Density-Based Multiple Access for Detection in Wireless Sensor Networks

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***Abstract*—We consider a binary hypothesis testing problem using Wireless Sensor Networks (WSNs). The decision is made by a fusion center and is based on received data from the sensors. We focus on an energy and spectrum efficient transmission scheme used to reduce the energy consumption and spectrum usage during the detection task. We propose a Density-Based Multiple Access (DBMA) transmission protocol that performs a censoring-type transmission based on the density of observations using multiple access channels (MAC). Specifically, in DBMA, only sensors with highly informative observations transmit their data in each data collection. The sensors transmit a common shaping waveform and the fusion center receives a superposition of the analog transmitted signals. DBMA has important advantages for detection tasks in WSNs. First, it is highly energy and bandwidth efficient due to transmissions saving and narrowband transmission over MAC. Second, it can be implemented by simple and dumb sensors (oblivious of observation statistics, and local data processing is not required) which simplifies the implementation as compared to existing MAC transmission schemes for detection in WSNs. We establish both finite sample analysis and asymptotic analysis of the error probability with respect to the network size and provide conditions for obtaining exponential decay of the error. Numerical examples are provided to demonstrate the DBMA performance.**

I. Introduction

We consider a binary detection problem in WSNs, in which sensors measure a certain phenomenon and upon request (i.e., data collection event) transmit some function of their observations to the Fusion Center (FC) through a block fading channel. The FC makes decisions whether an unknown hypothesis is H_0 or H_1 based on the received data. We assume that observation statistics is available only at the FC[1]. The sensors might be simple and dumb [2], [3] and are not aware of their task or the environment characteristics.

A. Main Results

We propose a Density-Based Multiple Access (DBMA) transmission protocol that performs a censoring-type transmission scheme based on the density of observations using multiple access channels (MAC). Specifically, in DBMA, only sensors with highly informative observations transmit their data in each data collection. The sensors transmit a common shaping waveform and the fusion center receives a superposition of the analog transmitted signals. We propose a closed-form detector that requires observation statistics only at the FC (and not at each sensor as required by LBMA scheme described in Section I-B) and channel mean information at the FC. Complete channel statistics at the FC is not required (as opposed to the minimum rate detector that was proposed under TBMA scheme in [4]). DBMA has important advantages for detection tasks in WSNs. First, reducing the number of transmitted sensors is desired in practical implementations of WSN tasks for reducing the energy consumption involved in each data collection (due to power consumption in transmissions and duty cycles). Second, in the traditional communication approach for detection in WSNs, sensors transmit some function of their observations over parallel channels (for instance, FDM/TDM fashion). However, the bandwidth increases linearly with the number of sensors in this scheme. Therefore, for a large-scale WSN, transmission over multiple access channels (MAC) is advantageous. Using MAC in DBMA, all sensors transmit simultaneously in one dimension (or a small number of dimensions). As a result, the bandwidth requirement does not depend on the number of sensors. Furthermore, the bandwidth usage does not depend on data dimension size, by contrast to TBMA scheme (that uses MAC as well), in which the bandwidth increases linearly with the number of (independent) data dimensions. Third, DBMA can be implemented by simple and dumb sensors (oblivious of observation statistics and local data processing is not required) which simplifies the implementation as compared to existing MAC transmission schemes for detection in WSNs, e.g., Type-Based Multiple Access (TBMA) and Likelihood-Based Multiple Access (LBMA) (a detailed discussion on existing methods is given in Section I-B).

We establish both finite sample analysis and asymptotic analysis of the error probability with respect to the network size. Specifically, we use large deviation (LD) theory to characterize the detector's error exponent when the number of sensors approaches infinity. We also establish performance bounds on the error probability for a finite number of sensors. For the case of i.i.d. observations and equal channel gains, we provide a tighter finite-sample bound that coincides with the asymptotic error exponent. By contrast, under TBMA, there is a gap between the finite sample bounds and the asymptotic error exponent [3], [4]. Finally, design principles that relate the network size and the transmitted energy are developed for obtaining exponential decay for the error probability.

