Large Sensor System Performance of Decentralized Detection in Noisy, Bandlimited Channels

Sudharman K. Jayaweera
Department of Electrical and Computer Engineering
Wichita State University, Wichita, KS 67260, USA.
Email: sudharman.jayaweera@wichita.edu

***Abstract*— In this paper we investigate the performance of decentralized detection assuming a noisy and bandlimited channel between the local sensors and the fusion center. We formulate the problem as in a distributed wireless sensor network subjected to a total average power constraint and all nodes sharing a common bandwidth. The bandwidth constraint is taken into account by assuming non-orthogonal communication between sensors and the data fusion center via direct-sequence code-division multiple-access (DS-CDMA).**

To facilitate the closed-form analysis we consider large sensor systems and random spreading, and derive the decentralized detection performance assuming independent and identically distributed (iid) sensor observations. For the first time, we apply random matrix theory to obtain decentralized detection performance in large sensor networks. Our results show that, even under both power and bandwidth constraints, it is better to combine many not-so-good local decisions rather than relying on one (or a few) very-good local decisions.

***Index Terms*— Data fusion, decentralized detection, distributed detection, hypothesis testing, large-system analysis, multi-sensor detection, random spreading, sensor networks.**

I. Introduction

Low-power, dense wireless sensor networks are increasingly gaining importance in various military, homeland security and civilian applications [1]–[4]. Decentralized detection and data fusion are common problems that arise in the context of distributed sensor systems. The motivation for distributed detection arises from the fact that the relaying of only the local distributed decisions, as opposed to directly sending the sensor observations, to a central fusion center can significantly save system resources in terms of both required communication bandwidth and sensor power. The two related problems of decentralized detection and data fusion have been researched for more than two decades (see, for example, [5]–[8]). However, in the specific context of resource-constrained wireless sensor networks, the distributed detection problem has gained attention only in recent years [9], [10].

In this paper we consider decentralized detection in energy-constrained, large wireless sensor networks in the presence of both noisy and band-limited channels. Although there is a considerable amount of previous work on the subject of distributed detection, most of them used to ignore the effect of noisy channels between the local sensors and data fusion center. Although this may be justified in a wired system without a strict energy constraint, in the context of low-power wireless sensor networks one must consider them. Even less is the attention received by bandlimited noisy channels in the context of decentralized detection. For example, while distributed detection performance of an energy-constrained wireless sensor network over a noisy channel has been considered recently [11], it assumes orthogonal sensor-to-fusion center communication leading to an infinite bandwidth assumption. However, in applications involving dense, low-power, distributed wireless sensor networks it is more likely that all nodes will share a common available bandwidth. In this case, the assumption of large sensor systems implies non-orthogonal communication between the sensor nodes and the fusion sensor (even if individual sensors do not transmit often, the high node density may require non-orthogonal schemes). In this paper, the bandwidth constraint is taken into account by assuming non-orthogonal direct-sequence code-division multiple-access (DS-CDMA) communication between sensors and the data fusion center. Note that, spread spectrum techniques have already been considered for wireless sensor networks in [12] (although, to the best of our knowledge, this is the first time the problem of distributed detection has been formulated in this context).

One of the most important design objectives in low-power wireless sensor systems is to extend the whole network lifetime. Thus, a sensible constraint on the sensor system is a finite total energy or power. The decentralized detection problem has only recently been considered under such total system power constraints [11]. The performance behavior is even less well-understood when this is combined with the assumption of both a noisy and bandlimited channel. In this paper we investigate the decentralized detection performance in both noisy and band-limited channels subjected to a total average power constraint on the sensor network. The main contribution of this paper is the derivation of the decentralized detection performance, in closed-form, under a total power constraint when the communication channel between the local sensors and the fusion center is both bandlimited and noisy. As we will see, and as one would expect, the performance is a function of the exact signalling codes used by the distributed sensors for any finite-size sensor network. However, once we consider asymptotically very large sensor systems and random spreading codes, we show that a result on random matrices leads us to an elegant and simple closed-form expression that is independent of the exact spreading codes. This is our main result and, as we will see, it allows us to draw general conclusions regarding the design of wireless sensor systems under such total power constraints for practical noisy and bandlimited channels.

