Blind Channel Estimation and Equalization in Wireless Sensor Networks Based on Correlations Among Sensors

Xiaohua Li, *Member, IEEE*

***Abstract*—In densely deployed wireless sensor networks, signals of adjacent sensors can be highly cross-correlated. This paper proposes to utilize such a property to develop efficient and robust blind channel identification and equalization algorithms. Blind equalization can be performed with complexity as low as $O(\tilde{N})$, where $\tilde{N}$ is the length of equalizers. Transmissions can be more power and bandwidth efficient in multipath propagation environment, which is especially important for wideband sensor networks such as those for acoustic location or video surveillance. The cross-correlation property of sensor signals and the finite sample effect are analyzed quantitatively to guide the design of low duty-cycle sensor networks. Simulations demonstrate the superior performance of the proposed method.**

***Index Terms*—Adaptive algorithm, blind equalization, channel identification, cross-correlation, wireless sensor network.**

I. INTRODUCTION

WIRELESS sensor networks have aroused much research interest recently due to their potential wide applications [1], [2]. They usually consist of a large number of densely deployed sensors whose data can be transmitted to the desired user through multihop relays. Since the density may be very high, e.g., tens of sensors per square meter [3], signals from adjacent sensors are highly cross-correlated [4], [5].

Sensors should be extremely power efficient because once deployed, they may not be recharged or replaced. Since wireless transceivers usually consume a major portion of battery power [3], it is critical to improve their power efficiency. Nevertheless, one of the major difficulties comes from the harsh communication environment with multipath propagation and severe fading [2]. Sophisticated and yet computationally efficient techniques must be used for reliable and efficient signal demodulation and detection. Although much research has been performed on various aspects of sensor networks [3], [6]–[8], energy-efficient wireless transmission techniques are mostly still open. In particular, blind channel estimation and equalization may be used to mitigate multipath propagation and to improve both bandwidth and energy efficiency. This is especially important for wideband sensor networks such as those for acoustic location [9] or video surveillance [10].

For channel equalization, traditional training-based methods [11] waste not only bandwidth but power as well. Because sensors usually work with low duty-cycle in time-varying channels, a sufficiently long training sequence has to be embedded in each data packet. Blind equalization is useful to enhance power and bandwidth efficiency by removing training. There is, of course, a tradeoff because blind algorithms are usually more complex and, thus, consume more power in computation. Blind equalization methods with the same complexity as training methods, if possible, would then be very desirable. Unfortunately, many traditional blind methods may not be appropriate for sensor networks. For those based on a single-input single-output (SISO) framework, higher than second-order statistics or nonlinear optimization are often required [12]–[14], which causes problems such as local and slow convergence [11]. On the other hand, blind methods based on a single-input multiple-output (SIMO) framework [15]–[17] are also questionable since multiantenna or oversampling unnecessarily reduces power efficiency. In fact, multiantenna is not applicable in tiny sensors. The most severe problem comes from the ill-conditioned channels such as those with zeros on the unit circle or with common zeros among subchannels [11].

Traditional methods usually assume that signals from different users (or sensors) are uncorrelated. This is not true in densely deployed wireless sensor networks. In this paper, we show that the cross-correlation among sensors can be exploited for blind channel identification and equalization. In particular, we develop an adaptive algorithm that has linear complexity and is robust to even ill-conditioned channels. The cross-correlation property and its effect on channel estimation are analyzed quantitatively.

The organization of this paper is as follows. In Section II, we introduce the signal and system model in wireless sensor networks. In Section III, we derive the blind algorithms. In Section IV, we study the cross-correlation property and the finite sample effect. Simulations are shown in Section V, and conclusions are presented in Section VI.

II. PROBLEM FORMULATION

In wireless sensor networks with time division multiple access or similar channel access schemes where sensors take turns to transmit data packets in their own slots, we consider the case that a sensor receives signals from multiple other sensors, e.g.,

Manuscript received May 8, 2003; revised April 8, 2004. Part of this work is published in the Proceedings of ICASSP'04, Montreal, QC, Canada, May 17-21, 2004. The associate editor coordinating the review of this manuscript and approving it for publication was Prof. Zhi Ding.

The author is with the Department of Electrical and Computer Engineering, State University of New York at Binghamton, Binghamton, NY 13902 USA (e-mail: xli@binghamton.edu).

Digital Object Identifier 10.1109/TSP.2005.843744

node 1 receives signals from sensor 1 to J, as illustrated in Fig. 1(a). This happens when multiple sensors transmit their sensing values to a remote receiver or when multiple nodes relay packets to the next hop. Note that the latter case is also addressed in [18] with an approach called multitransmission.

The transmission of each sensor i is illustrated in Fig. 1(b). The sensing values are first processed by a data processor with output $b_i(n)$, which is then scrambled before transmission. The baseband symbols, which are denoted as $s_i(n)$, are transmitted through a wireless channel $\{h_i(n)\}$.

Among the J transmitting sensors, the sensors i and j need to transmit two highly cross-correlated, ergodic, and wide-sense stationary (WSS) sequences $\{b_i(n)\}$ and $\{b_j(n)\}$. The cross-correlation [19] is $r_{ij}^b(\tau) = E[b_i(n)b_j^*(n+\tau)] = \lim_{M_b\to\infty}(1/M_b)\sum_{n=1}^{M_b} b_i(n)b_j^*(n+\tau)$, where $(\cdot)^*$ denotes complex conjugation. From the sequences $\{b_i(n)\}$ and $\{b_j(n)\}$, we can find two subsequences $\{b_i(n_{i\ell}) : n_{i\ell} \in I_i\}$ and $\{b_j(n_{j\ell}) : n_{j\ell} \in I_j\}$, respectively, so that

$$r_{ij} \triangleq \lim_{M\to\infty} \frac{1}{M} \sum_{\ell=1}^{M} b_i(n_{i\ell})b_j^*(n_{j\ell}) \neq 0 \tag{1}$$

where the index sets are defined as $I_i = \{n_{i1}, n_{i2}, \ldots\}$ and $I_j = \{n_{j1}, n_{j2}, \ldots\}$. Without loss of generality, the indices in I_i and I_j are in increasing order. By choosing appropriate I_i and I_j, we can obtain as large a cross correlation r_{ij} in (1) as possible, which will aid our blind channel estimation and equalization in Section III. This is necessary because, as can be seen in Section IV, some symbol pairs may be more highly correlated than others.

In order to introduce some special structure on the cross correlation of the transmitted symbol sequences, we use scrambling: a technique widely used in practical systems. The two sensors can use two pseudo-noise (PN) sequences $\{c_i(n)\}$ and $\{c_j(n)\}$ for scrambling so that $s_i(n) = c_i^*(n)b_i(n)$ and $s_j(n) = c_j^*(n)b_j(n)$, respectively. We assume that the two PN sequences are different, but both have (asymptotically) zero mean and unit energy, i.e., $\lim_{M_c\to\infty}(1/M_c)\sum_{n=1}^{M_c} c_i(n) = 0, |c_i(n)|^2 = 1$. For example, the sensors can use different long codes defined in the IS-95 CDMA specification [20].