[1]Learning the observation statistics is typically done by scattering reference nodes in the field [1].

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B. Related Work

Developing energy and spectrum efficient transmission protocols for WSNs has attracted much attention in past and recent years. In traditional communication protocols for inference tasks in WSNs, each sensor transmits using orthogonal channels (e.g., FDM/TDM). Such methods have been focused on various aspects for reducing the energy consumption. In [5]–[8], the focus is on exploiting the channel diversity among sensors for scheduling sensors that experience better channels for transmission so as to reduce the transmission energy. In [9]–[11], the focus is on exploiting certain measures of the quality of observations for scheduling sensors with better informative observations so as to reduce the number of transmissions. Such approach is also known as *censoring* [9]. A distributed access protocol that reduces the number of transmissions by ordering transmissions according to the magnitude of the likelihood-ratio was proposed in [12], [13]. In our previous work we have developed a method that combines both channel state and quality of observations for obtaining energy saving [14]. However, these schemes require the knowledge of observation statistics at the sensors for local data processing, which is assumed known only at the FC in this paper. Furthermore, the bandwidth increases linearly with the network size when using parallel channels (i.e., a dedicated orthogonal channel per sensor). Therefore, for large-scale WSNs, transmissions over multiple access channels (MAC) is advantageous in terms of bandwidth efficiency, in which we focus in this paper.

It is well known that digital communication (where sensors convert their observations into a bit stream) does not lead to optimal performance in general network problems. The correct way of understanding the nature of information is in an analog form, whereas bits are inappropriate [15]. In [16], joint source-channel strategies over MAC were developed that often outperform separation-based strategies. A well known transmission scheme that uses MAC for detection is the Likelihood Based Multiple Access (LBMA) [3], [17] (also used for estimation tasks in [18]). In LBMA, each sensor computes the log-likelihood ratio (LLR) locally based on its current random observation, and then amplifies the transmitted waveform by the LLR. However, computing the LLR locally requires the knowledge of the distribution observation under each hypothesis at each sensor, which is assumed known only at the FC in this paper. Furthermore, the implementation is more involved than DBMA since the random LLRs might be truncated due to saturation effect in analog amplifiers. A well known access scheme that can be implemented by dumb sensors is the Type Based Multiple Access (TBMA) [3], [4]. In TBMA, the observations are quantized before communication to K possible levels. Sensors that observe level k transmit a corresponding waveform k from a set of K orthonormal waveforms. In each data collection all sensors transmit their waveforms in a one-shot transmission and the FC receives a superposition of the waveforms over MAC. In TBMA scheme, the observation statistics is needed only at the FC. In terms of bandwidth requirement, TBMA is much less efficient than DBMA. The bandwidth requirement grows linearly with K and the number of (independent) data dimensions (since each dimension must be quantized and transmitted to obtain its type at the FC). By contrast, under DBMA, the bandwidth requirement is independent of d. Generalizations of TBMA using non-coherent transmissions and i.i.d. observations have been studied in [19], [20]. However, here we assume coherent transmissions by phase correction at the transmitter as in [4], [17], [21] and non-i.i.d. observation case which make the problem fundamentally different. Other related works investigated MAC for detection in WSNs using multiple antennas at the FC [22], detection with a non-linear sensing behavior [23], and detecting a stationary random process distributed in space and time with a circularly-symmetric complex Gaussian distribution [24], [25]. However, these studies are fundamentally different from the settings considered in this paper.

II. Detection Scheme using Density Based Multiple Access (DBMA)

We consider a binary detection problem using a WSN containing N sensors. The sensors measure a certain phenomenon and deliver some function of their observations to a FC through a multiple access channel. We assume that sensor n experiences a block fading channel h_n with a non-zero channel mean[2] $\mu_{h,n}$. The FC determines whether an unknown hypothesis is H_0 or H_1 based on the received data from sensors. The a-priori probabilities of the two hypotheses H_0, H_1 are denoted by $P(H_0)$ and $P(H_1)$, respectively. Let x_n and $f_{X_n}(x|H_m)$ be the random observation at sensor n and the Probability Density Function (PDF) of x_n conditioned on H_m, respectively.

