Iterative Distributed Amplitude Optimization for Distributed Detection in Wireless Sensor Networks

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***Abstract*—In this paper, an iterative distributed approach is studied for the signal amplitude optimization when the distributed detection is carried out with a symmetric signaling constraint in a wireless sensor network (WSN) consisting of a fusion center (FC) and multiple sensors. In the conventional distributed detection, if sensors' characteristics change due to aging problems or varying operating conditions, they have to be available at the FC for a best combining result. On the other hand, in the proposed approach, each sensor can adjust its signal amplitude using a type-based multiple access (TBMA) technique to provide a best performance at the FC through an iterative approach without sending their individual characteristics.**

Keywords: wireless sensor networks, distributed detection, distributed optimization

I. Introduction

Wireless sensor networks (WSNs) can be used for various environmental and industrial monitoring and surveillance purposes [1]. In WSNs, sensors are equipped with wireless transceivers and sensing devices and both signal processing and communications should be integrated for efficient use [2]. For a given sensing area, sensors are distributed and detect an unknown target or event locally. Each sensor makes a decision based on its own observations and sends its local decision to a fusion center (FC). This process can be called distributed detection [3]. To see the performance of distributed detection when the number of sensors increases, asymptotic analysis is considered in [4]. For independent and identically distributed (iid) observations at each sensor, it is shown that the error probability of decision fusion can decay exponentially to zero.

An optimal decision fusion rule is derived in [5] when sensors have conditionally independent observations and make their decisions individually. A better performance can be obtained if the decision fusion rule at the FC and local decision rules at sensors can be jointly optimized. However, this joint optimization is exceedingly sophisticate when sensors have different characteristics. Thus, the approach in [5] seems practical in many applications. Although the decision fusion rule in [5] is relatively simple, there are some problems. The FC should know all sensors' characteristics to weight their local decision in decision fusion. If sensors' characteristics are unknown or changed due to aging, the decision fusion becomes difficult. To avoid this problem, sensors can send their local decision characteristics to the FC. For decision fusion without the knowledge of sensors' characteristics at the FC, there is an approach that scales sensors' decisions according to their characteristics. However, this results in asymmetric signaling that may cause unequal transmission powers and possibly error probabilities in signal transmissions from sensors to the FC.

In this paper, we consider symmetric signaling from sensors to the FC and optimization for their amplitudes so that the FC can perform decision fusion without the knowledge of sensors' characteristics. Each sensor transmits its decision using symmetric signaling with different amplitude depending on its reliability on decision and a superposition of sensors' signals is received at the FC using type-based multiple access (TBMA) [6], [7]. In order to perform the signal amplitude optimization, a distributed optimization algorithm is derived using the Lagrangian dual optimization approach. Through iterations between sensors and the FC, the sensors can decide their signal amplitudes to meet a certain performance of decision fusion.

II. System Model

Suppose that there are L sensors and one FC. A common phenomenon is observed by all the sensors. The number of hypotheses is M and each hypothesis is denoted by H_m, $m = 0, 1, \ldots, M-1$. We have the following assumptions:

A1) The local observation at sensor l is independent under H_m.

A2) Each sensor makes a decision, which is denoted by u_l, independently, without communications between the other sensors and feedback from the FC. The FC can receive all sensors' decisions, $\{u_l\}$, for decision fusion.

For the sake of simplicity, we focus on the case of $M = 2$, i.e., binary hypothesis testing. Thus, it is assumed that $u_l = 0$ if sensor l accepts H_0 and 1 otherwise. At the FC, all the decisions from sensors are to be collected to make a final decision. For the likelihood ratio (LR)-based fusion rule, the log-likelihood ratio (LLR) at the FC can be given by

$$\text{LLR}(u_1, \ldots, u_L) = \log \frac{\Pr(\{u_l\}|H_1)}{\Pr(\{u_l\}|H_0)} = \sum_{l=1}^{L} \log \frac{\Pr(u_l|H_1)}{\Pr(u_l|H_0)}.$$

