since only the second condition in (5) holds, inequality $d_c^2 < d_e^2$ can be written as:

$$\mathbf{r}^T\left\{\mathbb{E}[\mathbf{\Delta}_m]^2 - \frac{\mathbb{E}[\mathbf{\Delta}_m]\mathbf{s}\mathbf{s}^T\mathbb{E}[\mathbf{\Delta}_m]^2\mathbf{s}\mathbf{s}^T\mathbb{E}[\mathbf{\Delta}_m]}{\left(\mathbf{s}^T\mathbb{E}[\mathbf{\Delta}_m]\mathbf{s}\right)^2}\right\}\mathbf{r} < 0 \tag{12}$$

By taking $\mathbf{U} = \mathbf{I} - \frac{\mathbf{s}\mathbf{s}^T\mathbb{E}[\mathbf{\Delta}_m]^2\mathbf{s}\mathbf{s}^T}{(\mathbf{s}^T\mathbb{E}[\mathbf{\Delta}_m]\mathbf{s})^2}$, a necessary condition for (12) to hold for some $\mathbf{r}$ is that $\lambda_{\text{min}}(\mathbf{U}) < 0$. Then:

$$\lambda_{\text{min}}(\mathbf{U}) = 1 - \mathcal{E}\frac{\mathbf{s}^T\mathbb{E}[\mathbf{\Delta}_m]^2\mathbf{s}}{\left(\mathbf{s}^T\mathbb{E}[\mathbf{\Delta}_m]\mathbf{s}\right)^2} = 1 - \frac{d^2}{d_c^2}$$

Since $d_c < d$ for a suboptimal case, the previous eigenvalue is always negative and expression (12) holds for some value of vector $\mathbf{r}$, and $d_c^2 < d_e^2$ for this specific vector. □

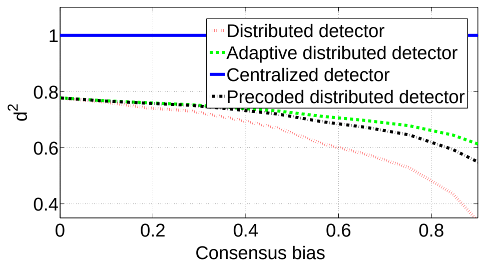
Given the log-normality of the entries of $\mathbf{m}$, the distribution of $T_c(\mathbf{y}, \mathbf{m})$ and $T_e(\mathbf{y}, \mathbf{m}, \mathbf{r})$ under either hypothesis is the sum of N normal log-normal mixtures (NLNM) [15]. The optimal threshold for a given false alarm probability can be computed by numerical methods. However, it is well known that the log-normal distribution approximates a Gaussian as the ratio between the variance and the expectation tends to zero. In our case, it can be shown that m_i follows a normal distribution for small enough values of $\sigma_{m_i}^2$. On the other hand, the product of two Gaussian variables is non Gaussian. However, as the variance of one of the factors tends to zero, the product approximates a normal distribution. Again, in our case, it can be shown that for values of $\sigma_{m_i}^2$ small enough to make m_i Gaussian, the distribution of the product Ny_im_i is also Gaussian. Finally, if several Gaussian variables are jointly Gaussian, the sum of them is also Gaussian. Therefore, and considering the above, for values of $[\sigma_{m_1}^2, \ldots, \sigma_{m_i}^2]$ small enough the distribution of both $T_c(\mathbf{y}, \mathbf{m})$ and $T_e(\mathbf{y}, \mathbf{m}, \mathbf{r})$ can be approximated by a Gaussian, and the threshold for a given false alarm probability can be computed by (3) using the variance $\text{var}\left(T_e; \mathcal{H}_0\right)$ in (9).

3.2. Derivation of the optimal detector

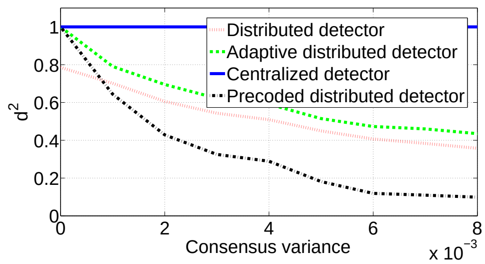
We aim to find the vector $\mathbf{r}^*$ that maximizes the performance expressed in (10), or similarly:

$$\mathbf{r}^* = \min_{\mathbf{r}, \|\mathbf{r}\|_2^2 = \mathcal{E}} \frac{\mathbf{r}^T\mathbb{E}[\mathbf{\Delta}_m^2]\mathbf{r}}{\mathbf{r}^T\mathbb{E}[\mathbf{\Delta}_m]\mathbf{s}\mathbf{s}^T\mathbb{E}[\mathbf{\Delta}_m]\mathbf{r}}$$

To solve this non-convex problem, we consider the Jagannathan's Theorem [16]. Given the problem: $\min\left\{\tau(x) = \frac{\Phi(x)}{\Psi(x)} : x \in X\right\}$, where $\Psi(x) > 0$ for all $x \in X$, then x^* is an optimal solution if and only if it is also an optimal solution of the problem $\min\left\{\Phi(x) - \tau(x^*)\Psi(x) : x \in X\right\}$.