A. Transmission Scheme

Under DBMA, all sensors that observe x_n in a predetermined transmission region of observations transmit a common waveform. Let Γ_n be the (multi-dimensional) transmission region of sensor n observation, and let

$$p_{0,n} \triangleq \int_{x\in\Gamma_n} f_{X_n}(x|H_0)dx, \quad p_{1,n} \triangleq \int_{x\in\Gamma_n} f_{X_n}(x|H_1)dx \,, \tag{1}$$

so that $p_{i,n}$ is the probability that sensor n transmits under H_i. In practice, the transmission region is predetermined by the FC based on the density of observations so that to increase the distance between the hypotheses under constraint on the expected number of transmissions. A discussion about design principles of Γ_n is given later. Throughout the paper we will focus on the detector performance assuming that Γ_n is given.

Let $s(t),\ 0 < t < T$ be a baseband equivalent normalized waveform, $\int_0^T s^2(t)dt = 1$. In each data collection, all sensors that observe x_n in the transmission region Γ_n transmit $A_n\sqrt{E_N}\cdot s(t)$. All other sensors do not transmit. E_N can be any fixed constant or a function of the number of sensors N, such that power constraint is satisfied. A_n is a finite amplification and is given by:

$$A_n = \log\left(\frac{(1-p_{0,n})p_{1,n}}{(1-p_{1,n})p_{0,n}}\right)e^{-j\phi_{h_n}} \,. \tag{2}$$

[2]As explained in the introduction, this is done by correcting the phase at the transmitter.

It is assumed that channel phase is corrected by amplifying A_n by $e^{-j\phi_{h_n}}$, as in [4], [17], [21]. Note that synchronization error less than $\pi/4$ is sufficient for getting positive I, Q, components at the receiver in which the results in this paper hold. We discuss the amplifier A_n later. Let $\mathbf{1}_\Gamma(x_n)=1$ if $x_n\in\Gamma_n$, or $\mathbf{1}_\Gamma(x_n)=0$ if $x_n\notin\Gamma_n$ be the indicator function. The received signal at the FC is given by:

$$r(t)=\sum_{n=1}^{N}h_nA_n\mathbf{1}_\Gamma(x_n)\sqrt{E_N}\cdot s(t)+w(t)\ \ ,0<t<T\ ,$$

where $w(t)$ is the channel AWGN with zero mean and Power Spectrum Density (PSD) σ^2, and h_n is a non-zero mean r.v. due to phase correction.

After matched-filtering by the corresponding waveform at the FC, we have: $r=\sqrt{E_N}\sum_{n=1}^{N}h_nA_n\mathbf{1}_\Gamma(x_n)+w$, where $w\sim N(0,\sigma^2)$. Let

$$y_{_N}\triangleq\frac{r}{N\sqrt{E_N}}=\frac{1}{N}\sum_{n=1}^{N}h_nA_n\mathbf{1}_\Gamma(x_n)+\tilde{w},\tag{3}$$

where $\tilde{w}\sim N(0,\sigma^2/N^2E_N)$.

We propose the following threshold-based detector:
Decide H_1 if:

$$\frac{y_{_N}}{\mu_h}>\frac{\log(\eta)}{N}+\frac{1}{N}\sum_{n=1}^{N}\log\left(\frac{1-p_{0,n}}{1-p_{1,n}}\right).\tag{4}$$

Otherwise, decide H_0.
Under the MAP criterion $\eta=P(H_0)/P(H_1)$, and under the Neyman Pearson (NP) criterion η is determined according to the desired false-alarm probability.