The remainder of the paper is organized as follows: In Section II we present our system model. Next, in Section III we use random matrix theory to derive a closed-form expression for the decentralized detection performance in a large-scale sensor system followed by a discussion of our analysis. Finally, in Section IV we conclude by summarizing our results.

II. System Model Description

A typical scenario in a (dense) low-power wireless sensor network is that a collection of ad-hoc distributed sensor nodes observes information on an event of interest. Each node performs some basic local processing (in order to reduce the dimensionality of data, for example) and the resulting local decision is relayed to a processing center, named the fusion center, in order to make a collective decision on the event of interest. This is the classical problem of decentralized detection, which stems from the fact that, relaying of only the local decisions, as opposed to directly sending the complete sensor observations, to a central fusion center may significantly save system resources in terms of both communication bandwidth and sensor power consumption. Often, it is assumed that these local decisions are received at the fusion center perfectly. i.e. the assumption of a noise-less channel. Even in treatises which allows for erroneous reception of local decisions it is assumed that the only source of errors is the channel noise. i.e. an unlimited channel bandwidth is available for communication.

We consider a binary hypothesis testing problem in an N_s-node wireless sensor network connected to a data fusion center via distributed parallel architecture [6] (our analysis below can be extended to distributed multiple hypothesis testing). Let us denote by H_0 and H_1 the null and alternative hypotheses, respectively, having corresponding prior probabilities $P(H_0) = p_0$ and $P(H_1) = p_1$. To be specific, we will consider that the observed stochastic process consists of one of two possible Gaussian signals corrupted by additive white Gaussian noise. The two Gaussian signals of interest, denoted by $X_{0,n}$ and $X_{1,n}$, are thus completely characterized by their means and the covariance functions.

Under the two hypotheses the n-th local sensor observation z_n, for $n = 1, \cdots N_s$, can be written as

$$\begin{aligned} H_0: \quad z_n &= X_{0,n} + v_n \\ H_1: \quad z_n &= X_{1,n} + v_n \end{aligned} \qquad (1)$$

where the observation noise v_n is assumed to be zero-mean Gaussian with the collection of noise samples having a covariance matrix Σ_v. Each local sensor processes its observation z_n independently to generate a local decision $u_n(z_n)$ which are sent to the fusion center. Let us denote by $\mathbf{r}(u_1(z_1), u_2(z_2), \cdots, u_{N_s}(z_{N_s}))$ the received signal at the fusion center. The fusion center makes a final decision based on the decision rule $u_0(\mathbf{r})$. The problem at hand is to choose $u_0(\mathbf{r}), u_1(z_1), u_2(z_2), \cdots, u_{N_s}(z_{N_s})$ so that a chosen performance metric is optimized.

The solution to this problem is known to be too complicated under the most general conditions. The reason is that optimization will require a search over all possible decision functions (rules). However, it is known that if local observations are independent of each other conditioned on the true hypothesis, then all decision rules simplify to a set of likelihood ratio based decision rules at local sensors but with possibly coupled thresholds [5]. Once the conditional independence assumption is dropped the analysis could get unwieldy, and in particular, the optimality of simple threshold tests may be lost.

While optimal local processing schemes have been investigated, and have derived under certain special assumptions, a class of especially important local processers are those that simply amplify the observations before retransmission to the fusion center [11]. It has been shown that such simple local processing performs fairly well when the local observations are corrupted by additive noise, as in our formation [9]. Moreover, this type of amplify-and-relay local processing seems to be well-suited for low-power, tiny wireless sensor networks that are becoming popular. Thus, the local sensor decisions sent to the fusion center are given by

$$u_n = g z_n \quad \text{for } n = 1, \cdots N_s \qquad (2)$$

where $g > 0$ is the analog relay amplifier gain at each node.

Most current literature on low-power wireless sensor networks assumes orthogonal sensor-to-fusion center communication (leading to an infinite bandwidth assumption). However, in our system model all sensor nodes share a common bandwidth and a total available energy. Thus, in a dense distributed wireless sensor networks it is more appropriate to consider non-orthogonal sensor communication. For analytical reasons, as well as due to their practical relation to DS-CDMA communications, in this paper we consider bandwidth sharing non-orthogonal communication based on spreading.