- *Cross-correlation assumption:* We assume that there exist index sets I_i, I_j, and PN sequences $\{c_i(n)\}$ and $\{c_j(n)\}$ such that

$$\lim_{M\to\infty} \frac{1}{M} \sum_{\ell=1}^{M} c_i(n_{i\ell})s_i(n_{i\ell}+d_i)s_j^*(n_{j\ell}+d_j)c_j^*(n_{j\ell}) = r_{ij}\delta(d_i)\delta(d_j) \tag{2}$$

where $n_{i\ell} \in I_i, n_{j\ell} \in I_j, i \neq j$, and $\delta(\cdot)$ is the Kronecker-delta function.

The credibility of the assumption (2) can be justified as follows. With $s_i(n) = c_i^*(n)b_i(n)$ and $s_j(n) = c_j^*(n)b_j(n)$, (2) gives

$$\lim_{M\to\infty} \frac{1}{M} \sum_{\ell=1}^{M} [c_i(n_{i\ell})c_i^*(n_{i\ell}+d_i)][c_j^*(n_{j\ell}) \times c_j(n_{j\ell}+d_j)][b_i(n_{i\ell}+d_i)b_j^*(n_{j\ell}+d_j)]. \tag{3}$$

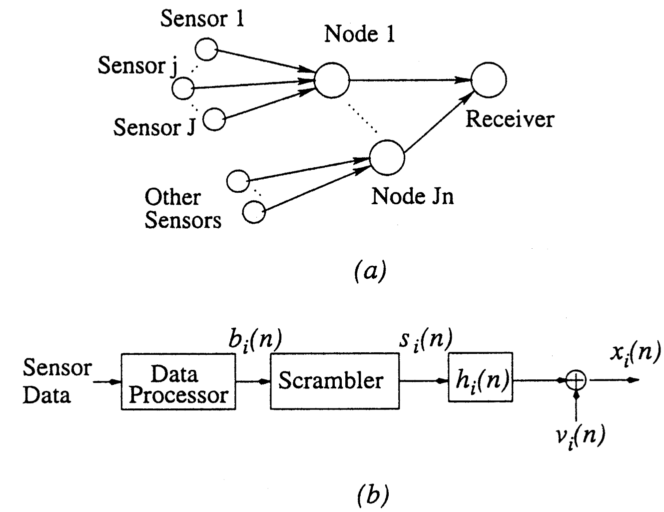

Fig. 1. (a) System model of wireless sensor networks. (b) Transmission block diagram of each sensor.

When M is large, the correlation characteristics of PN sequences are indistinguishable from those of pure random sequences [21]. Therefore, if we substitute $c_i(n)$ and $c_j(n)$ with $\tilde{c}_i(n)$ and $\tilde{c}_j(n)$, respectively, and assume $\tilde{c}_i(n), \tilde{c}_j(n), b_i(n)$, and $b_j(n)$ are realizations of four independent WSS ergodic random processes, then (3) approaches $E[\tilde{c}_i(n_{i\ell})\tilde{c}_i^*(n_{i\ell}+d_i)\tilde{c}_j^*(n_{j\ell})\tilde{c}_j(n_{j\ell}+d_j)b_i(n_{i\ell}+d_i)b_j^*(n_{j\ell}+d_j)]$, which equals $E[\tilde{c}_i(n_{i\ell})\tilde{c}_i^*(n_{i\ell}+d_i)]E[\tilde{c}_j^*(n_{j\ell})\tilde{c}_j(n_{j\ell}+d_j)]E[b_i(n_{i\ell}+d_i)b_j^*(n_{j\ell}+d_j)]$. Then, it is easy to see that (3) equals r_{ij} if $d_i = d_j = 0$ and equals zero if $d_i \neq 0$ or $d_j \neq 0$.

Equation (2) defines the time-averaged cross-correlation among the subsequences extracted from the transmitted symbol sequences. With shifting parameters d_i and d_j, we first find two subsequences $\{\tilde{s}_i(\ell) : \tilde{s}_i(\ell) = s_i(n_{i\ell}+d_i)\}$ and $\{\tilde{s}_j(\ell) : \tilde{s}_j(\ell) = s_j(n_{j\ell}+d_j)\}$. Then, we calculate their cross-correlation weighted with

$$w_{ij}(\ell) \triangleq c_i(n_{i\ell})c_j^*(n_{j\ell}). \tag{4}$$

The cross-correlation becomes nonzero only for the subsequences defined on I_i and I_j or, in other words, with zero-shiftings $d_i = d_j = 0$.

Note that, in fact, we require (2) to be satisfied for a limited range of d_i and d_j only, as can be seen from the Proof of Proposition 1. In addition, some other schemes differently from the scrambling one are also applicable. For example, the two sensors can use random interleavers such as those used in Turbo codes to randomize the order of $\{b_i(n)\}$ and $\{b_j(n)\}$. Another scheme is the direct-sequence spread-spectrum transmission, where our method can be used to reduce residual intersymbol interference after despreading. However, to simplify the presentation, we focus on the scrambling scheme only.

The receiving node receives signals from all J sensors sequentially, i.e., without overlapping. The received baseband signal from sensor i is

$$x_i(n) = \sum_{k=0}^{L} h_i(k)s_i(n-k) + v_i(n) \tag{5}$$

where $x_i(n)$ is the received sample at the sampling time instant n, $h_i(k)$ denotes the channel with order L, and $v_i(n)$ is the additive white Gaussian noise (AWGN).

Let $N \geq L$. We stack $N+1$ received samples together as sample vectors $\mathbf{x}_i(n)$. Define

$$\mathbf{x}_i(n) = \begin{bmatrix} x_i(n) \\ \vdots \\ x_i(n-N) \end{bmatrix}, \quad \mathbf{s}_i(n) = \begin{bmatrix} s_i(n) \\ \vdots \\ s_i(n-N-L) \end{bmatrix}$$
$$\mathbf{v}_i(n) = \begin{bmatrix} v_i(n) \\ \vdots \\ v_i(n-N) \end{bmatrix}. \tag{6}$$

Then, from (5), we have

$$\mathbf{x}_i(n) = \mathcal{H}_i \mathbf{s}_i(n) + \mathbf{v}_i(n) \tag{7}$$

where the $(N+1) \times (N+L+1)$ channel matrix is

$$\mathcal{H}_i = \begin{bmatrix} h_i(0) & \cdots & h_i(L) & & \\ & \ddots & & \ddots & \\ & & h_i(0) & \cdots & h_i(L) \end{bmatrix}. \tag{8}$$

For simplicity, we assume that all sensors have the same (maximum) channel length L and that all channels are normalized, i.e., $\sum_{k=0}^{L} |h_i(k)|^2 = 1$. The AWGN $v_i(n)$ and $v_j(n)$ are stationary with zero mean and variance $\sigma_{v_i}^2$ and $\sigma_{v_j}^2$, respectively, and are uncorrelated with symbols of all sensors. In addition, they are independent if $i \neq j$. The symbols $\{s_i(n)\}$ are i.i.d., and satisfy (2).