B. Implementation of DBMA

The implementation of DBMA scheme has important advantages for detection using WSNs. First, it is highly bandwidth-efficient. Only a single (or few) waveform is transmitted by the sensors. Note that DBMA readily applies to the case where sensors measure d-dimensional observations. In this case, all sensors that measure a d-dimensional observation that lies inside the d-dimensional transmission region transmit the same waveform $s(t)$. As a result, the bandwidth requirement does not depend on[3] d. Second, the number of transmissions can be significantly reduced, depending on the desired detection performance (which is developed in Section III) and system constraints. Third, it can be implemented by dumb and simple sensors (oblivious of observation statistics and without local data processing at sensors) with only few instructions from the FC. For instance, when detecting a parameter θ in AWGN, the observation distributions are given by $x_n\sim N(0,\sigma_v^2)$ under H_0 and $x_n\sim N(\theta,\sigma_v^2)$ under H_1. A good choice of Γ_n should be $\Gamma_n=\{x:X_{Th}<x_n<\infty\}$, since the distance between $p_{0,n}$ and $p_{1,n}$ increases in this region. It can be shown that when $P(H_0)=P(H_1)$, then $X_{Th}=\theta/2$ maximizes the error exponent and the expected number of transmitted sensors is $N/2$. Increasing X_{Th} reduces the number of transmissions with the price of reducing the error exponent (see [29] for more details). On the other hand, when detecting a normal distributed signal $\theta\sim N(0,\sigma_\theta^2)$ in AWGN, we have $x_n\sim N(0,\sigma_v^2)$ under H_0 and $x_n\sim N(0,\sigma_\theta^2+\sigma_v^2)$ under H_1. Therefore, a good choice of Γ_n in this case should be $\Gamma_n=\{x:X_{Th}<|x_n|<\infty\}$.

Note that in a case of conditionally i.i.d observations, we ignore the gain A_n in (2), since it is equal for all sensors. Amplifying the signal by A_n leads to analog superposition of the statics measure at the receiver in the non-i.i.d case as will be discussed later. Note that sensors that are located close to each other measure approximately identically distributed observations under H_i and transmit with equal gain A_n. The FC can send the amplifier information A_n to the sensors. Other option is to use orthogonal transmissions between geographical areas (say K areas) and to amplify the received signal from different areas by the corresponding amplification A_n at the FC. The later reduces communication between FC and sensors, but has a price of increasing the bandwidth by K times. Note that the implementation of DBMA is much more simpler than the implementation of LBMA [3], [17], in which each sensor transmits its random log-likelihood ratio (LLR) based on the current measurement (which requires the knowledge of the distribution observation under each hypothesis at each sensor). Also, the random LLR value might be truncated due to nonlinear effects.

It should be noted that the proposed threshold-based detector is given in a simple closed-form and does not require the knowledge of the channel statistics at the FC. It only requires the knowledge of channel mean μ_h, which can be relatively simpler to compute from superposition of low-power pilot signal transmissions over MAC.

[3] By contrast, under TBMA scheme [3], [4], each dimension must be quantized and transmitted to obtain the type of each dimension at the FC. While efficient fusion can be done when features are correlated by whitening or Distributed KLT methods [26]–[28], in worst case the bandwidth requirement grows linearly with d when dimensions are independent.

III. Performance Analysis

In this section, we analyze the performance of the proposed threshold-based detector (4) in a case of finite N and in the asymptotic regime (where $N\to\infty$). We first provide notations that will be used in this section. For Bernoulli random variables (r.v) x,z with success probability q_0 and q_1, respectively, the Kullback Leibler (KL) divergence between x,z is defined by:

$$D(x||z)\triangleq D(q_0||q_1)=q_0\log\left(\tfrac{q_0}{q_1}\right)+(1-q_0)\log\left(\tfrac{1-q_0}{1-q_1}\right).\tag{5}$$

Note that under DBMA, $\mathbf{1}_\Gamma(x_n)$ is a Bernoulli r.v with success probability $p_{i,n}$ under H_i. Let

$$\overline{D}(p_i||p_j)\triangleq\frac{1}{N}\sum_{n=1}^{N}D(p_{i,n}||p_{j,n})\text{ , for } i,j=0,1\tag{6}$$

denote the average KL divergence across the sensors, and let

$$\Lambda(t)\triangleq\lim_{N\to\infty}\frac{1}{N}\log E\left\{e^{Nty_{_N}}\right\}\ .\tag{7}$$

The existence of the limit will be discussed later.