The second equality results from **A1)** and **A2)**. The false alarm (FA) probability at sensor l is denoted by $\alpha_l = \Pr(u_l = 1|H_0)$. The miss probability at sensor l is denoted by $\beta_l = \Pr(u_l = 0|H_1)$. Then, we have $\log \frac{\Pr(u_l|H_1)}{\Pr(u_l|H_0)} = \log \frac{\beta_l}{1-\alpha_l}$ if $u_l = 0$ and

$\log \frac{1-\beta_l}{\alpha_l}$ if $u_l = 1$. It follows that

$$\text{LLR}(u_1, \ldots, u_L) = \sum_{u_l=0} \log \frac{\beta_l}{1-\alpha_l} + \sum_{u_l=1} \log \frac{1-\beta_l}{\alpha_l}. \quad (1)$$

The resulting LR-based fusion rule with this LLR is called Chair-Varshney fusion rule [5].

III. Symmetric Binary Signaling and Amplitude Optimization

A. Symmetric Binary Signaling When Sensors' Characteristics Are Unknown

For a homogeneous WSN, where all the sensors are identical and their operating characteristics are the same, we have $\alpha_l = \alpha$ and $\beta_l = \beta$, $l = 1, 2, \ldots, L$. In this case, Chair-Varshney fusion rule can be readily implemented as from (1), the LLR is given by

$$\begin{aligned} &\text{LLR}(u_1, \ldots, u_L) \\ &= \left(\log \frac{(1-\alpha)(1-\beta)}{\alpha\beta}\right) L_1 + \left(\log \frac{\beta}{1-\alpha}\right) L, \end{aligned} \quad (2)$$

where L_1 is the number of the sensors that choose H_1.

In general, a WSN may have sensors whose operating characteristics are different or different types of sensors. This WSN is referred to as a heterogeneous WSN in this paper. A WSN can be a heterogeneous WSN although identical sensors are deployed. As sensors have a finite lifetime, it is necessary to deploy another group of sensors to keep the WSN working. In this case, new sensors may have different characteristics from old sensors. In the context of Chair-Varshney fusion rule, each sensor can be characterized by $\{\alpha_l, \beta_l\}$ on receiver operating characteristics (ROC) curves when different types of sensors are employed in a WSN. For example, as shown in Fig. 1, sensors 1 and 2 could be identical, but have different operating characteristics. On the other hand, sensor 3 is superior to the other sensors, sensors 1 and 2.

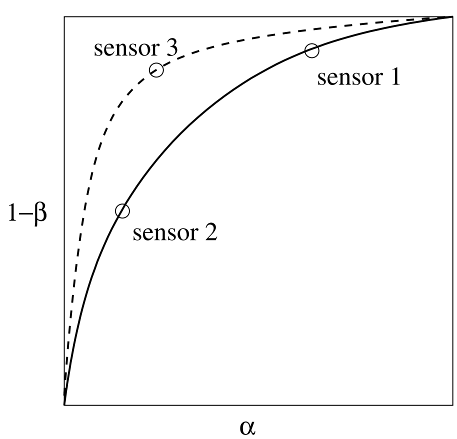


Fig. 1. ROCs of two different types of sensors in a heterogeneous WSN.

If the FC knows each sensor's characteristics, then Chair-Varshney fusion rule can be carried out with the binary signals, u_l, from sensors. As shown in (1), provided that $\{\alpha_l, \beta_l\}$ are available at the FC, the signs of the transmitted signals from sensors are sufficient to find the LLR for Chair-Varshney fusion rule. However, if the FC does not know sensors' characteristics or sensors may change their characteristics due to some reasons, $\{\alpha_l, \beta_l\}$ are no longer available at the FC.

In this paper, we assume that a symmetric pulse amplitude modulation (PAM) is employed at sensors to transmit their decisions to the FC as follows.

A3) The transmitted signal from sensor l to the FC is

$$x_l = A_l s(u_l), \quad (3)$$

where $s(u_l) = 1$ if $u_l = 1$ and -1 if $u_l = 0$. That is, $x_l = -A_l$ if sensor l chooses H_0 and $x_l = A_l$ if sensor l chooses H_1.