III. Blind Channel Estimation and Equalization

A. Blind Channel Estimation

With the knowledge about the index set I_i of sensor $i, 1 \leq i \leq J$, we choose the received sample vectors from (6) and (7) as $\mathbf{x}_i(n_{i\ell}+p) = \mathcal{H}_i \mathbf{s}_i(n_{i\ell}+p) + \mathbf{v}_i(n_{i\ell}+p)$. If p and N satisfy

$$L \leq p \leq N \tag{9}$$

then the symbol $s_i(n_{i\ell})$ is corresponding to the $(p+1)$th column $\mathbf{h}_i(p)$ of the matrix $\mathcal{H}_i$ that contains all the channel coefficients [cf. (8)]

$$\mathbf{h}_i(p) = [\mathbf{0}_{p-L}, h_i(L), \ldots, h_i(0), \mathbf{0}_{N-p}]^T \tag{10}$$

where $\mathbf{0}_k$ is a k dimensional vector, and $(\cdot)^T$ denotes transposition.

Proposition 1: Define the cross-correlation matrix

$$\mathbf{R}_{ij} \triangleq \lim_{M\to\infty} \frac{1}{M} \sum_{\ell=1}^{M} \mathbf{x}_i(n_{i\ell}+p)\mathbf{x}_j^H(n_{j\ell}+p) w_{ij}(\ell) \tag{11}$$

where $(\cdot)^H$ denotes Hermitian. If $L \leq p \leq N$ and $i \neq j$, we have

$$\mathbf{R}_{ij} = r_{ij} \mathbf{h}_i(p) \mathbf{h}_j^H(p). \tag{12}$$

Proof: Let $\mathbf{Z}_p$ be an $(N+L+1) \times (N+L+1)$ square matrix such that only the $(p+1, p+1)$th element is 1, and all other elements are zero. From the cross-correlation assumption (2), we have

$$\lim_{M\to\infty} \frac{1}{M} \sum_{\ell=1}^{M} \mathbf{s}_i(n_{i\ell}+p)\mathbf{s}_j^H(n_{j\ell}+p) w_{ij}(\ell) = r_{ij} \mathbf{Z}_p. \tag{13}$$

Since the noises are independent from each other, from the symbols, and from $w_{ij}(\ell)$, we have

$$\begin{aligned}\mathbf{R}_{ij} &= \mathcal{H}_i \left\{ \lim_{M\to\infty} \frac{1}{M} \sum_{\ell=1}^{M} \mathbf{s}_i(n_{i\ell}+p)\mathbf{s}_j^H(n_{j\ell}+p) w_{ij}(\ell) \right\} \mathcal{H}_j^H \\ &= r_{ij} \mathcal{H}_i \mathbf{Z}_p \mathcal{H}_j^H.\end{aligned}$$

Hence, (12) is obtained. □

Note that to derive (13), we require (2) to be satisfied under $p-N-L \leq d_i \leq p$ and $p-N-L \leq d_j \leq p$ only. In practice, we can estimate $\mathbf{R}_{ij}$ as

$$\hat{\mathbf{R}}_{ij} = \frac{1}{M} \sum_{\ell=1}^{M} \mathbf{x}_i(n_{i\ell}+p)\mathbf{x}_j^H(n_{j\ell}+p) w_{ij}(\ell) \tag{14}$$

with a finite number of samples.

Without loss of generality, we consider estimating the channel of sensor i with signals from all J sensors. From (11), we have an $(N+1) \times [(J-1)(N+1)]$ matrix

$$\mathbf{R}_i = [\mathbf{R}_{i1}, \ldots, \mathbf{R}_{i,i-1}, \mathbf{R}_{i,i+1}, \ldots, \mathbf{R}_{iJ}]. \tag{15}$$

Since, from (12), each column in the matrix $\mathbf{R}_i$ is simply a weighted version of the column $\mathbf{h}_i(p)$, the matrix is with rank 1. The vector $\mathbf{h}_i(p)$ can be estimated as the left singular vector corresponding to the largest singular value of $\mathbf{R}_i$.

To reduce complexity, we can instead use the following two more efficient ways to estimate $\mathbf{h}_i(p)$. The first way is to simply use a column in the matrix $\mathbf{R}_i$ with a sufficiently large magnitude as channel estimation. The second way is to combine all the columns in $\mathbf{R}_i$ together recursively. To begin, we initialize with any nonzero column from $\mathbf{R}_i$. Let such a column be $\mathbf{R}_i(:, m)$, where we use the MATLAB notation to denote the mth column. Then, we can estimate the channel recursively as in (16), shown at the bottom of the next page.

Proposition 2: The recursive procedure (16) converges to

$$\hat{\mathbf{h}}_i = \mathbf{h}_i(p) e^{j\theta} \sum_{0 \leq j \leq J, j \neq i} |r_{ij}|^2 \tag{17}$$

i.e., channel estimation with a scalar ambiguity, where θ is the phase.

Proof: See Appendix A. □

B. Blind Equalization

Once channels are estimated blindly, we can estimate linear filter equalizers $\mathbf{f}_i$ by a constrained minimum-output-energy (MOE) optimization

$$\arg\min_{\mathbf{f}_i} E\left[\left\| \mathbf{f}_i^H \tilde{\mathbf{x}}_i(n) \right\|^2 \right], \text{s.t.}, \quad \mathbf{f}_i^H \tilde{\mathbf{h}}_i = 1 \tag{18}$$

where $\tilde{\mathbf{x}}_i(n) = [x_i(n), \ldots, x_i(n-\tilde{N})]^T$ is constructed similarly as $\mathbf{x}_i(n)$ (6) but with a larger dimension $\tilde{N}$ (generally linear with N), and $\tilde{\mathbf{h}}_i = [\mathbf{0}_{d_f}, \hat{\mathbf{h}}_i^T, \mathbf{0}_{\tilde{N}-N-d_f}]^T$ is an extended version of $\hat{\mathbf{h}}_i$ with zero-padding for proper equalization delay $d_f + p$.

It is well known that (18) results in the MMSE equalizer [22]

$$\mathbf{f}_i = \mathbf{R}_{\tilde{x},i}^{-1}\tilde{\mathbf{h}}_i \left(\tilde{\mathbf{h}}_i^H \mathbf{R}_{\tilde{x},i}^{-1}\tilde{\mathbf{h}}_i\right)^{-1} \tag{19}$$

where the correlation is

$$\mathbf{R}_{\tilde{x},i} = E\left[\tilde{\mathbf{x}}_i(n)\tilde{\mathbf{x}}_i^H(n)\right]. \tag{20}$$

It is not necessary to estimate $\mathbf{R}_{\tilde{x},i}$. Instead, the $\mathbf{R}_{\tilde{x},i}^{-1}$ in (19) can be estimated directly and efficiently by the matrix inversion formula to avoid explicit matrix inversion [22]

$$\begin{aligned}(\hat{\mathbf{R}}_{\tilde{x},i}^{-1})^{(n+1)} &= \left(\hat{\mathbf{R}}_{\tilde{x},i}^{-1}\right)^{(n)} - \left(\hat{\mathbf{R}}_{\tilde{x},i}^{-1}\right)^{(n)} \tilde{\mathbf{x}}_i(n)\tilde{\mathbf{x}}_i^H(n) \\ &\quad \times \left(\hat{\mathbf{R}}_{\tilde{x},i}^{-1}\right)^{(n)H} \left[1 + \tilde{\mathbf{x}}_i^H(n)(\hat{\mathbf{R}}_{\tilde{x},i}^{-1})^{(n)}\tilde{\mathbf{x}}_i(n)\right]^{-1}\end{aligned} \tag{21}$$

where $n = 0, 1, 2, \ldots$. Therefore, a batch algorithm can be constructed from (14)–(16), (19), and (21), with computational complexity $O(\tilde{N}^2)$.