The error probability $P_{e,N}$ under DBMA used in a WSN that contains N sensors is defined by:

$$P_e = P(H_0)P_N(H_0 \to H_1) + P(H_1)P_N(H_1 \to H_0) \ , \tag{8}$$

where $P_N(H_0 \to H_1)$ is the probability to decide H_1 when H_0 is true (Type-I error probability), and $P_N(H_1 \to H_0)$ is the probability to decide H_0 when H_1 is true (Type-II error probability) in a WSN that contains N sensors. Note that $P_e, P(H_0 \to H_1), P(H_1 \to H_0)$ depend on the number of sensors N. However, for convenience we often remove the index N. We are interested in characterizing the rate at which P_e approaches zero as N increases.

We next use LD theory and concentration bounds for characterizing the exponential decay rate. We refer the reader to the extended version of this paper [29] for more details on LD theory. Due to space limit, we focus on analyzing the performance under the non-fading case (i.e., $h_n = h_m \ \forall 1 \leq n, m \leq N$). Analysis for detection over fading channels is given in [29].

Theorem 1: *Assume that the proposed threshold-based detector (4) is implemented. Let* $\overline{\Delta}_{0,N} = \overline{D}(p_0||p_1) + \log(\eta)/N$ *and* $\overline{\Delta}_{1,N} = \overline{D}(p_1||p_0) - \log(\eta)/N$. *Let* N_0 *be the minimal number of sensors such that* $\overline{\Delta}_{0,N} > 0$ *and* $\overline{\Delta}_{1,N} > 0$. *Then:*

a) *Consider the case of independent observations under* H_i. *Then, for all* $N > N_0$, *the error probability is upper bounded by:*

$$\begin{aligned} P(H_0 \to H_1) &\leq \exp\left\{-N\frac{2\overline{\Delta}_{0,N}^2}{\frac{1}{N}\sum_{n=1}^N A_n^2 + 4\sigma^2/NE_N}\right\}, \\ P(H_1 \to H_0) &\leq \exp\left\{-N\frac{2\overline{\Delta}_{1,N}^2}{\frac{1}{N}\sum_{n=1}^N A_n^2 + 4\sigma^2/NE_N}\right\}. \end{aligned} \tag{9}$$

b) (tighter bound (coincides with (11)) under the conditionally i.i.d. case:) *Consider the case of i.i.d. observations under* H_i. *Let* $A \triangleq A_n, \ p_0 \triangleq p_{0,n}, \ p_1 \triangleq p_{1,n}, \ \Gamma \triangleq \Gamma_n \ , \forall 1 \leq n \leq N$ *equal for all sensors. Then, for all* $N > N_0$, *the error probability is upper bounded by:*

$$\begin{aligned} &P(H_0 \to H_1) \\ &\quad \leq \exp\left\{-N\left[D\left(p_0 + \overline{\Delta}_{0,N}/A||p_0\right) - \epsilon_0(N)\right]\right\}, \\ &P(H_1 \to H_0) \\ &\quad \leq \exp\left\{-N\left[D\left(p_1 - \overline{\Delta}_{1,N}/A||p_1\right) - \epsilon_1(N)\right]\right\}, \end{aligned} \tag{10}$$

where

$$\epsilon_0(N) = \frac{\sigma^2}{2NA^2E_N}\log^2\left(1 + \frac{\overline{\Delta}_{0,N}/A}{p_0(1-p_0-\overline{\Delta}_{0,N}/A)}\right),$$

$$\epsilon_1(N) = \frac{\sigma^2}{2NA^2E_N}\log^2\left(1 + \frac{\overline{\Delta}_{1,N}/A}{\left(p_1-\overline{\Delta}_{1,N}/A\right)(1-p_1)}\right).$$

Furthermore, if $E_N = \Omega\left(N^{\epsilon-1}\right)$, *for any* $\epsilon > 0$, *then in the asymptotic regime* ($N \to \infty$) *the following holds:*

c) *Assume that sensors observations are independent but non-necessarily identically distributed (i.ni.d) under* H_i. *Then, the error exponent under DBMA scheme is maximized, and achieves the best error exponent which is achieved by the maximum likelihood detector with respect to the transmitted signal* $\mathbf{1}_\Gamma(x_n)$.