It is noteworthy that if sensors can employ asymmetric PAM for weighted decisions to transmit such as $x_l = \log \frac{\beta_l}{1-\alpha_l}$, if H_0 is accepted, and $x_l = \log \frac{1-\beta_l}{\alpha_l}$ if H_1 is accepted, the sum of weighted decisions, x_l, i.e. $\sum_{l=1}^{L} x_l$, is identical to the LLR in (1). In this case, although the FC does not know sensors' characteristics, Chair-Varshney fusion rule can be carried out. However, this asymmetric PAM may not be suitable if α_l or β_l is too small. In this case, the amplitude of x_l can be very large, which requires a significant transmission power. In order to avoid this problem, pulse position modulation (PPM) can be employed. In this case, as the range of signal positions, which is proportional to $|\log \frac{1-\beta_l}{\alpha_l} - \log \frac{\beta_l}{1-\alpha_l}|$, can be wide, the required transmission time can be long.

B. Type-Based Multiple Access

Suppose that a common channel (i.e., multiple access channel (MAC)) is used to send sensors' signals to the FC. If we assume an additive white Gaussian noise (AWGN) channel, the received signal at the FC, which is a superposition of weighted sensors' local decisions, is given by

$$\begin{aligned} y &= \sum_{l=1}^{L} x_l + n \\ &= \sum_{l=1}^{L} A_l s(u_l) + n, \end{aligned} \quad (4)$$

where $n \sim \mathcal{N}(0, \sigma^2)$. If the sensors' characteristics are the same and $A_l = A$ for all l, y becomes the LLR in (2) if the background noise, n, is negligible. This approach is referred to as TBMA in [6], [7] and used for the distributed detection. The main advantage of TBMA over the conventional distributed detection is that only one MAC is required.

For the case where the transmitted signals from the sensors to the FC experience fading, the received signal in (4) becomes

$$y = \sum_{l=1}^{L} h_l x_l + n,$$

where h_l denotes the channel gain from sensor l to the FC. In this case, the amplitude A_l can be modified to include h_l, i.e., $A_l = h_l a_l$, where a_l is the signal amplitude for binary signaling at sensor l. In this case, we do not need to modify the signal model in (4).

If sensors' characteristics are different, as mentioned earlier, asymmetric signaling could be used in TBMA, which unfortunately results in a significant transmission power consumption at some sensors if α_l or β_l is too small.

C. Amplitude Optimization using Upper-Bounds

If symmetric PAM is employed for signaling from sensors to the FC, the performance of decision fusion is worse than that of optimal Chair-Varshney fusion rule. To minimize the performance loss, we can consider the amplitude optimization. That is, $\{A_l\}$ are to be optimized to maximize the performance of decision fusion. To this end, we need to derive closed-form expressions for error probabilities. Unfortunately, it is not easy to derive closed-form expressions for approximate error probability even for the case of sensors of identical characteristics [8]. Thus, in this subsection, we consider upper-bounds on error probabilities using the Chernoff bound to obtain closed-form expressions.

To derive closed-form expressions for upper-bounds on error probabilities, we consider the following assumption.

A4) There are D different classes of sensors. For the sensors of class d, the characteristics are decided by the pair of error probabilities, $\{\alpha_{(d)}, \beta_{(d)}\}$.

The amplitude of signal for a sensor of class d is denoted by $A_{(d)}$. Let $\mathcal{L}_d$ denote the index set of the sensors of class d and $L_d = |\mathcal{L}_d|$. Then, the decision statistic is given by

$$\Lambda = \sum_{d=1}^{D} \sum_{l \in \mathcal{L}_d} x_l = \sum_{d=1}^{D} \sum_{l \in \mathcal{L}_d} A_{(d)} s(u_l). \tag{5}$$

If the background noise, n, in (4), is negligible, the received signal, y, becomes this decision statistic, i.e., $y \approx \Lambda$.

