Nondata-Aided Channel Estimation for OFDM Systems With Space-Frequency Transmit Diversity

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***Abstract*—This paper proposes a computationally efficient nondata-aided maximum *a posteriori* (MAP) channel-estimation algorithm focusing on the space-frequency (SF) transmit diversity orthogonal frequency division multiplexing (OFDM) transmission through frequency-selective channels. The proposed algorithm properly averages out the data sequence and requires a convenient representation of the discrete multipath fading channel based on the Karhunen–Loeve (KL) orthogonal expansion and estimates the complex channel parameters of each subcarrier iteratively, using the expectation maximization (EM) method. To further reduce the computational complexity of the proposed MAP algorithm, the optimal truncation property of the KL expansion is exploited. The performance of the MAP channel estimator is studied based on the evaluation of the modified Cramer–Rao bound (CRB). Simulation results confirm the proposed theoretical analysis and illustrate that the proposed algorithm is capable of tracking fast fading and improving overall performance.**

***Index Terms*—Expectation maximization (EM) algorithm, maximum *a posteriori* (MAP) channel estimation, orthogonal frequency division multiplexing (OFDM) systems, space-frequency coding.**

I. Introduction

TRADITIONAL wireless technologies are not very well suited to meet the demanding requirements of providing very high data rates with ubiquity and mobility. Given the scarcity and exorbitant cost of the radio spectrum, such data rates dictate the need for extremely high spectral efficient coding and modulation schemes [1]. The combined application of transmit-antenna diversity and orthogonal frequency division multiplexing (OFDM) modulation appears to be capable of enabling the types of capacities and data rates needed for broadband wireless services [1], [2].

Transmit-antenna diversity has been exploited recently to develop high-performance space-time/frequency codes and simple maximum likelihood (ML) decoders for transmission over flat fading channels [3]–[5]. Unfortunately, their practical application can present a real challenge to channel-estimation algorithms, especially when the signal suffers from frequency-selective multipath channels. One of the solutions for alleviating frequency selectivity is through the use of OFDM together with transmit diversity which combats the long channel impulse response by transmitting parallel symbols over many orthogonal subcarriers, yielding unique reduced complexity physical layer capabilities [1].

Channel estimation for transmit-diversity OFDM systems has attracted much attention with the pioneering studies of Li [6], [7]. Among many other techniques, an iterative procedure based on the expectation maximization (EM) algorithm was also applied to the channel estimation problem in the context of space-time block coding (STBC) [8], [9] as well as transmit-diversity OFDM systems [10]–[13]. In [10], both the ML and the maximum *a posteriori* (MAP) iterative receivers for STBC-OFDM systems based on the EM algorithm are proposed to directly detect transmitted symbols under the assumption that fading processes remain constant across several OFDM words contained in one STBC code word. Note that even this approach pretends to bypass the channel-estimation process; it iterates between the ML data detection and the channel estimation consecutively until the convergence is reached. Although this approach is certainly optimal, its convergence rate is slow; the initial selection of the channel parameters is very critical and its implementation is quite complex.

An EM approach proposed for the general estimation from superimposed signals [15] is applied to the channel estimation for OFDM systems with transmitter- diversity systems and is compared with the space-alternating generalized EM (SAGE) version in [12]. Moreover, in [13], a modified version of [12] is proposed for STBC-OFDM and space-frequency (SF) block-coding (SFBC)-OFDM systems.

Unlike the EM approaches treated in [10]–[13], we adopt a two-step detection procedure: 1) Use the EM algorithm to estimate the channel, and 2) use the estimated channel to perform coherent detection. The major contribution of this paper is to obtain a new efficient nondata-aided MAP EM channel-estimation algorithm for OFDM systems with transmitter diversity using SFBC. A different approach is adapted here to explicitly model the channel parameters by a Karhunen–Loeve (KL) series representation, since a KL expansion allows one to tackle the estimation of correlated parameters as a parameter estimation problem of the uncorrelated coefficients. Note that

Manuscript received August 8, 2003; revised June 17, 2004 and August 2, 2005. This work was conducted within the NEWCOM Network of Excellence in Wireless COMmunications funded through the EC Sixth Framework Programme and was supported in part by the Research Fund of Istanbul University under Projects 220/29042004, UDP-599/28042005, and UDP-599/28072005, and The Scientific and Technological Research Council of Turkey (TUBITAK) under Grant 104E166. The review of this paper was coordinated by Dr. E. Larsson.