d) *Consider the case of non-i.i.d observations under* H_i. *Assume that* $\Lambda(t)$ *(7) exists as an extended real number, smooth and continuous. Then,* y *satisfies the LDP with a rate function:* $I_i(x) = \sup_{t\in\mathbb{R}}(xt - \Lambda(t)) \ , x \in \mathbb{R}$, *under* H_i *and the error probability decays exponentially with* N. *Furthermore, if the observations are i.i.d under* H_i, *then the rate function is given by* $I_i(x) = D(x||p_i)$ *under* H_i. *The asymptotic error exponent is given explicitly by:*

$$\begin{aligned} &-\lim_{N\to\infty}\frac{1}{N}\log\left(P(H_0 \to H_1)\right) \\ &= -\lim_{N\to\infty}\frac{1}{N}\log\left(P(H_1 \to H_0)\right) \\ &= D(p_0 + D(p_0||p_1)/A||p_0) = D(p_1 - D(p_1||p_0)/A||p_1) \ . \end{aligned} \tag{11}$$

Proof: The proof is given in the extended version of this paper [29].

Remark 1: Note that the noise decay in (3) implies that the detector's performance could be improved by increasing the number of sensors in the network without increasing the total transmission energy. Theorem 1 characterizes the decay rate of the error probability, which holds if the transmitted energy satisfies $E_N = \Omega\left(N^{\epsilon-1}\right)$. These results provides important design principles for detection under resource constraints. For non-i.i.d. observations, the conditions on $\Lambda(t)$ are used to apply the Gartner-Ellis Theorem so as to obtain the rate function. Next, we demonstrate common cases in WSNs when the conditions hold. First, consider a common scenario where sensors are located in K different areas ($N(k)$ sensors in area k) and their observations are independent but not necessarily identically distributed under H_i. However, sensor observations in the same area k ($1 \leq k \leq K$) are assumed to be i.i.d under H_i. In this common scenario, we have:

$$\begin{aligned} &\frac{1}{N}\log\left(E\left\{e^{Nty}\right\}\right) \\ &\longrightarrow E\left\{\log E_k\left\{e^{th_n\ell_n}\right\}\right\} = \Lambda(t) \ , \text{as } N \to \infty \ . \end{aligned}$$

Another common scenario in which the conditions hold is when sensors transmit their data using spatially correlated Markovian fading channels [30].

In Fig. 1, we demonstrate the performance of DBMA. The signal is assumed i.i.d across sensors, and the observation at sensor n under H_0 and H_1 is given by $x_n = v_n$, and $x_n = \theta_n + v_n$, respectively, where $v_n \sim N(0,1)$ is the additive Gaussian observation noise. The observation noise is assumed to be i.i.d across sensors. The transmission region was set to $\Gamma \triangleq \Gamma_n = \{x : X_L < |x_n| < \infty\} \ , \forall n$, where X_L is set such that the average number of transmissions under DBMA equals to $0.2 \cdot N$. We consider equal channel gain, where the channel AWGN is set to $w \sim N(0,5)$. We compared the performance of the proposed DBMA algorithm to the well known TDMA scheme (where each sensor transmits its exact observation in different time slot). Note that the bandwidth increases linearly with N under TDMA scheme, while only a single waveform is required under DBMA scheme. We simulated TDMA using a noise-free channel, as well, to apply a bench-mark on the detection performance when the FC directly access the observations at the sensors. Fig. 1 confirms the results of Theorem 1. The transmission energy of each sensor is $E_N = 1$, i.e., DBMA saves 80% transmission energy over TDMA. Fig. 1 shows that the error probability decays exponentially with N and achieves the theoretical error exponent (11) in Theorem 1. Note that DBMA outperforms TDMA in a noisy channel scenario, although all the sensors transmit their exact measurements under TDMA scheme. The reason is that TDMA suffers from channel noise in each dimension, while it becomes negligible under DBMA scheme (due to a single-dimension transmission). Other simulation examples can be found in the extended version of this paper [29].