Thus, the local decisions u_n's are transmitted to the fusion center over a bandlimited wireless channel. The bandwidth sharing is assumed to be achieved by assigning each sensor node a signature code of length N. If the n-th sensor node is assigned the code $\mathbf{s}_n$, the received chip-matched filtered and sampled discrete-time signal at the fusion center can be written as

$$\mathbf{r} = g \sum_{k=1}^{N_s} \mathbf{s_n} z_n + \mathbf{w} = g\mathbf{S}\mathbf{z} + \mathbf{w} \qquad (3)$$

where $\mathbf{r}$ and $\mathbf{w}$ are N-dimensional received vector and the receiver noise, respectively. We assume that the receiver noise is a white Gaussian noise process so that the filtered noise vector $\mathbf{w} \sim \mathcal{N}(\mathbf{0}, \sigma_w^2 \mathbf{I}_N)$. Note that the n-th column of the $N \times N_s$ matrix $\mathbf{S}$ is equal to the vector $\mathbf{s}_n$. It is easily seen that the received signal $\mathbf{r}$ is Gaussian distributed such that

$$\begin{aligned} H_0: \quad \mathbf{r} &\sim \mathcal{N}(\mathbf{m}_0, \Sigma_0) \\ H_1: \quad \mathbf{r} &\sim \mathcal{N}(\mathbf{m}_1, \Sigma_1) \end{aligned} \qquad (4)$$

where

$$\mathbf{m}_j \quad = \quad g\mathbf{S}\mathbb{E}\{\mathbf{X}_j\} \quad \text{for} \quad j = 0, 1 \tag{5}$$

and

$$\Sigma_j \quad = \quad g^2\mathbf{S}\left(Cov(\mathbf{X}_j) + \Sigma_v\right)\mathbf{S}^T + \sigma_w^2\mathbf{I}_N \text{ for } j = 0, 1 \tag{6}$$

Now the detection problem at the fusion center is given by (4). It is well known that threshold tests in which the log-likelihood ratio is compared to a threshold are the optimal (for example, in the sense of either Bayesian or Naymen-Pearson optimality) tests for a problem of the type (4). To be specific, let us consider the detection of a deterministic signal so that $\mathbf{X}_1 = -\mathbf{X}_0 = m\mathbf{1}$ is known $(m > 0)$ and $\Sigma_0 = \Sigma_1 = \Sigma$ where ($\mathbf{1}$ is the vector of all ones)

$$\Sigma \quad = \quad g^2\mathbf{S}\Sigma_v\mathbf{S}^T + \sigma_w^2\mathbf{I}_N. \tag{7}$$

With these assumptions, from (5), we also have that

$$\mathbf{m}_1 \quad = \quad -\mathbf{m}_0 \;=\; gm\mathbf{S}\mathbf{1}. \tag{8}$$

The radiated power of node n is then given by

$$\mathbb{E}\{|u_n|^2\} \quad = \quad g^2\mathbb{E}\{|z_n|^2\} \;=\; g^2(m^2 + \sigma_v^2). \tag{9}$$

Let us define the total power constraint the whole sensor system is subjected to as P. Then, the amplifier gain g is related to the size of the sensor system and the total available power P as

$$g \quad = \quad \sqrt{\frac{P}{N_s(m^2 + \sigma_v^2)}}. \tag{10}$$

Computing the log-likelihood ratio (llr), it can be shown that the optimal threshold rule at the fusion center is of the form

$$\delta_{opt}(\mathbf{r}) \quad = \quad \begin{cases} 1 & \\ & \text{if} \quad T(\mathbf{r}) \quad \begin{matrix} \geq \\ \\ < \end{matrix} \quad \tau' \\ 0 & \end{cases}, \tag{11}$$

where we have defined the decision variable T as

$$\begin{aligned} T(\mathbf{r}) \quad &= \quad (\mathbf{m}_1 - \mathbf{m}_0)^T\,\Sigma^{-1}\mathbf{r} \\ &= \quad 2gm\mathbf{1}^T\mathbf{S}^T\left(g^2\mathbf{S}\Sigma_v\mathbf{S}^T + \sigma_w^2\mathbf{I}_N\right)^{-1}\mathbf{r}, \end{aligned} \tag{12}$$

and τ' is the threshold that depends on the specific optimality criteria. It can be shown that the false-alarm P_f and miss P_m probabilities of the detector (11) are given by