To further reduce complexity, we can develop an extremely efficient adaptive algorithm. First, to avoid the explicit estimation of the correlation matrix (15), we use the first way in Section III-A for channel estimation, i.e., iteratively look for only one column of the correlation matrix as the channel estimation

$$\hat{\mathbf{h}}_i^{(\ell)} = \beta\hat{\mathbf{h}}_i^{(\ell-1)} + \mathbf{x}_i(n_{i\ell}+p)x_j^*(n_{j\ell}+q)w_{ij}(\ell) \qquad n_{i\ell} \in I_i, \quad n_{j\ell} \in I_j \tag{22}$$

where $\beta \in (0,1]$ is used to track time-variation, and we need to choose j and $q \in [0, L]$ online to increase $\|\hat{\mathbf{h}}_i^{(\ell)}\|$. Then, with the temporarily estimated channel, we adaptively implement (18) for equalizer estimation by the Frost's Algorithm [22]

$$\begin{aligned}\mathbf{f}_i^{(n+1)} &= \tilde{\mathbf{h}}_i^{(n)} + \left[\mathbf{I} - \tilde{\mathbf{h}}_i^{(n)}\left(\tilde{\mathbf{h}}_i^{(n)}\right)^H\right] \\ &\quad \times \left[\mathbf{f}_i^{(n)} - \mu\tilde{\mathbf{x}}_i(n)\tilde{\mathbf{x}}_i^H(n)\mathbf{f}_i^{(n)}\right]\end{aligned} \tag{23}$$

where $\tilde{\mathbf{h}}_i^{(n)} = [\mathbf{0}_{d_f}, \hat{\mathbf{h}}_i^{(\ell)T}, \mathbf{0}_{\tilde{N}-N-d_f}]^T$ for all $n_{i\ell} \le n < n_{i,\ell+1}$, $\mathbf{I}$ is an identity matrix, and the parameter μ is used to adjust convergence. Note that during all iterations n, where $n_{i\ell} \le n < n_{i,\ell+1}$, we use the temporary channel estimation $\hat{\mathbf{h}}_i^{(\ell)}$. During the channel estimation, only a subsequence of sample vectors $\{\mathbf{x}_i(n_{i\ell}+p) : n_{i\ell} \in I_i\}$ are used, while for equalizer estimation, all available sample vectors $\{\tilde{\mathbf{x}}_i(n), \forall n\}$ are used.

Equations (22) and (23) form the adaptive algorithm with computational complexity $O(\tilde{N})$. In addition, thanks to the special cross-correlation property (2), the new algorithms are robust to nonideal or ill channel conditions, as can be easily seen from (12) and (19).

IV. Cross-Correlations and Channel Estimation

In densely deployed wireless sensor networks, the cross-correlation of the sensing values of adjacent sensors is high, which is determined by the source signals' signal-to-noise ratio (S-SNR). However, for the blind methods in Section III, what we need is the cross-correlation among the transmitted symbols. Since noise in the source signal makes many data bits in the sensing values lose cross-correlation [which is why we use I_i and I_j in (2)], the number of symbols may be severely limited for cross-correlation calculation, especially in low duty-cycle sensor networks.

In this section, we study quantitatively how S-SNR affects the symbol cross-correlation r_{ij}, and how large the symbol amount M should be for a given estimation error γ. It explains that I_i and I_j can be determined offline from the data structure according to specific applications, e.g., they can be set to include the most-significant-bits (MSBs) of each source sample.

To simplify the problem, we consider binary signaling, and all variables are thus real. As a matter of fact, binary signaling is used in many sensor network prototypes [3], [6].

A. Source Cross-Correlation and Symbol Cross-Correlation

Consider that the sensor i samples a source $z_i(m)$ with noise $u_i(m)$. The sampling values (before quantizing and encoding to a binary sequence) are

$$a_i(m) = z_i(m) + u_i(m) \tag{24}$$

where $a_i(m), z_i(m)$, and $u_i(m)$ are random variables with zero mean. Assuming noise $u_i(m)$ depends primarily on the electronic circuits of the sensors, then it is independent of $z_i(m)$, and $u_i(m)$ and $u_j(m)$ are independent of each other if $i \neq j$. The S-SNR is defined as $\alpha = 10\log_{10}(E[z_i^2(m)]/E[u_i^2(m)])$. For simplicity, we use α to denote the S-SNR for all sensors.

Assuming $|a_i(m)| \le 2^{L_a - 1}$, we define the normalized source signal cross-correlation between sensor i and j as

$$r_{ij}^a \triangleq \frac{1}{2^{2L_a-2}} E[a_i(m)a_j(m)] \tag{25}$$

$$\begin{aligned}\hat{\mathbf{h}}_i^{(0)} &= \mathbf{R}_i(:,m)\|\mathbf{R}_i(:,m)\|, \quad \text{if } \mathbf{R}_i(:,m) \neq \mathbf{0} \\ \hat{\mathbf{h}}_i^{(k)} &= \begin{cases} \hat{\mathbf{h}}_i^{(k-1)} + \dfrac{\mathbf{R}_i(:,k)\mathbf{R}_i^H(:,k)\hat{\mathbf{h}}_i^{(k-1)}}{\|\hat{\mathbf{h}}_i^{(k-1)}\|}, & k = 1, \ldots, (J-1)(N+1), \quad k \neq m. \\ \hat{\mathbf{h}}_i^{(k-1)}, & k = m. \end{cases}\end{aligned} \tag{16}$$

where we consider them after synchronization, i.e., r_{ij}^a is the maximum cross-correlation. Due to the independence of noise, we have, if $i \neq j$

$$r_{ij}^a \leq \frac{1}{2^{2L_a-2}} E\left[z_i^2(m)\right] = \frac{E\left[a_i^2(m)\right]}{2^{2L_a-2}(1+10^{-\alpha/10})}. \quad (26)$$

Although more complicated encoding schemes may be used during A/D conversion, for simplicity, we consider encoding $a_i(m)+2^{L_a-1}$ into L_a-bit words $\sum_{k=0}^{L_a-1} q_{ik}(m)2^k$ only, where $q_{ik}(m) \in \{1, 0\}$. If $q_{ik}(m)$ is directly used in the binary transmission, the symbol is $s_{ik}(m) = 2q_{ik}(m) - 1$.