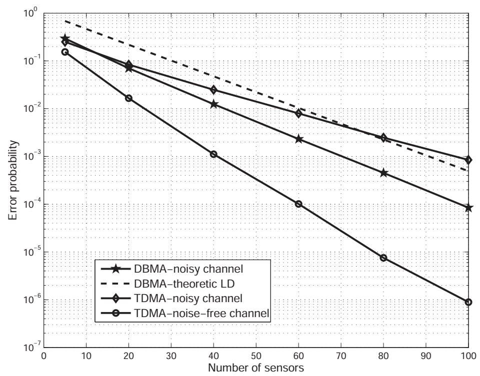

Fig. 1. Error probability as a function of the number of sensors. Simulation parameters: Equal channel gain, i.i.d observations under H_i, fixed transmission energy.

IV. Conclusion

We proposed a Density-Based Multiple Access (DBMA) scheme for energy and spectrum efficient detection in WSNs. In DBMA, only sensors with highly informative observations transmit their data in each data collection using a common analog waveform. We established both finite sample analysis and asymptotic analysis of the error probability with respect to the network size. Conditions for obtaining exponential decay were derived. Numerical examples demonstrate strong performance of DBMA.

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References

[1] Y. Hong, K. Lei, and C. Chi, "Channel-aware random access control for distributed estimation in sensor networks," *IEEE Trans. on Signal Process.*, vol. 56, pp. 2967–2980, Jul. 2008.
[2] S. Marano, V. Matta, P. Willett, and L. Tong, "DOA estimation via a network of dumb sensors under the SENMA paradigm," *IEEE Signal Process. Letters*, vol. 12, pp. 709–712, Oct. 2005.
[3] K. Liu and A. Sayeed, "Type-based decentralized detection in wireless sensor networks," *IEEE Trans. on Signal Process.*, vol. 55, pp. 1899 –1910, May 2007.
[4] G. Mergen, V. Naware, and L. Tong, "Asymptotic detection performance of type-based multiple access over multiaccess fading channels," *IEEE Trans. on Signal Process.*, vol. 55, pp. 1081 –1092, Mar. 2007.
[5] Q. Zhao and L. Tong, "Opportunistic carrier sensing for energy-efficient information retrieval in sensor networks," *EURASIP J. Wireless comm. Netw.*, vol. 2, pp. 231–241, 2005.
[6] Y. Chen and Q. Zhao, "An integrated approach to energy aware medium access for wireless sensor networks," *IEEE Trans. on Signal Process.*, vol. 55, pp. 3429–3444, July 2007.
[7] K. Cohen and A. Leshem, "Time-varying opportunistic protocol for maximizing sensor networks lifetime," *in Proc. of the 2009 IEEE International Conference on Acoustics, Speech and Signal Process. (ICASSP).*, pp. 2421–2424, Apr. 2009.
[8] K. Cohen and A. Leshem, "A time-varying opportunistic approach to lifetime maximization of wireless sensor networks," *IEEE Trans. on Signal Process.*, vol. 58, pp. 5307–5319, Oct. 2010.
[9] C. Rago, P. Willett, and Y. Bar-Shalom, "Censoring sensors: A low communication-rate scheme for distributed detection," *IEEE Trans. on Aerospace and Electronic Sys.*, vol. 32, pp. 554Ű–568, Apr. 1996.
[10] S. Appadwedula, V. V. Veeravalli, and D. L. Jones, "Decentralized detection with censoring sensors," *IEEE Trans. on Signal Process.*, vol. 56, pp. 1362–1373, Apr. 2008.
[11] N. Patwari, A. O. Hero, and B. M. Sadler, "Hierarchical censoring sensors for change detection," *Statistical Signal Process., 2003 IEEE Workshop on*, pp. 21–24, Sep. 2003.
[12] R. S. Blum and B. M. Sadler, "Energy efficient signal detection in sensor networks using ordered transmissions," *IEEE Trans. on Signal Process.*, vol. 56, pp. 3229–3235, Jul. 2008.
[13] J. Zhang, Z. Chen, R. S. Blum, X. Lu, and W. Xu, "Ordering for reduced transmission energy detection in sensor networks testing a shift in the mean of a gaussian graphical model," *IEEE Transactions on Signal Processing*, vol. 65, no. 8, pp. 2178–2189, 2017.