$$P_f = P(H_1|H_0) \;=\; Q\left(\frac{\tau' + 2g^2m^2\mathbf{1}^T\mathbf{S}^T\Sigma^{-1}\mathbf{S}\mathbf{1}}{2gm\sqrt{\mathbf{1}^T\mathbf{S}^T\Sigma^{-1}\mathbf{S}\mathbf{1}}}\right), \tag{13}$$

and

$$P_m = P(H_0|H_1) \;=\; Q\left(\frac{2g^2m^2\mathbf{1}^T\mathbf{S}^T\Sigma^{-1}\mathbf{S}\mathbf{1} - \tau'}{2gm\sqrt{\mathbf{1}^T\mathbf{S}^T\Sigma^{-1}\mathbf{S}\mathbf{1}}}\right). \tag{14}$$

For example, in the case of Neyman-Pearson optimality at the fusion center, τ' is chosen to minimize P_m subject to an upper bound on P_f. On the other hand under Bayesian minimum probability of error optimality one would choose τ' to minimize $P_e = p_0P_f + p_1P_m$. In any case, (13) and (14) characterize the performance of the decentralized detection scheme in a wireless sensor network when communication is over a noisy, bandlimited channel. As one would expect, the performance of course depends on the particular codes assigned to each sensor node. As such, it is not clear how to draw any general conclusions regarding the performance of the decentralized detection system from (13) and (14) (although it is possible to evaluate the performance for any given set of system parameters).

III. Decentralized Detection Performance in a Large Sensor System

In this section we show that the theory of random matrices can be used to facilitate the performance analysis of decentralized detection systems of the type assumed above in the case of large sensor networks. To that end, we assume that the spreading codes are chosen randomly (i.e. the elements of spreading codes $\mathbf{s}_n$ are iid random variables). As we will shortly see, once we consider asymptotically large sensor systems, this assumption combined with the theory of random matrices lead us to an elegant and simple closed-form performance expression that is independent of the choice of spreading codes. The resulting expression may be use to facilitate the drawing of general conclusions regarding the decentralized system performance as well as to provide an approximation to the performance of a finite system. Thus, let us assume that each sensor node is assigned a random signalling code $\mathbf{s}_n$ of length N where each element of $\mathbf{s}_n$ takes either $\frac{1}{\sqrt{N}}$ or $-\frac{1}{\sqrt{N}}$ with equal probability (note that, in general it is enough that these elements are zero-mean with finite eighth moments). Moreover, let us assume independent sensor observations such that $\Sigma_v = \sigma_v^2\mathbf{I}$.

Let us assume a large sensor system such that both N_s and N are large such that

$$\lim_{N\longrightarrow\infty}\frac{N_s}{N} \quad = \quad \alpha. \tag{15}$$

We will need the following theorem which was proven in [13] with the help of a convergence result on the empirical distribution of eigenvalues of a large random matrix:

Theorem 1: Suppose X is a $N \times N_s$ matrix of iid complex random variables with zero-mean and variance $\frac{1}{N}$ and assume that $\lim_{N\longrightarrow\infty}\frac{N_s}{N} = \alpha$. Suppose T is a random, non-negative definite, $N_s \times N_s$ Hermitian matrix independent of X such that almost surely F^T, the empirical distribution function of the eigenvalues of T, converges to a fixed distributed function F as $N \longrightarrow \infty$. Let $\mathbf{q} = \frac{1}{\sqrt{N}}[q_1, q_2, \cdots, q_N]^T$ where the q_i's are iid complex random variables with zero-mean, unit variance and finite eighth moment. Let $\mathbf{t}$ be a similar vector independent of $\mathbf{q}$. Then, as $N \longrightarrow \infty$, almost surely

$$\mathbf{q}^H\left(\mathbf{X}\mathbf{T}\mathbf{X}^H + \sigma^2\mathbf{I}\right)^{-1}\mathbf{t} \quad \longrightarrow \quad 0$$

and

$$\mathbf{q}^H\left(\mathbf{X}\mathbf{T}\mathbf{X}^H + \sigma^2\mathbf{I}\right)^{-1}\mathbf{q} \quad \longrightarrow \quad \beta^*$$

where β^* is the unique positive solution to the fixed point equation

$$\beta^* \quad = \quad \left[\sigma^2 + \alpha \int \frac{p}{1+p\beta^*} dF(p)\right]^{-1}.$$