(a)



(b)

Fig. 1. Detection performance as a function of (a) consensus bias, (b) consensus variance.

Based on that, the work in [17] presents the following iterative method for solving non-linear fractional problems where the function $\Psi(x)$ is concave and $\Phi(x)$ is convex:

1. Take any x_1, set $\tau_1 = \Phi(x_1)/\Psi(x_1)$ and $k = 1$.
2. Solve the following convex subproblem (x_{k+1}):
$$f(\tau_k) = \min \{\Phi(x) - \tau_k \Psi(x) : x \in X\}$$
3. If $f(\tau_k) = 0$, stop and take x_{k+1} as the solution. Otherwise, $\mu_{k+1} = \Phi(x_{k+1})/\Psi(x_{k+1})$, $k = k + 1$, go to step 2.

The convergence of this iterative algorithm for the case of general non-convex fractional problem is proven in [18]. In our case, the optimization subproblem in step 2 becomes:

$$f(\tau_k) = \min_{\mathbf{r}, \|\mathbf{r}\|_2^2 = \mathcal{E}} \mathbf{r}^T \left\{ \mathbb{E}[\boldsymbol{\Delta}_m^2] - \tau_k \mathbb{E}[\boldsymbol{\Delta}_m] \mathbf{s}\mathbf{s}^T \mathbb{E}[\boldsymbol{\Delta}_m] \right\} \mathbf{r}$$

whose solution is the eigenvector of the matrix $\mathbb{E}[\boldsymbol{\Delta}_m^2] - \mu_k \mathbb{E}[\boldsymbol{\Delta}_m] \mathbf{s}\mathbf{s}^T \mathbb{E}[\boldsymbol{\Delta}_m]$ associated to its smallest eigenvalue.

4. NUMERICAL RESULTS

We present some numerical results that confirm the validity of our approach. The setup includes $N = 40$ nodes randomly deployed in a square area of $L = 50$ meters side, with transmission power and attenuation such that the connectivity of the network is guaranteed. Besides, $\mathcal{E} = 1$ and $\sigma^2 = 1$. The consensus process is based on the Laplacian matrix, such that $\mathbf{W}(k) = \mathbf{I} - \epsilon \mathbf{L}(k)$, with a value of $\epsilon = 1/N$ to ensure convergence [9]. Fig. 1 shows, as a function of the consensus properties, the performance of the different detectors: centralized detector, consensus based distributed detector and adaptive distributed detector. We have also included an additional detector, also based in consensus, but with a trivial precoding, where each node divides its initial observation y_i by μ_{m_i} to compensate the average deviation. In Fig. 1(a) horizontal axis reflects the bias of vector $\mathbf{m}$, defined by the distance between $\boldsymbol{\mu}_m$ and $\frac{1}{N}\mathbf{1}$. The adaptive detector outperforms the consensus based detector as the bias increases. Besides, the performance of the precoded detector follows the one of the adaptive detector, but starts dropping for large biases. In Fig. 1(b), horizontal axis reflects the variance of the consensus process. Although both the adaptive and the precoded detectors compensate the bias and attain the optimal performance for a variance equal to zero, as this variance increases the performance of the precoded detector falls. Fig. 2 compares the receiver operating characteristic (ROC) curves of the centralized detector with those of the consensus based and adaptive detectors, for $\frac{\mathcal{E}}{\sigma^2} = 4$. We have assumed a Gaussian distribution of both $T_c(\mathbf{y}, \mathbf{m})$ and $T_e(\mathbf{y}, \mathbf{m}, \mathbf{r}^*)$, and computed the different thresholds accordingly. It can be seen that despite the Gaussian approximation, the thresholds give a reasonable performance for both distributed detectors.

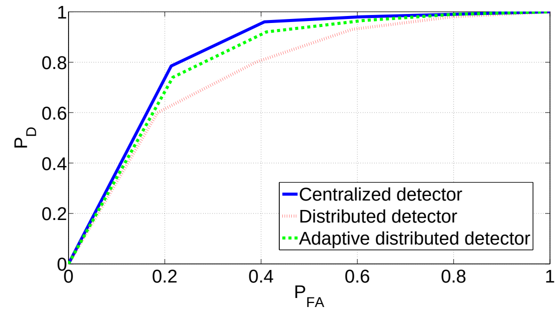


Fig. 2. ROC of the different detectors. It shows the probability of false alarm as a function of the probability of detection

5. CONCLUSIONS

Due to the randomness of instantaneous connectivities, a consensus-based distributed detector is, in general, suboptimal. We propose an adaptive distributed detector, which considers the properties of the probabilistic consensus, and compensates deviations from the average. We show that both the deflection coefficient and the ROC curves of the adaptive detector outperform those of the consensus based one, and approximate the performance of the centralized detector.

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