Let $C_d = A_{(d)} \sum_{l \in \mathcal{L}_d} s(u_l)$. It can be shown that $C_d = A_{(d)}(2k - L_d)$ if k denotes the number of the sensors of class d that choose H_1. Using this, the moment generating function (mgf) of C_d can be found as

$$\Phi_d(s) = \mathbb{E}[\mathrm{e}^{sC_d}] = \mathrm{e}^{-sA_{(d)}L_d} \left(1 + p_d(\mathrm{e}^{2A_{(d)}s} - 1)\right)^{L_d}, \tag{6}$$

where $p_d = \alpha_{(d)}$ under H_0 and $1 - \beta_{(d)}$ under H_1. The mgf of Λ is denoted by $\Phi_{\Lambda,m}(s) = \mathbb{E}[\mathrm{e}^{s\Lambda}|H_m]$.

Let τ denote the decision threshold at the FC. Thus, using the Chernoff bound, an upper-bound on the FA probability can be found as

$$\begin{aligned}\Pr(\Lambda \geq \tau | H_0) &\leq \min_{s \geq 0} \mathrm{e}^{-s\tau} \Phi_{\Lambda,0}(s) \\ &= \min_{s \geq 0} \mathrm{e}^{-s\tau} \sum_{d=1}^{D} \zeta^{L_d}(\alpha_{(d)}, sA_{(d)}),\end{aligned}$$

where $\zeta(p, A) = p\mathrm{e}^{A} + (1-p)\mathrm{e}^{-A}$. Define

$$\Gamma(\tau; A_{(1)}, \ldots, A_{(D)}) \leq \min_{s \geq 0} \mathrm{e}^{-s\tau} \Phi_{\Lambda,0}(s), \tag{7}$$

which is an upper-bound on the FA probability for a given threshold level τ, $\Pr(\Lambda \geq \tau | H_0)$. In addition, we define

$$\Psi(\tau; A_{(1)}, \ldots, A_{(D)}) = \min_{s \geq 0} \mathrm{e}^{s\tau} \Phi_{\Lambda,1}(s). \tag{8}$$

Then, it can be shown that

$$\begin{aligned}&\Pr(\Lambda \geq \tau | H_0) \leq \Gamma(\tau, A_{(1)}, \ldots, A_{(D)}); \\ &\Pr(\Lambda \leq \tau | H_1) \leq \Psi(\tau, A_{(1)}, \ldots, A_{(D)}),\end{aligned} \tag{9}$$

where $\Psi(\tau; A_{(1)}, \ldots, A_{(D)})$ is an upper-bound on the probability of type II error (miss detection). If the target FA probability is given at the FC as $\bar{P}_{\mathrm{FA}}$, in order to decide $\{\tau, A_{(1)}, \ldots, A_{(D)}\}$, the following optimization according to the Neyman-Pearson formulation can be considered:

$$\begin{aligned}&\min\nolimits_{\tau, A_{(1)}, \ldots, A_{(D)}} \Psi(\tau; A_{(1)}, \ldots, A_{(D)}) \\ &\text{subject to } \ \Gamma(\tau; A_{(1)}, \ldots, A_{(D)}) \leq \bar{P}_{\mathrm{FA}}.\end{aligned} \tag{10}$$

Since this optimization problem is difficult to solve, we can consider a slightly different problem to decide $\{A_{(1)}, \ldots, A_{(D)}\}$ with assuming that $\tau = 0$ as a nominal threshold value. With $\tau = 0$, we have

$$\begin{aligned}\Gamma(0; A_{(1)}, \ldots, A_{(D)}) &= \prod_{d=1}^{D} \zeta^{L_d}(\alpha_{(d)}, A_{(d)}); \\ \Psi(0; A_{(1)}, \ldots, A_{(D)}) &= \prod_{d=1}^{D} \zeta^{L_d}(\beta_{(d)}, A_{(d)}).\end{aligned} \tag{11}$$