Proposition 3: Assume $E[s_{ik}(m)] = E[s_{jk}(m)] = 0$. The cross-correlation of symbol sequences depends on that of source signals through

$$\sum_{k=0}^{L_a-1}\sum_{\ell=0}^{L_a-1} E[s_{ik}(m)s_{j\ell}(m)]2^{k+\ell-2L_a} = r_{ij}^a + 1 - (1-2^{-L_a})^2. \quad (27)$$

Proof: See Appendix B. □

To analyze (27), we consider some appropriate approximations. First, we skip all terms within the double summation in the left-hand side except the three terms with $E[s_{ik}(m)s_{jk}(m)], k \in \{L_a-3, L_a-2, L_a-1\}$. This is reasonable because i) these three terms refer to the three MSBs of the $a_i(m)$ and $a_j(m)$, which are usually more highly cross-correlated than others, and ii) these three terms have larger weighting coefficients than others. Second, because the three MSBs are affected less by noise, we assume that $E[s_{ik}(m)s_{jk}(m)] = r_{ij}$ for $k \in \{L_a-3, L_a-2, L_a-1\}$, i.e., the three symbol pairs have the same cross-correlation, which is just the symbol (bit) cross-correlation. Then, from (27), we have

$$r_{ij} = \frac{64}{21}\left[r_{ij}^a + 1 - (1-2^{-L_a})^2\right]. \quad (28)$$

Note that (28) may give an overestimated cross-correlation value, which can be inferred from (27) since all terms $E[s_{ik}(m)s_{jk}(m)]$ usually have the same sign with decreasing values.

Since L_a is usually large enough, a rule of thumb about the relation between source signal cross-correlation and symbol cross-correlation can be obtained from (28) as

$$r_{ij} \approx 3r_{ij}^a. \quad (29)$$

Note that from (26), we have $r_{ij}^a \leq 1/3$ because $r_{ij}^a \leq (1+2^{-2L_a+1})/[3(1+10^{-\alpha/10})]$ if $a_i(m)$ is evenly distributed, and the equality holds for noiseless case with infinite precision.

The results in (26) and (28) have been verified through numerical experiments shown in Fig. 2 with $L_a = 12$. Noise is added to a random source sequence to generate sensors' sampling values. Then symbol cross-correlations are calculated both by (28) for the analysis results and by Monte Carlo simulation for the simulated results. In addition, we also evaluate the cross-correlation after data fusion, where a linearly constrained least squares data fusion method [23] is applied to fuse signals

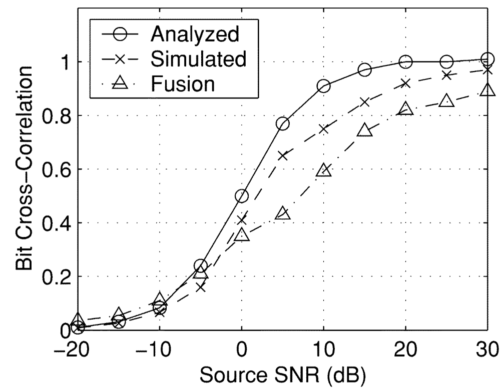

Fig. 2. Symbol (bit) cross-correlations as functions of source SNR. ○: Analysis results from (28). ×: Simulation results without data fusion. △: Simulation results with data fusion.

from every three sensors. The fused signals are used to calculate the symbol cross-correlation. Fig. 2 shows that the analysis results fit well with the simulated results. In addition, although symbol cross-correlation decreases during data fusion, it is still high enough for our purpose.

B. Finite Sample Effect on Blind Channel Estimation

When calculating cross-correlation with finite number of samples, from (2), we have

$$\frac{1}{M}\sum_{\ell=1}^{M} s_i(n_{i\ell})s_j(n_{j\ell})w_{ij}(\ell) = \hat{r}_{ij}. \quad (30)$$

Since $s_i^2(n_{i\ell}) = s_j^2(n_{j\ell}) = 1$ and $w_{ij}^2(\ell) = 1$, we can model $\hat{r}_{ij} - r_{ij}$ as a random variable [19] with zero mean and variance $\sigma_{ss}^2 = 1/M$. For symbol cross-correlations with nonzero shiftings, we find that

$$\varepsilon_s(d_i, d_j) = \frac{1}{M}\sum_{\ell=1}^{M} s_i(n_{i\ell}+d_i)s_j(n_{j\ell}+d_j)w_{ij}(\ell) \quad (31)$$

is a random variable with zero mean and variance σ_{ss}^2, where $d_i \neq 0$ or $d_j \neq 0$.

For the noise $v_i(n)$ and $v_j(n)$, similarly, their cross-correlation may not be strictly zero in case of finite samples. Instead

$$\varepsilon_v(d_i, d_j) = \frac{1}{M}\sum_{\ell=1}^{M} v_i(n_{i\ell}+d_i)v_j(n_{j\ell}+d_j)w_{ij}(\ell) \quad (32)$$

is a random variable with zero mean and variance $\sigma_{v_i}^2\sigma_{v_j}^2/M$. In addition, the cross-correlation between the symbols and the noise is either

$$\varepsilon_{sv}(d_i, d_j) = \frac{1}{M}\sum_{\ell=1}^{M} s_i(n_{i\ell}+d_i)v_j(n_{j\ell}+d_j)c_i(n_{i\ell}) \quad (33)$$

which is a random variable with zero mean and variance $\sigma_{v_j}^2/M$, or

$$\varepsilon_{vs}(d_i, d_j) = \frac{1}{M}\sum_{\ell=1}^{M} v_i(n_{i\ell}+d_i)s_j(n_{j\ell}+d_j)c_j(n_{j\ell}) \quad (34)$$

which is a random variable with zero mean and variance $\sigma_{v_i}^2/M$.

Then, the estimation of the cross-correlation matrix (14) becomes

$$\hat{\mathbf{R}}_{ij} = r_{ij}\mathcal{H}_i\mathbf{Z}_p\mathcal{H}_j^H + \mathcal{H}_i\mathbf{E}_s\mathcal{H}_j^H + \mathcal{H}_i\mathbf{E}_{sv}^H + \mathbf{E}_{vs}\mathcal{H}_j^H + \mathbf{E}_v \quad (35)$$

where the $(m+1, n+1)$th elements in the matrices $\mathbf{E}_s, \mathbf{E}_{sv}, \mathbf{E}_{vs}$, and $\mathbf{E}_v$ are $\varepsilon_s(p-m, p-n), \varepsilon_{sv}(p-m, p-n), \varepsilon_{vs}(p-m, p-n)$, and $\varepsilon_v(p-m, p-n)$, respectively.

For simplicity, consider the estimation of $\mathbf{h}_i(p)$ with *known* $\mathbf{h}_j(p)$. Although the known $\mathbf{h}_j(p)$ assumption limits the accuracy of the analysis result, it provides us with tractable solutions. On the other hand, results without such an assumption, if available, may not be more accurate due to the approximations that would have to be made. From (12), the best estimation is

$$\hat{\mathbf{h}}_i = \frac{1}{r_{ij}}\hat{\mathbf{R}}_{ij}\mathbf{h}_j(p). \quad (36)$$

Define the normalized root-mean-square error (RMSE) of the estimation as RMSE $\triangleq \sqrt{E[\|\hat{\mathbf{h}}_i - \mathbf{h}_i(p)\|^2]}/\|\mathbf{h}_i(p)\|$ [15]. Since all channels are assumed normalized, we have the following.