[14] K. Cohen and A. Leshem, "Energy-efficient detection in wireless sensor networks using likelihood ratio and channel state information," *IEEE Journal on Selected Areas in Comm.*,, vol. 29, pp. 1671–1683, Sep. 2011.
[15] M. Gastpar, "Uncoded transmission is exactly optimal for a simple gaussian ŞsensorŤ network," *IEEE Transactions on Information Theory*, vol. 54, no. 11, pp. 5247–5251, 2008.
[16] B. Nazer and M. Gastpar, "Computation over multiple-access channels," *IEEE Transactions on information theory*, vol. 53, no. 10, pp. 3498–3516, 2007.
[17] K. Cohen and A. Leshem, "Performance analysis of likelihood-based multiple access for detection over fading channels," *IEEE Transactions on Information Theory*, vol. 59, no. 4, pp. 2471–2481, 2013.
[18] S. Marano, V. Matta, T. Lang, and P. Willett, "A likelihood-based multiple access for estimation in sensor networks," *IEEE Trans. on Signal Process.*, vol. 55, pp. 5155–5166, Nov. 2007.
[19] A. Anandkumar and L. Tong, "Type-based random access for distributed detection over multiaccess fading channels," *IEEE Transactions on Signal Processing*, vol. 55, no. 10, pp. 5032–5043, 2007.
[20] F. Li, J. S. Evans, and S. Dey, "Decision fusion over noncoherent fading multiaccess channels," *IEEE Transactions on Signal Processing*, vol. 59, no. 9, p. 4367, 2011.
[21] T. Wimalajeewa and P. K. Varshney, "Wireless compressive sensing over fading channels with distributed sparse random projections," *IEEE Transactions on Signal and Information Processing over Networks*, vol. 1, no. 1, pp. 33–44, 2015.
[22] I. Nevat, G. W. Peters, and I. B. Collings, "Distributed detection in sensor networks over fading channels with multiple antennas at the fusion centre," *IEEE transactions on signal processing*, vol. 62, no. 3, pp. 671–683, 2014.
[23] P. Zhang, I. Nevat, G. W. Peters, and L. Clavier, "Event detection in sensor networks with non-linear amplifiers via mixture series expansion," *IEEE Sensors Journal*, vol. 16, no. 18, pp. 6939–6946, 2016.
[24] J. A. Maya, L. R. Vega, and C. G. Galarza, "Optimal resource allocation for detection of a gaussian process using a mac in wsns," *IEEE Transactions on Signal Processing*, vol. 63, no. 8, pp. 2057–2069, 2015.
[25] J. A. Maya, C. G. Galarza, and L. R. Vega, "Exploiting spatial correlation in energy constrained distributed detection," *arXiv preprint arXiv:1509.04119*, 2015.
[26] M. Gastpar, P. L. Dragotti, and M. Vetterli, "The distributed karhunen–loeve transform," *IEEE Transactions on Information Theory*, vol. 52, no. 12, pp. 5177–5196, 2006.
[27] H. I. Nurdin, R. R. Mazumdar, and A. Bagchi, "Reduced-dimension linear transform coding of distributed correlated signals with incomplete observations," *IEEE Transactions on Information Theory*, vol. 55, no. 6, pp. 2848–2858.
[28] A. Amar, A. Leshem, and M. Gastpar, "Recursive implementation of the distributed karhunen-loève transform," *IEEE Transactions on Signal Processing*, vol. 58, no. 10, pp. 5320–5330, 2010.
[29] K. Cohen and A. Leshem, "Spectrum and energy efficient multiple access for detection in wireless sensor networks," *submitted to IEEE Transactions on Signal Processing, available at arXiv*.
[30] A. Dembo and O. Zeitouni, "Large deviations techniques and applications," *New York: Springer*, 1998.