Using the above theorem we may prove the following proposition, which is the main result of this paper:

Proposition 1: With $\mathbf{S}$ and Σ defined as above, as $N \longrightarrow \infty$, almost surely

$$g^2 \mathbf{1}^T \mathbf{S}^T \Sigma^{-1} \mathbf{S} \mathbf{1} \quad \longrightarrow \quad \left(\frac{\sigma_v^2}{N_s} + \frac{m^2+\sigma_v^2}{P\beta_0}\right)^{-1}, \qquad (16)$$

where

$$\beta_0 = \frac{\sqrt{\left(\gamma+\sigma_w^2\right)^2 \alpha^2 + 2\gamma(\sigma_w^2-\gamma)\alpha + \gamma^2} - \left(\gamma+\sigma_w^2\right)\alpha + \gamma}{2\gamma\sigma_w^2} \qquad (17)$$

with $\gamma = \frac{P}{N\left(1+\frac{m^2}{\sigma_v^2}\right)}$ and $\Sigma_v = \sigma_v^2 \mathbf{I}$.

Proof: Using the definitions of $\mathbf{S}$ and $\mathbf{1}$, we can write

$$g^2 \mathbf{1}^T \mathbf{S}^T \Sigma^{-1} \mathbf{S} \mathbf{1} = g^2 \left(\sum_{n=1}^{N_s} \mathbf{s}_n^T \Sigma^{-1} \mathbf{s}_n + \sum_{n=1}^{N_s} \sum_{\substack{n'=1 \\ n' \neq n}}^{N_s} \mathbf{s}_n^T \Sigma^{-1} \mathbf{s}_{n'}\right) \qquad (18)$$

Let $\mathcal{I}$ denote a set of sensor indices (i.e. $\mathcal{I} \subset \{1, 2, \cdots, N_s\}$), $\mathbf{S}_{\mathcal{A}}$ denote the matrix $\mathbf{S}$ with column indices specified by set $\mathcal{A}$ deleted, $\mathbf{\Lambda}_n = g^2\sigma_v^2 \mathbf{I}_n$ and $\mathbf{Q}_{\mathcal{A}} = \left(\mathbf{S}_{\mathcal{A}} \mathbf{\Lambda}_{N_s-|\mathcal{A}|} \mathbf{S}_{\mathcal{A}} + \sigma_w^2 \mathbf{I}_N\right)$ where $\mathbf{I}_n$ and $|\mathcal{A}|$ are the $n \times n$ identity matrix and the cardinality of set $\mathcal{A}$, respectively. Then, for $n = 1, \cdots, N_s$, using the matrix inversion lemma we have that

$$\begin{aligned} \mathbf{s}_n^T \Sigma^{-1} \mathbf{s}_n \quad &= \quad \mathbf{s}_n^T \left(g^2 \sigma_v^2 \mathbf{s}_n \mathbf{s}_n^T + \mathbf{S}_{\{n\}} \mathbf{\Lambda}_{N_s-1} \mathbf{S}_{\{n\}} + \sigma_w^2 \mathbf{I}_N\right)^{-1} \mathbf{s}_n \\ &= \quad \frac{\mathbf{s}_n^T \mathbf{Q}_{\{n\}}^{-1} \mathbf{s}_n}{1 + g^2 \sigma_v^2 \mathbf{s}_n^T \mathbf{Q}_{\{n\}}^{-1} \mathbf{s}_n} \end{aligned} \qquad (19)$$

But, applying theorem 1 (and after some manipulations using (10) and (15)), we can show that

$$\mathbf{s}_n^T \mathbf{Q}_{\{n\}}^{-1} \mathbf{s}_n \quad \longrightarrow \quad \beta_0 \qquad (20)$$

almost surely, where β_0 is as given by (17) with $\gamma = \frac{P}{N\left(1+\frac{m^2}{\sigma_v^2}\right)}$. Substituting (20) in (19) we have almost surely

$$\mathbf{s}_n^T \Sigma^{-1} \mathbf{s}_n \quad \longrightarrow \quad \left(\frac{1}{\beta_0} + g^2 \sigma_v^2\right)^{-1}. \qquad (21)$$