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Digital Object Identifier 10.1109/TVT.2005.863427

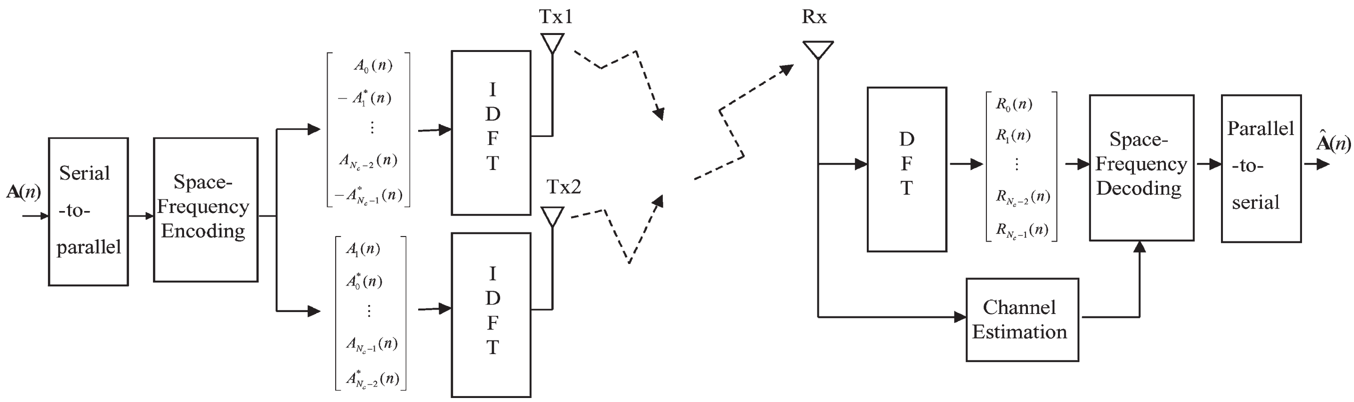

Fig. 1. SF block-coded OFDM scheme.

the KL expansion is well known for its optimal truncation property [19]. That is, the KL expansion requires the minimum number of terms among all possible series expansions in representing a random channel for a given mse. Thus, the optimal truncation property of the KL expansion results in a smaller computational load on the channel-estimation algorithm. Moreover, except for a few pilot symbols for initialization, the technique does not need any training sequence to acquire the channel and more information carrying signals can be transmitted.

Due to the orthogonality of the SFBC system based on the Alamouti orthogonal design, as well as the KL expansion of the multipath channel that yields simple exact iterative expressions for the unknown channel parameters in frequency domain which do not require any matrix inversion [18], [19]. Moreover, the optimal truncation property of the KL expansion can further reduce the computational load on the channel-estimation algorithm.

II. SFBC-OFDM Systems

Resorting to coding across tones, the set of generally correlated OFDM subchannels is first divided into groups of subchannels. This subchannel grouping with appropriate system parameters preserves the diversity gain while simplifying not only the code construction, but the decoding algorithm as well [14]. A block diagram of a two-branch SF OFDM transmitter-diversity system is shown in Fig. 1. To cast the received signal model, we first define $N_c \times 1$ the data vector $\mathbf{A}(n)$ as $\mathbf{A}(n) = [A(nN_c), A(nN_c+1), \ldots, A(nN_c + N_c - 1)]^T$. Following the notation of [14], let $A_k(n)$ denote the kth forward polyphase component of the serial data symbols, i.e, $A_k(n) = A(nN_c + k)$ for $k = 0, \ldots, N_c - 1$. The polyphase component $A_k(n)$ can also be viewed as the data symbol to be transmitted on the kth tone during the block instant n. The data symbol vector $\mathbf{A}(n)$ can therefore be expressed as $\mathbf{A}(n) = [A_0(n), A_1(n), \ldots, A_{N_c-1}]^T$. Resorting the subchannel grouping, $\mathbf{A}(n)$ is coded into two vectors $\mathbf{A}_e(n)$ and $\mathbf{A}_o(n)$ by the SF encoder as

$$\begin{aligned}\mathbf{A}_e(n) &= [A_0(n), A_2(n), \ldots, A_{N_c-4}(n), A_{N_c-2}(n)]^T \\ \mathbf{A}_o(n) &= [A_1(n), A_3(n), \ldots, A_{N_c-3}(n), A_{N_c-1}(n)]^T \end{aligned} \quad (1)$$

where $\mathbf{A}_e(n)$ and $\mathbf{A}_o(n)$ actually corresponds to the even and odd polyphase component vectors of $\mathbf{A}(n)$. Then, the SF block code transmission matrix may be represented by

$$\begin{array}{cc} & \text{frequency} \rightarrow \\ \text{space} \downarrow & \begin{bmatrix} \mathbf{A}_e(n) & -\mathbf{A}_o^*(n) \\ \mathbf{A}_o(n) & \mathbf{A}_e^*(n) \end{bmatrix} \end{array} \quad (2)$$

where * stands for the complex conjugation.