Proposition 4: If the transmission signal-to-noise ratio (T-SNR $= 10\log_{10} E[|x_i(n) - v_i(n)|^2]/E[|v_i(n)|^2]$) is high and the channel $\mathbf{h}_j(p)$ is known, in order to achieve RMSE $= \gamma$ during the estimation of $\mathbf{h}_i(p)$, the number of symbols used in correlation calculation should satisfy

$$\frac{N+1}{\gamma^2 r_{ij}^2} \leq M \leq \frac{(N+1)(2L+1)}{\gamma^2 r_{ij}^2}. \quad (37)$$

Proof: See Appendix C. □

With J sensors, the estimated channel can be simply the average of $J-1$ estimations (36). If $r_{ij} = r_{ik}$ for all $j \neq i$ and $k \neq i$, then we obtain

$$\frac{N+1}{\gamma^2 r_{ij}^2 (J-1)} \leq M \leq \frac{(N+1)(2L+1)}{\gamma^2 r_{ij}^2 (J-1)}. \quad (38)$$

To obtain RMSE $\leq \gamma$, we need $M \geq (N+1)/(\gamma^2 r_{ij}^2 (J-1))$. However, RMSE $\leq \gamma$ may not be achieved with all M in (38). Instead, it can be guaranteed with $M > ((N+1)(2L+1))/(\gamma^2 r_{ij}^2 (J-1))$, conditioned on the approximations we made.

V. SIMULATIONS

In this section, we present simulation results for the blind algorithms in Section III with the analysis in Section IV as a guide on our choice of parameters. We compared our new algorithms with training-based algorithms [11], the cumulant-based (high order statistics) blind algorithm (HOS) [14], the blind constant modulus algorithm (CMA) [12], and the blind subspace method [16].

We used some randomly chosen speech signals, such as 0.5 s of the word *Hello*. Random noise and delay (within maximum 5 ms) were added to generate source signals for sensors with various S-SNR. We applied the regular pulse excitation with long-term prediction codec of the Global System for Mobile Telecommunications (GSM) [20] to compress each 20-ms speech signal into a 260-bit binary sequence, which in our case is treated as a data packet. Among the 260 bits, about one third are highly cross-correlated, which include, e.g., eight reflection coefficients, pitch and gain coefficients, and even MSB of residues.

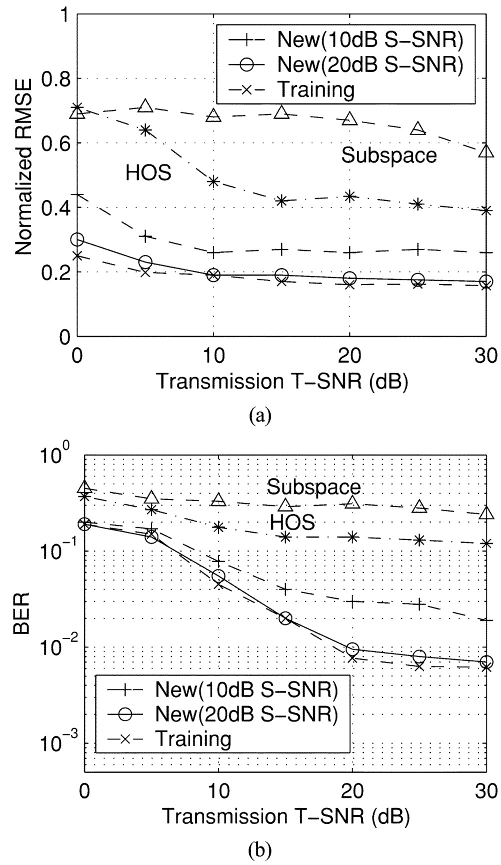

Fig. 3. (a) Channel estimation error and (b) equalization BER of the batch algorithms as functions of T-SNR. Only one data packet (260 symbols) used. Ten sensors.

BPSK was used for transmission after scrambling. RMSE and bit-error-rate (BER) were used to measure the performance. We used 100 Monte Carlo runs to obtain the average RMSE and BER for each experiment. With length $L+1 = 5$, channels for each sensor were randomly generated during each Monte Carlo run, which means every time we used a different and possibly ill-conditioned channel. For channel estimation, we used $N = 6$, whereas the equalizer length was $\tilde{N} = 15$. For the subspace method, each sensor had three receiving antennas.

Experiment 1: We used only one data packet during each run to evaluate the batch algorithms with finite sample amount. For our batch algorithm, we tried two S-SNR values: 10 and 20 dB. In addition, we used one third of the symbols (i.e., 80 bits) to calculate cross-correlations. HOS and training methods were all implemented as batch algorithms. For the training method, we used 20% of the symbols, or 52 bits, for training (similar to GSM). From Fig. 3(a) and (b), we see that with 20 dB S-SNR, our blind method achieved almost the same performance as training method. Under 20 dB S-SNR, we have $r_{ij} = 0.95$. From (38), we require $21 < M < 194$ to achieve $\gamma = 0.2$, whereas we used 80 bits to successfully achieve this objective. Note that such a result exist only

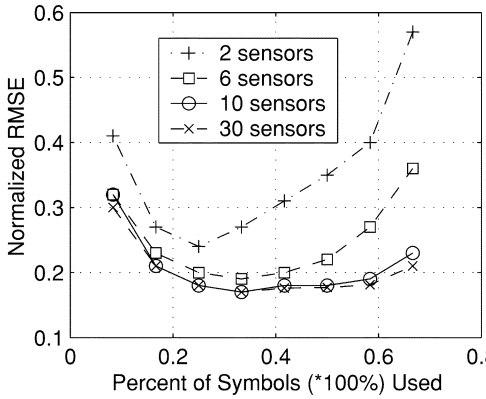

Fig. 4. Channel estimation error as a function of sensor number J as well as percentage of symbols used for calculating cross correlations. S-SNR 20 dB, and T-SNR 20 dB. One data packet.

with sufficiently high T-SNR. On the other hand, 80 bits are not enough for the 10 dB S-SNR case.

Then, we evaluated our batch algorithm with various sensor numbers J and percentage of symbols for cross-correlation. As shown in Fig. 4, about 30–40% symbols could be used to achieve best performance. Using more than two sensors, the algorithm worked reliably with 15% to 50% symbols for cross-correlation, which indicates robustness within a sufficiently large range. However, the performance became saturated when the number of sensors was greater than 10, which means more data packets are required for further improvement.

Experiment 2: We used more data packets to evaluate both our batch and adaptive algorithms, with one third of each data packet used for cross-correlation. Similarly, for the batch training method, 20% of each data packet was dedicated for training. As shown in Fig. 5, both the new batch and adaptive algorithms achieved the performance of the training method and outperformed greatly the blind HOS. More important, the new adaptive algorithm rapidly converged to the batch algorithm within ten data packets.

Experiment 3: We compared the convergence property of our new adaptive algorithm, the training-based MMSE equalizer, and the CMA equalizer, with the same setup as the second experiment. The initial conditions were randomly generated for all three algorithms. We used $\beta = 0.99, \mu = 0.005$ for our algorithm. As shown in Fig. 6, our algorithm converged fast to the training method within 10 data packets. CMA might suffer from local and slow convergence on some randomly generated channels.