Similarly, repeated application of matrix inversion lemma twice followed by the use of theorem 1 show that, for $n \neq n'$

$$\begin{aligned} \mathbf{s}_n^T \Sigma^{-1} \mathbf{s}_{n'} \quad &= \quad \frac{\mathbf{s}_n^T \mathbf{Q}_{\{n,n'\}}^{-1} \mathbf{s}_{n'}}{\left(1 + g^2\sigma_v^2 \mathbf{s}_n^T \mathbf{Q}_{\{n\}}^{-1} \mathbf{s}_n\right)\left(1 + g^2 \sigma_v^2 \mathbf{s}_{n'}^T \mathbf{Q}_{\{n,n'\}}^{-1} \mathbf{s}_{n'}\right)} \\ &\longrightarrow \quad 0, \end{aligned} \qquad (22)$$

almost surely. Substituting (21) and (22) in (18) gives (16), completing the proof.

The proposition 1 leads to the following corollary on the asymptotically large sensor system performance of decentralized detection in noisy bandlimited channels:

Corollary 1: With all notation as defined above, when $\lim_{N\longrightarrow\infty} \frac{N_s}{N} = \alpha$, the large sensor network performance of the decentralized detection is given by

$$P_f \quad \longrightarrow \quad Q\left(\frac{\tau' + 2m^2\left(\frac{\sigma_v^2}{N_s} + \frac{m^2+\sigma_v^2}{P\beta_0}\right)^{-1}}{2m\left(\frac{\sigma_v^2}{N_s} + \frac{m^2+\sigma_v^2}{P\beta_0}\right)^{-\frac{1}{2}}}\right),$$

and

$$P_m \quad \longrightarrow \quad Q\left(\frac{2m^2\left(\frac{\sigma_v^2}{N_s} + \frac{m^2+\sigma_v^2}{P\beta_0}\right)^{-1} - \tau'}{2m\left(\frac{\sigma_v^2}{N_s} + \frac{m^2+\sigma_v^2}{P\beta_0}\right)^{-\frac{1}{2}}}\right).$$

The above corollary leads to insights on large sensor system performance of decentralized detection in noisy, bandlimited channels as well as to important system design considerations. For instance, consider the special case of minimum probability of error optimality design at the fusion center which leads to $\tau' = 0$. Then according to corollary 1, the large system probability of error is asymptotically given by

$$\begin{aligned} P_e(\alpha) \quad &= \quad Q\left(mg\sqrt{\mathbf{1}^T \mathbf{S}^T \Sigma^{-1} \mathbf{S} \mathbf{1}}\right) \\ &\longrightarrow \quad Q\left(\sqrt{m^2\left(\frac{\sigma_v^2}{N_s} + \frac{m^2+\sigma_v^2}{P\beta_0}\right)^{-1}}\right) \end{aligned} \qquad (23)$$

where convergence is almost surely.

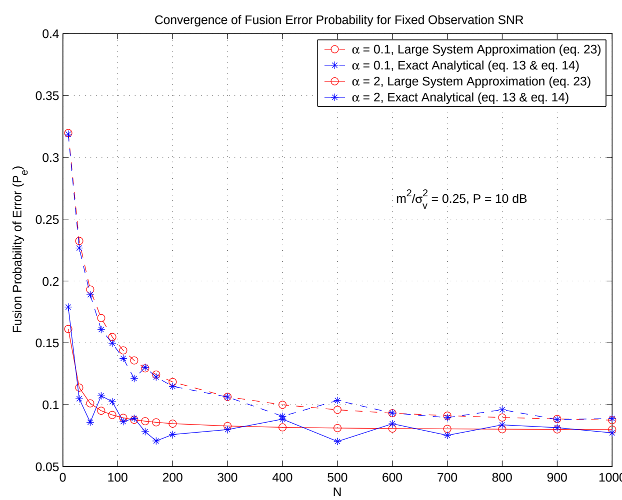

Fig. 1. Large Sensor System Approximation to the Decentralized Detection Performance in a Noisy, Bandlimited Channel Subjected to a Total Power Constraint.