If the received signal sequence is also parsed in even and odd blocks of N_c tones, $\mathbf{R}_e(n) = [R_0(n), R_2(n), \ldots, R_{N_c-2}(n)]^T$ and $\mathbf{R}_o(n) = [R_1(n), R_3(n), \ldots, R_{N_c-1}(n)]^T$, the received signal can be expressed in vector form as

$$\begin{aligned}\mathbf{R}_e(n) &= \mathcal{A}_e(n)\mathbf{H}_{1,e}(n) + \mathcal{A}_o(n)\mathbf{H}_{2,e}(n) + \mathbf{W}_e(n) \\ \mathbf{R}_o(n) &= -\mathcal{A}_o^\dagger(n)\mathbf{H}_{1,o}(n) + \mathcal{A}_e^\dagger(n)\mathbf{H}_{2,o}(n) + \mathbf{W}_o(n) \end{aligned} \quad (3)$$

where $\mathcal{A}_e(n)$ and $\mathcal{A}_o(n)$ are $N_c/2 \times N_c/2$ diagonal matrices whose elements are $\mathbf{A}_e(n)$ and $\mathbf{A}_o(n)$, respectively, and † denotes the conjugate transpose. $\mathbf{H}_{\mu,e}(n) = [H_{\mu,0}(n), H_{\mu,2}(n), \ldots, H_{\mu,N_c-2}(n)]^T$ and $\mathbf{H}_{\mu,o}(n) = [H_{\mu,1}(n), H_{\mu,3}(n), \ldots, H_{\mu,N_c-1}(n)]^T$ are $N_c/2$ length vectors denoting the even and odd component vectors of the channel attenuations between the μth transmitter and the receiver. Finally, $\mathbf{W}_e(n)$ and $\mathbf{W}_o(n)$ are $N_c/2 \times 1$ zero mean and independent identically distributed (i.i.d.) Gaussian vectors that model additive noise in the N_c tones, with a variance of $\sigma^2/2$ per dimension.

Equation (3) shows that the information symbols $\mathcal{A}_e(n)$ and $\mathcal{A}_o(n)$ are transmitted twice in two consecutive adjacent subchannel groups through two different channels. In order to estimate the channels and decode $\mathcal{A}$ with the embedded diversity gain through the repeated transmission, for each n, we can write the following equation from (3) as

$$\begin{bmatrix} \mathbf{R}_e(n) \\ \mathbf{R}_o(n) \end{bmatrix} = \begin{bmatrix} \mathcal{A}_e(n) & \mathcal{A}_o(n) \\ -\mathcal{A}_o^\dagger(n) & \mathcal{A}_e^\dagger(n) \end{bmatrix} \begin{bmatrix} \mathbf{H}_{1,e}(n) \\ \mathbf{H}_{2,e}(n) \end{bmatrix} + \begin{bmatrix} \mathbf{W}_e(n) \\ \mathbf{W}_o(n) \end{bmatrix} \quad (4)$$

where the complex channel gains between the adjacent subcarriers are assumed to be approximately constant, i.e., $\mathbf{H}_{1,e}(n) \approx \mathbf{H}_{1,o}(n)$ and $\mathbf{H}_{2,e}(n) \approx \mathbf{H}_{2,o}(n)$. The effect of this assumption allows us to omit the dependence of $\mathbf{H}_{1,e}(n)$ and $\mathbf{H}_{2,e}(n)$ on the even channel components. Using (4) and dropping subscript "$_e$," we have

$$\begin{bmatrix}\mathbf{R}_e(n)\\ \mathbf{R}_o(n)\end{bmatrix} = \begin{bmatrix}\mathcal{A}_e(n) & \mathcal{A}_o(n)\\ -\mathcal{A}_o^\dagger(n) & \mathcal{A}_e^\dagger(n)\end{bmatrix}\begin{bmatrix}\mathbf{H}_1(n)\\ \mathbf{H}_2(n)\end{bmatrix} + \begin{bmatrix}\mathbf{W}_e(n)\\ \mathbf{W}_o(n)\end{bmatrix} \tag{5}$$