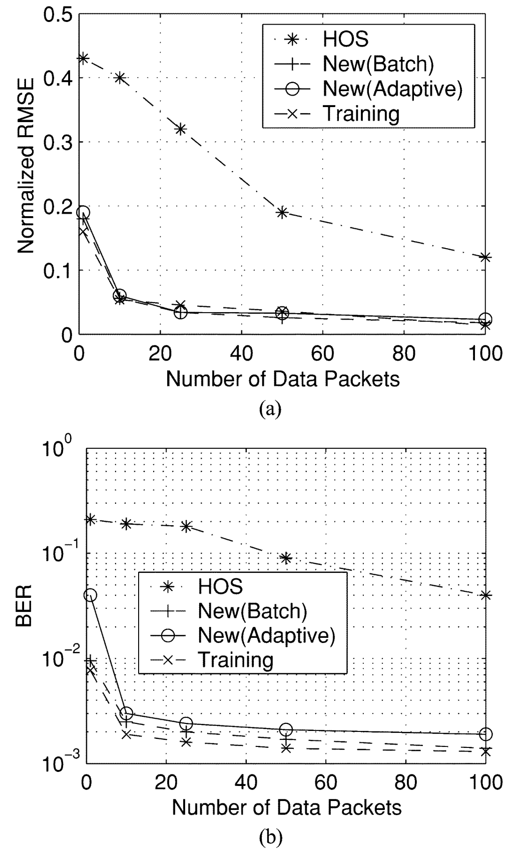

Fig. 5. (a) Channel estimation error and (b) equalization BER, as functions of number of data packets. S-SNR 20 dB, and T-SNR 20 dB. Two hundred sixty bits per data packet. Ten sensors.

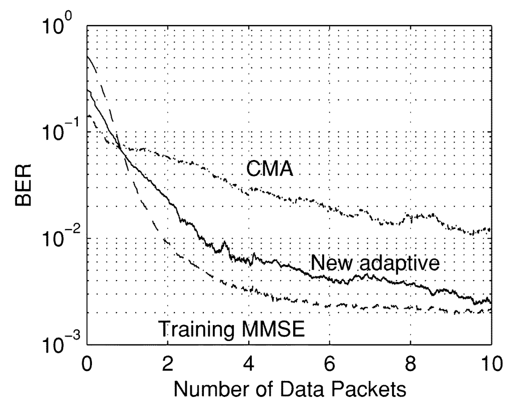

Fig. 6. Convergence of the adaptive algorithms versus number of data packets used.

VI. Conclusion

In this paper, we showed that cross-correlation among sensors can be used to develop efficient blind channel estimation and equalization algorithms in densely deployed wireless sensor networks. The complexity of the algorithms can be as low as $O(\tilde{N})$, where $\tilde{N}$ is the equalizer length. Their superior performance is demonstrated by simulations. We have also analyzed the cross-correlation property of sensor signals and the effect of finite sample amount. Before transmitting, the data sequence may be optionally processed by, e.g., compression, multiplexing, and channel encoding. The analysis of their effects on symbol cross-correlation remains an open problem.

Appendix A
Proof of Proposition 2

Note that channels are assumed normalized. Since each vector in $\mathbf{R}_i$ is a weighted version of $\mathbf{h}_i(p)$, if the initial condition $\hat{\mathbf{h}}_i^{(0)}$ is obtained from $\mathbf{R}_i(:,m) = \mathbf{h}_i(p)\alpha_0 e^{j\theta}$, where α_0 is the scalar magnitude, then $\hat{\mathbf{h}}_i^{(0)} = \mathbf{h}_i(p)\alpha_0^2 e^{j\theta}$.

Let the estimation at iteration $k-1$ be

$$\hat{\mathbf{h}}_i^{(k-1)} = \mathbf{h}_i(p)\alpha_{k-1}^2 e^{j\theta} \tag{39}$$

where α_{k-1} is positive. Let the kth vector in $\mathbf{R}_i$ be $\mathbf{R}_i(:,k) = \mathbf{h}_i(p)\beta_k e^{j\theta_k}$, where β_k is the magnitude part of the weighting, and θ_k is the phase. Then, from (16), we have

$$\begin{aligned}\hat{\mathbf{h}}_i^{(k)} &= \hat{\mathbf{h}}_i^{(k-1)} + \frac{\mathbf{h}_i(p)\beta_k e^{j\theta_k} e^{-j\theta_k}\beta_k \mathbf{h}_i^H(p)\mathbf{h}_i(p)\alpha_{k-1}^2 e^{j\theta}}{\alpha_{k-1}^2} \\ &= \mathbf{h}_i(p)(\alpha_{k-1}^2 + \beta_k^2)e^{j\theta} \\ &\triangleq \mathbf{h}_i(p)\alpha_k^2 e^{j\theta}. \qquad (40)\end{aligned}$$

From (10), (12), and (15), we know that

$$\beta_{(N+1)(j-1)+q+1} = \begin{cases} 0, & \text{if } 0 \le q \le P-L-1 \\ |r_{ij}h_j(p-m)|, & \text{if } p-L \le q \le p \\ 0, & \text{if } p+1 \le q \le N \end{cases} \qquad (41)$$

where $j = 1, \ldots, J$ and $j \neq i$. Hence (17) is readily available.

Appendix B
Proof of Proposition 3

Define

$$J = 2^{-2L_a} E\left[(a_i(m) + 2^{L_a-1})(a_j(m) + 2^{L_a-1})\right]. \qquad (42)$$

Since $a_i(m)$ and $a_j(m)$ are with zero mean, from (25), we have

$$J = \frac{E[a_i(m)a_j(m)] + 2^{2L_a-2}}{2^{2L_a}} = \frac{r_{ij}^a + 1}{4}. \qquad (43)$$

On the other hand, skipping the residual quantization error, we have

$$\begin{aligned}J &= 2^{-2L_a} E\left[\sum_{k=0}^{L_a-1} q_{ik}(m)2^k \sum_{\ell=0}^{L_a-1} q_{j\ell}(m)2^\ell\right] \\ &= 2^{-2L_a-2}\left[\sum_{k=0}^{L_a-1}\sum_{\ell=0}^{L_a-1} E[s_{ik}(m)s_{j\ell}(m)]2^{k+\ell} \right. \\ &\quad \left. + \sum_{k=0}^{L_a-1}\sum_{\ell=0}^{L_a-1} 2^{k+\ell}\right]. \qquad (44)\end{aligned}$$

Then, (27) can be readily proved.