In (11), $A_{(d)}$ absorbs s. That is, $A_{(d)}$ replaces $A_{(d)}s$ (thus, it is not necessary to optimize with respect to s in the case of $\tau = 0$ or it can be considered that s is fixed to be 1). The optimization problem in (10) reduces to

$$\begin{aligned}&\min\nolimits_{\{A_{(d)}\}} \sum\nolimits_{d=1}^{D} L_d \log \zeta(\beta_{(d)}, A_{(d)}) \\ &\text{subject to } \sum\nolimits_{d=1}^{D} L_d \log \zeta(\alpha_{(d)}, A_{(d)}) \leq -\eta,\end{aligned} \tag{12}$$

where $\eta = -\log \bar{P}_{\mathrm{FA}}$. Using the Lagrange multiplier, the constrained optimization problem in (12) can be the following unconstrained optimization problem:

$$\begin{aligned}&\min_{\{A_{(d)}\}} \sum_{d=1}^{D} L_d \log \zeta(\beta_{(d)}, A_{(d)}) + \lambda \sum_{d=1}^{D} L_d \log \zeta(\alpha_{(d)}, A_{(d)}) \\ &= \sum_{d=1}^{D} L_d \min_{A_{(d)}} \left[\log \zeta(\beta_{(d)}, A_{(d)}) + \lambda \log \zeta(\alpha_{(d)}, A_{(d)})\right],\end{aligned} \tag{13}$$

where λ is the Lagrange multipler. In (13), the optimization problem is decomposed into multiple subproblems.

We have the following results for each subproblem.

Theorem 1. *With a given $\lambda > 0$, if $0 < \alpha_{(d)}, \beta_{(d)}, < \frac{1}{2}$, there exists a unique solution of the following optimization problem:*

$$\min_{A_{(d)}} G_\lambda(A_{(d)}) \tag{14}$$

where $G_\lambda(A_{(d)}) = \log \zeta(\beta_{(d)}, A_{(d)}) + \lambda \log \zeta(\alpha_{(d)}, A_{(d)})$.

Proof: The first order derivative of the cost function is given by

$$\frac{\mathrm{d}G_\lambda(A_{(d)})}{\mathrm{d}A_{(d)}} = \frac{\beta_{(d)}\mathrm{e}^{A_{(d)}} - (1-\beta_{(d)})\mathrm{e}^{-A_{(d)}}}{\beta_{(d)}\mathrm{e}^{A_{(d)}} + (1-\beta_{(d)})\mathrm{e}^{-A_{(d)}}} + \lambda\frac{\alpha_{(d)}\mathrm{e}^{A_{(d)}} - (1-\alpha_{(d)})\mathrm{e}^{-A_{(d)}}}{\alpha_{(d)}\mathrm{e}^{A_{(d)}} + (1-\alpha_{(d)})\mathrm{e}^{-A_{(d)}}}. \quad (15)$$

The second order derivative is also given by

$$\frac{\mathrm{d}^2G_\lambda(A_{(d)})}{\mathrm{d}A_{(d)}^2} = \frac{4\beta_{(d)}(1-\beta_{(d)})}{(\beta_{(d)}\mathrm{e}^{A_{(d)}} + (1-\beta_{(d)})\mathrm{e}^{-A_{(d)}})^2} + \lambda\frac{4\alpha_{(d)}(1-\alpha_{(d)})}{(\alpha_{(d)}\mathrm{e}^{A_{(d)}} + (1-\alpha_{(d)})\mathrm{e}^{-A_{(d)}})^2}. \quad (16)$$

Since $0 < \alpha_{(d)}, \beta_{(d)} < \frac{1}{2}$, we have $\frac{\mathrm{d}^2G_\lambda(A_{(d)})}{\mathrm{d}A_{(d)}^2} > 0$. Thus, $G_\lambda(A_{(d)})$ has a unique minimum. Furthermore, this minimum (where $\frac{\mathrm{d}G_\lambda(A_{(d)})}{\mathrm{d}A_{(d)}} = 0$) exists as $\frac{\mathrm{d}G_\lambda(A_{(d)})}{\mathrm{d}A_{(d)}}$ is increasing and

$$\left.\frac{\mathrm{d}G_\lambda(A_{(d)})}{\mathrm{d}A_{(d)}}\right|_{A_{(d)}=0} = (2\beta_{(d)}-1) + \lambda(2\alpha_{(d)}-1) < 0;$$
$$\left.\frac{\mathrm{d}G_\lambda(A_{(d)})}{\mathrm{d}A_{(d)}}\right|_{A_{(d)}=\infty} = 1+\lambda > 0.$$