or in a more succinct form

$$\mathbf{R}(n) = \mathcal{A}(n)\mathbf{H}(n) + \mathbf{W}(n). \tag{6}$$

Based on (6), our main objective in this paper is to develop a channel-estimation algorithm in accordance with the MAP criterion. The channel variations are considered as random processes and the KL orthogonal series expansion is applied. Prompted by the general applicability of the KL expansion, in this paper, we consider the components of $\mathbf{H}_\mu(n)$ to be expressed by a linear combination of orthonormal base vectors as $\mathbf{H}_\mu(n) = \mathbf{\Psi}\mathbf{G}_\mu(n)$, where $\mathbf{\Psi} = [\psi_0, \psi_1, \ldots, \psi_{N_c-1}]$, ψ_i's are the orthonormal basis vectors corresponding to the eigenvectors of the channel autocorrelation matrix $\mathbf{C}_{\mathbf{H}_\mu} = E[\mathbf{H}_\mu \mathbf{H}_\mu^\dagger]$. $\mathbf{G}_\mu(n)$ is an $N_c \times 1$ zero-mean i.i.d. Gaussian vector whose components $\mathbf{G}_\mu(n)[k] = \mathbf{G}_\mu(n,k)$, $k = 0, 1, \ldots, N_c - 1$ correspond to the weights of the KL expansion. Note that the covariance matrix of $\mathbf{G}_\mu(n)$ is $\mathbf{\Lambda} = \mathrm{diag}(\lambda_0, \lambda_1, \ldots, \lambda_{N_c-1})$, where λ_k's are the eigenvalues of $\mathbf{C}_{\mathbf{H}_\mu}$. Therefore, $\mathbf{C}_{\mathbf{H}_\mu}$ can be expressed as

$$\mathbf{C}_{\mathbf{H}_\mu} = \mathbf{\Psi}\mathbf{\Lambda}\mathbf{\Psi}^\dagger. \tag{7}$$

Thus, the channel estimation problem in this application is equivalent to estimating the i.i.d. Gaussian vector $\mathbf{G}_\mu$ of the KL expansion coefficients.

III. Nondata-Aided EM-Based MAP Channel Estimation

In the nondata-aided MAP estimation approach, we choose $\widehat{\mathbf{G}}$ to maximize the posterior probability density function (PDF), $\widehat{\mathbf{G}} = \arg\max_{\mathbf{G}} p(\mathbf{G}|\mathbf{R})$ where $\mathbf{G} = [\mathbf{G}_1^T, \mathbf{G}_2^T]^T$. To find the MAP estimator, we must equivalently maximize $p(\mathbf{R}|\mathbf{G})p(\mathbf{G})$. The prior PDF of the KL expansion coefficient r.v.'s of the fading channel can be expressed as $p(\mathbf{G}) \sim \exp(-\mathbf{G}^\dagger \widetilde{\mathbf{\Lambda}}^{-1}\mathbf{G})$, where $\widetilde{\mathbf{\Lambda}} = \mathrm{diag}(\mathbf{\Lambda}\ \mathbf{\Lambda})$.

Hence, the MAP estimator equivalently takes the form

$$\widehat{\mathbf{G}}_{\mathrm{MAP}} = \arg\max_{\mathbf{G}} \left[\ln p(\mathbf{R}|\mathbf{G}) + \ln p(\mathbf{G})\right] \tag{8}$$

where $p(\mathbf{R}|\mathbf{G}) = E_{\mathcal{A}}[p(\mathbf{R}|\mathbf{A},\mathbf{G})$.

Given the transmitted signals $\mathcal{A}$, coded according to the SF transmit-diversity scheme and the discrete channel orthonormal series expansion representation coefficients $\mathbf{G}$ and taking into account the independence of the noise components, the conditional PDF of the received signal $\mathbf{R}$ can be expressed as

$$p(\mathbf{R}|\mathcal{A},\mathbf{G}) \sim \exp\left[-(\mathbf{R} - \mathcal{A}\widetilde{\mathbf{\Psi}}\mathbf{G})^\dagger \widetilde{\mathbf{\Sigma}}^{-1}(\mathbf{R} - \mathcal{A}\widetilde{\mathbf{\Psi}}\mathbf{G})\right] \tag{9}$$

where $\widetilde{\mathbf{\Sigma}}$ is an $N_c \times N_c$ diagonal matrix with $\widetilde{\mathbf{\Sigma}}[k,k] = \sigma^2$, for $k = 0, 1, \ldots, N_c - 1$ and $\widetilde{\mathbf{\Psi}} = \mathrm{diag}(\mathbf{\Psi}\ \mathbf{\Psi})$.