Appendix C
Proof of Proposition 4

From (35) and (36), the channel estimation error is

$$\hat{\mathbf{h}}_i - \mathbf{h}_i(p) = \frac{1}{r_{ij}}\left(\mathcal{H}_i\mathbf{E}_s\mathcal{H}_j^H + \mathcal{H}_i\mathbf{E}_{sv}^H + \mathbf{E}_{vs}\mathcal{H}_j^H + \mathbf{E}_v\right)\mathbf{h}_j(p). \qquad (45)$$

Then, in the case of high T-SNR, since the noise-induced variances are much smaller than σ_{ss}^2, the contribution of noise to the RMSE can be omitted, which gives

$$E[\|\hat{\mathbf{h}}_i - \mathbf{h}_i(p)\|^2] = \frac{1}{r_{ij}^2}\mathbf{h}_j^H(p)\mathcal{H}_j E\left[\mathbf{E}_s^H\mathcal{H}_i^H\mathcal{H}_i\mathbf{E}_s\right]\mathcal{H}_j^H\mathbf{h}_j(p). \qquad (46)$$

Since elements in the matrix $\mathbf{E}_s$ are i.i.d. (31), after some direct deduction, we have

$$E\left[\mathbf{E}_s^H\mathcal{H}_i^H\mathcal{H}_i\mathbf{E}_s\right] = \sigma_{ss}^2 \mathrm{tr}\left(\mathcal{H}_i^H\mathcal{H}_i\right)\mathbf{I} = \frac{N+1}{M}\mathbf{I}. \qquad (47)$$

Then, $\gamma^2 = (N+1)/(Mr_{ij}^2)\mathbf{h}_j^H(p)\mathcal{H}_j\mathcal{H}_j^H\mathbf{h}_j(p)$. Since $1 \le \mathbf{h}_j^H(p)\mathcal{H}_j\mathcal{H}_j^H\mathbf{h}_j(p) \le 2L+1$, (37) is proved.

Acknowledgment

The author would like to thank Prof. H. Fan of the University of Cincinnati and Prof. M. Fowler of the State University of New York at Binghamton for their help in revising this paper. He would also like to thank the associate editor and the anonymous reviewers for their valuable comments.

References

[1] D. Estrin, L. Girod, G. Pottie, and M. Srivastava, "Instrumenting the world with wireless sensor networks," in *Proc. ICASSP*, vol. 4, Salt Lake City, UT, May 2001, pp. 2033–2036.

[2] I. F. Akyildiz, W. Su, Y. Sankarasubramianiam, and E. Cayirci, "A survey on sensor networks," *IEEE Commun. Mag.*, vol. 40, no. 8, pp. 102–114, Aug. 2002.

[3] R. Min, M. Bhardwaj, S. Cho, N. Ickes, E. Shih, A. Sinha, A. Wang, and A. Chandrakasan, "Energy-centric enabling technologies for wireless sensor networks," in *IEEE Wireless Commun.*, vol. 9, Aug. 2002, pp. 28–39.

[4] S. S. Pradhan, J. Kusuma, and K. Ramchandran, "Distributed compression in a dense microsensor network," *IEEE Signal Processing Mag.*, vol. 19, no. 2, pp. 51–60, Mar. 2002.

[5] A. Scaglione and S. D. Servetto, "On the interdependence of routing and data compression in multi-hop sensor networks," in *Proc. Annu. Int. Conf. Mob. Comput. Net.*, 2002, pp. 140–147.

[6] C. Chien, I. Elgorriaga, and C. McConaghy, "Low-power direct-sequence spread-spectrum modem architecture for distributed sensor networks," in *Proc. ISLPED*, Huntington Beach, CA, Aug. 2001.

[7] W. R. Heinzelman, J. Kulik, and H. Balakrishnan, "Energy-efficient communication protocol for wireless sensor networks," in *Proc. IEEE Hawaii Int. Conf. Syst. Sci.*, Jan. 2000, pp. 1–10.

[8] W. Ye, J. Heidemann, and D. Estrin, "Medium Access Control with Coordinated, Adaptive Sleeping for Wireless Sensor Networks," Univ. Southern Calif., Los Angeles, CA, USC/ISI Tech. Rep. ISI-TR-567, Jan. 2003.

[9] J. Nemeroff, L. Garcia, D. Hampel, and S. DiPierro, "Applications of sensor network communications," in *Proc. IEEE MILCOM*, vol. 1, McLean, VA, Oct. 2001, pp. 336–341.

[10] H. Gharavi and K. Ban, "Multi-hop sensor network design for wide-band communications," *Proc. IEEE*, vol. 91, no. 8, pp. 1221–1234, Aug. 2003.

[11] J. Tugnait, L. Tong, and Z. Ding, "Single user channel estimation and equalization," *IEEE Signal Process. Mag.*, vol. 17, no. 3, pp. 17–28, May 2000.

[12] D. N. Godard, "Self-recovering equalization and carrier tracking in two-dimensional data communication systems," *IEEE Trans. Commun.*, vol. COM-28, pp. 1867–1875, Nov. 1980.

[13] G. B. Giannakis and J. M. Mendel, "Identification of nonminimum phase systems using higher-order statistics," *IEEE Trans. Acoust., Speech, Signal Process.*, vol. 37, no. 3, pp. 360–377, Mar. 1989.

[14] J. K. Tugnait, "Blind equalization and estimation of digital communication FIR channels using cumulant matching," *IEEE Trans. Commun.*, vol. 43, no. 2/3/4, pp. 1240–1245, Feb./Mar./Apr. 1996.

[15] L. Tong, G. Xu, and T. Kailath, "Blind identification and equalization based on second-order statistics: A time domain approach," *IEEE Trans. Inf. Theory*, vol. 40, no. 2, pp. 340–349, Mar. 1994.

[16] E. Moulines, P. Duhamel, J. Cardoso, and S. Mayrargue, "Subspace methods for the blind identification of multichannel FIR filters," *IEEE Trans. Signal Process.*, vol. 43, no. 2, pp. 516–525, Feb. 1995.

[17] D. T. M. Slock, "Blind fractionally-spaced equalization, perfect-reconstruction filter banks and multichannel linear prediction," in *Proc. Int. Conf. Acoust., Speech, Signal Processing*, vol. IV, Adelaide, Australia, 1994, pp. 585–588.

[18] X. Li and N. E. Wu, "Power efficient wireless sensor networks with distributed-transmission-induced space spreading," in *Proc. 37th Asilomar Conf. Signals.,Syst., Comput.*, Pacific Grove, CA, Nov. 2003.

[19] P. Z. Peebles Jr., *Probability, Random Variables, and Random Signal Principles*, Fourth ed. New York: McGraw-Hill, 2001.

[20] T. S. Rappaport, *Wireless Communications, Principle and Practice*, Second ed. Upper Saddle River, NJ: Prentice-Hall, 2002.

[21] E. H. Dinan and B. Jabbari, "Spreading codes for direct sequence CDMA and wideband CDMA cellular networks," *IEEE Commun. Mag.*, pp. 48–54, Sep. 1998.

[22] D. H. Johnson and D. E. Dudgeon, *Array Signal Processing, Concepts and Techniques*. Upper Saddle River, NJ: Prentice-Hall, 1993.

[23] Y. Xia, H. Leung, and E. Bosse, "Neural data fusion algorithms based on a linearly constrained least squares method," *IEEE. Trans. Neural Netw.*, vol. 13, no. 2, pp. 320–329, Mar. 2002.

Xiaohua Li (M'01) received the B.S. and M.S. degrees from Shanghai Jiao Tong University, Shanghai, China, in 1992 and 1995, respectively, and the Ph.D. degree from the University of Cincinnati, Cincinnati, OH, in 2000.

He has been an Assistant Professor with the Department of Electrical and Computer Engineering, State University of New York at Binghamton since 2000. His research interests are in the fields of adaptive and array signal processing, blind channel equalization, and digital and wireless communications.