This completes the proof. ■

As $\frac{\mathrm{d}G_\lambda(A_{(d)})}{\mathrm{d}A_{(d)}}$ is an increasing function of $A_{(d)}$, a numerical approach can be used to find the solution, which is denoted by

$$A^*_{(d)}(\lambda) = \arg\min_{A_{(d)}\geq 0} G_\lambda(A_{(d)}). \quad (17)$$

The Lagrange multiplier can be decided as follows:

$$\sum_{d=1}^{D} L_d \log\zeta(\alpha_{(d)}, A^*_{(d)}(\lambda)) \leq -\eta. \quad (18)$$

Note that the threshold for decision fusion is set to the nominal value $\tau = 0$ in (11). If τ is different from 0, from (7), $-\eta$ on the right hand side in (18) can be replaced with $-\eta + \tau$. In other words, a nominal value for the negative error exponent, say η^o, can be used to optimize the signal amplitudes and τ can be decided as $\tau = \eta - \eta^o$, where η is the negative exponent of the target FA probability.

IV. Distributed Optimization

Unfortunately, in order to solve the optimization problem in (12), the FC should know $\{\alpha_{(d)}, \beta_{(d)}\}$. Since this centralized approach to optimize the signal amplitudes is not desirable, a distributed approach is to be derived. As shown in (13), the optimization problem can be decomposed into multiple subproblems. For a given λ, each sensor can decide the optimal amplitude as in (17). Thus, at each senor, the value of the Lagrange multiplier is required. The FC can broadcast the value of the Lagrange multiplier to all the sensors. At the FC, in order to decide the value of the Lagrange multiplier, the Lagrange dual problem can be formulated as follows:

$$\min_\lambda \Big\{ \sum_{d=1}^{D} G_\lambda(A^*_{(d)}(\lambda)) + \lambda\left(-\eta - \sum_{d=1}^{D} L_d \log\zeta(\alpha_{(d)}, A^*_{(d)}(\lambda))\right) \Big\}$$
$$\text{subject to } \lambda \geq 0. \quad (19)$$

Using the results in [9], this can be solved by an iterative subgraident method as follows:

$$\lambda(t+1) = \left[\lambda(t) - \mu(t)\left(-\eta - \sum_{d=1}^{D} L_d z_d(t)\right)\right]^+, \quad (20)$$

where t is the discrete time index (for iterations), $\mu(t) > 0$ is the step size, $[x]^* = \max\{x, 0\}$, and

$$z_d(t) = \log\zeta(\alpha_{(d)}, A^*_{(d)}(\lambda(t))). \quad (21)$$

In summary, we can propose the following iterative distributed approach for the amplitude optimization:

S0) Let $t = 0$ and $\lambda(t) = \lambda_0 > 0$, which is the initial value of λ.
S1) The FC broadcasts $\lambda(t)$ to all the sensors.
S2) Each sensor finds the optimal amplitude as in (17).
S3) Each sensor sends $z_d(t)$ in (21) to the FC.
S4) The FC updates the Lagrange multiplier as in (20). If $|\lambda(t+1) - \lambda(t)| < \epsilon$, where $\epsilon > 0$ is a small constant, stop. Otherwise, let $t \leftarrow t+1$ and go to S1).

Note that signal transmissions between sensors and the FCs are assumed to be reliable.

The significance of the iterative distributed approach is that if new classes of sensors are deployed or characteristics of some groups of sensors are changed or modified, signal amplitudes can be easily re-adjusted through the iterative process.

Note that TBMA plays a crucial role in performing Step S3). Through a MAC in the amplitude optimization process, a sensor of class d transmits $z_d(t)$ at the tth iteration. At the FC, the received signal, which is a superposition of $z_d(t)$, becomes