Figure 1 shows the convergence of the random-spreading based decentralized detection performance as predicted by (23). Note that the exact analysis result in Fig. 1 was obtained for a random choice of the code matrix $\mathbf{S}$. As can be seen from Fig. 1, (23) provides a good approximation to the detection performance for large spreading lengths N, and thus for large-sensor systems (since $N_s = N\alpha$). Note also that, as α increases so does the required N for (23) to be a good approximation for a finite-size system.

More importantly, we can observe from Fig. 1 that for each fixed N, increasing α improves the decentralized detection performance. Since this is equivalent to increasing the number of sensors N_s allowed in the system for a fixed bandwidth we conclude that it is better to allow as many sensors to send their local decisions to the fusion center (even if this means the communication is non-orthogonal).

In fact, for large alpha, one can show that $\beta_0 \longrightarrow \frac{1}{\sigma_w^2}$, and as a result, in this case the error probability in (23) goes to

$$P_e(\alpha) \quad \longrightarrow \quad Q\left(\sqrt{\frac{\frac{P}{\sigma_w^2}}{\left(1+\frac{\sigma_v^2}{m^2}\right)}}\right). \tag{24}$$

On the other hand, if one were to allocate all available power P and the total bandwidth to just one sensor node the fusion center performance will be given by

$$P_{e,1} \quad = \quad Q\left(\sqrt{\frac{\frac{P}{\sigma_w^2}}{\frac{P/\sigma_w^2}{m^2/\sigma_v^2}+\left(1+\frac{\sigma_v^2}{m^2}\right)}}\right). \tag{25}$$

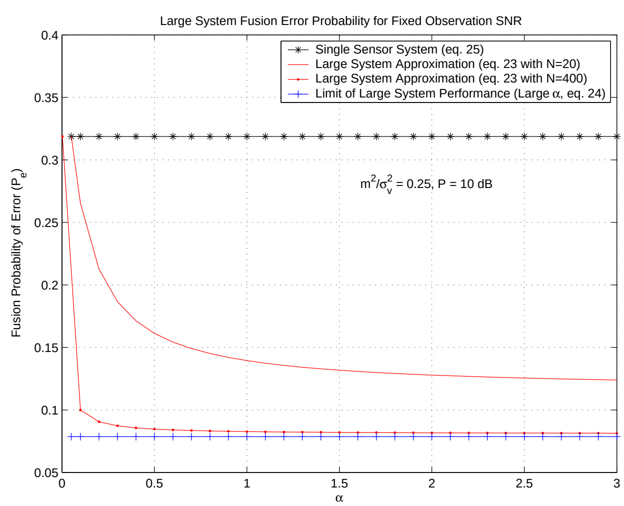

Fig. 2. Limit of Large Sensor System Approximation to the Decentralized Detection Performance in a Noisy, Bandlimited Channel Subjected to a Total Power Constraint when $\alpha \longrightarrow \infty$.

Comparison of (24) and (25) shows that allowing more sensor nodes in the network is better even if the channel is both noisy and bandlimited. This comparison is shown in Fig. 2. Included also in Fig. 2 is the decentralized detection performance for two finite values of N. First, we can observe from Fig. 2 that as N increases the fusion center performance improves. Secondly we see that as $N \longrightarrow \infty$, the performance for large α indeed goes (24). Third, Fig. 2 confirms that combining more local decisions is better than allocating all available power and bandwidth to one sensor. Moreover, the performance improves monotonically with increasing α (for a fixed N) showing that it is better to combine as many local decisions as possible at the fusion center. We should divide the available power among all nodes and allow all of them to share the available bandwidth even if they are to interfere with each other due to non-orthogonal communication. As seen by comparing (24) and (25), the final decentralized detection performance will still be better than just allowing only a single (or a few) sensor node to send its decisions using all available power and the bandwidth.

IV. Conclusions

In this paper we analyzed the decentralized detection performance of a total average power constrained wireless sensor network in a noisy, bandlimited channel. Assuming that the sensors-to-fusion center communication is based on DS-CDMA, we derived a closed form expression for the fusion performance. In order to obtain a detection performance that is independent of the chosen spreading codes we considered a large sensor system with random spreading and made use of random matrix theory. It was shown that in a noisy, bandlimited channel it is beneficial to combine as many sensor local decisions as possible even if this leads to non-orthogonal sensor-to-fusion center communication.

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