$$v(t) = \sum_{d=1}^{D} L_d z_d(t) + n(t),$$

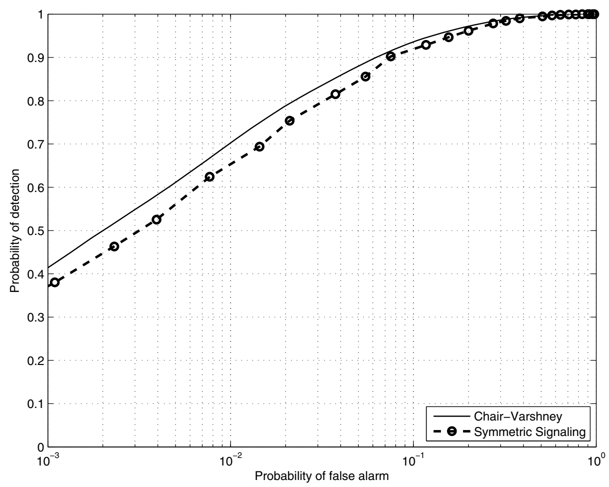
where $n(t)$ denotes the background noise. In this case, (20) is modified as

$$\lambda(t+1) = \left[\lambda(t) + \mu(t)\left(\eta + v(t)\right)\right]^+. \quad (22)$$

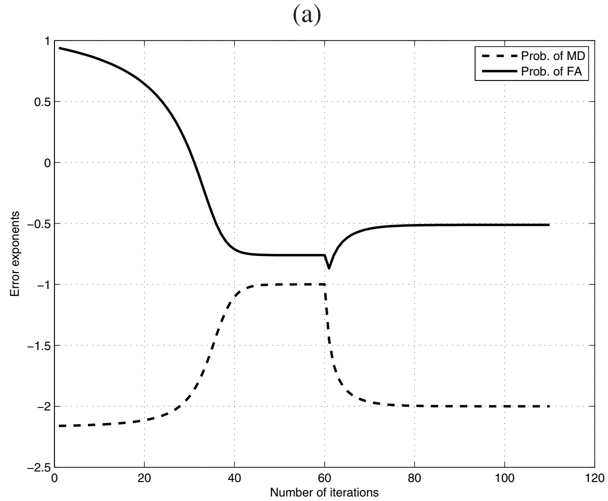
Therefore, the FC does not need to know $\{L_d\}$ and sensors' characteristics to adjust sensors' signal amplitude in the iterative distributed optimization.

V. Simulation Results

For simulations, we assume that $\{L_1, L_2, L_3\} = \{4, 4, 10\}$ (i.e. $D = 3$) with $\{\alpha_{(1)}, \beta_{(1)}\} = \{0.1, 0.45\}$, $\{\alpha_{(2)}, \beta_{(2)}\} = \{0.4, 0.2\}$, and $\{\alpha_{(3)}, \beta_{(3)}\} = \{0.4, 0.4\}$. Fig. 2 (a) shows ROC curves for the performance comparison between Chair-Varshney fusion rule and the fusion rule based on (5) using symmetric signaling. The signal amplitudes are optimized with the nominal value for the negative error exponent $\eta = 1$. We can see that although Chair-Varshney fusion rule outperforms the fusion rule using symmetric signaling, the performance gap is small. In Fig. 2 (b), learning curves of the iterative distributed algorithm for the amplitude optimization are illustrated using error exponents. It is assumed that a new type (the 4th type) of 6 sensors (of $\alpha_{(4)} = 0.3$ and $\beta_{(4)} = 0.4$) is deloyed just after 60 iterations (once the convergence is achieved with three different types of sensors) with $\eta = 1$ to $\eta = 2$. It is shown that after 40 iterations, the desired negative error exponent of the target FA probability, $\eta = 1$, has been achieved with 3 different types of sensors, and with the new deployment of the 4th type of sensors, the amplitudes can be re-adjusted to meet $\eta = 2$ through the iterative distributed algorithm.



(a)



(b)

Fig. 2. (a) ROC curves; (b) learning curves for the iterative distributed algorithm (dashed line: the probability of miss detection (MD); solid line: the probability of false alarm).

VI. Concluding Remarks

Signal amplitude optimization for symmetric signaling was studied for distributed detection in a WSN consisting of multiple different types of sensors and a FC when TBMA is employed. It was possible to derive a distributed optimization algorithm to optimize signal amplitudes using the Lagrangian dual optimization approach. Through simulation results, it was shown that the performance of the fusion rule based on symmetric signaling is slightly worse than that of the optimal Chair-Varshney fusion rule.

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