Obtaining the MAP estimate of $\mathbf{G}$ from (9) is a complicated optimization problem and does not yield a closed-form solution. The solution of such problems usually requires numerical methods, such as methods of scoring, Newton–Raphson, or some other gradient search algorithm. However, for the problem at hand, these numerical methods tend to be computationally complex. Fortunately, the solution can be easily obtained by means of the iterative EM algorithm. Since the EM algorithm has been studied and applied to a number of problems in communications over the years, the details of the algorithm will not be presented in this paper. See [20]–[22] for a general exposition to the EM algorithm and [18] its applications to the estimation problem related to this study. Basically, this algorithm inductively reestimates $\mathbf{G}$ so that a monotonic increase in the *a posteriori* conditional pdf in (9) is guaranteed. The monotonic increase is realized via the maximization of the auxiliary function

$$Q\left(\mathbf{G}|\mathbf{G}^{(i)}\right) = \sum_{\mathcal{A}} p\left(\mathbf{R}, \mathcal{A}, \mathbf{G}^{(i)}\right) \log p(\mathbf{R}, \mathcal{A}, \mathbf{G}) \tag{10}$$

where $\mathbf{G}^{(i)}$ is the estimation of $\mathbf{G}$ at the ith iteration.

Note that $p(\mathbf{R}, \mathcal{A}, \mathbf{G}) \sim p(\mathbf{R}|\mathcal{A}, \mathbf{G})p(\mathbf{G})$, since the data symbols $\mathcal{A} = \{A_k(n)\}$ are assumed to be independent of each other and are identically distributed and because of the fact that they are independent of $\mathbf{G}$. Therefore, (10) can be easily evaluated compared to a direct computation of (9).

Given the received signal $\mathbf{R}$, the EM algorithm starts with an initial value $\mathbf{G}^0$ of the unknown channel parameter $\mathbf{G}$. The $(i+1)$th estimate of $\mathbf{G}$ is obtained by the maximization step described by $\mathbf{G}^{(i+1)} = \arg\max_{\mathbf{G}} Q(\mathbf{G}|\mathbf{G}^{(i)})$. As described in Appendix I, the expression of the reestimated value of $\mathbf{G}_\mu^{(i+1)}$ $(\mu = 1, 2)$ can be obtained as follows:

$$\begin{aligned}\mathbf{G}_1^{(i+1)} &= (\mathbf{I} + \mathbf{\Sigma}\mathbf{\Lambda}^{-1})^{-1}\mathbf{\Psi}^\dagger\left[\mathbf{\Gamma}_1^{(i)\dagger}\mathbf{R}_e(n) - \mathbf{\Gamma}_2^{(i)}\mathbf{R}_o(n)\right]\\ \mathbf{G}_2^{(i+1)} &= (\mathbf{I} + \mathbf{\Sigma}\mathbf{\Lambda}^{-1})^{-1}\mathbf{\Psi}^\dagger\left[\mathbf{\Gamma}_2^{(i)\dagger}\mathbf{R}_e(n) + \mathbf{\Gamma}_1^{(i)}\mathbf{R}_o(n)\right]\end{aligned} \tag{11}$$

where it can be easily seen that

$$(\mathbf{I} + \mathbf{\Sigma}\mathbf{\Lambda}^{-1})^{-1} = \mathrm{diag}\left(\left[\left(\frac{1+\sigma^2}{\lambda_0}\right)^{-1}, \ldots, \left(\frac{1+\sigma^2}{\lambda_{N_c-1}}\right)^{-1}\right]\right) \tag{12}$$

and $\mathbf{\Gamma}_\mu^{(i)}$ in (11) is an $N_c/2 \times N_c/2$ dimensional diagonal matrix representing the *a posteriori* probabilities of the data symbols at the ith iteration step whose kth component is defined as

$$\Gamma_\mu^{(i)}(k) = \sum_{a_1}\sum_{a_2 \in S_k} a_\mu P\Big(A_{2k}(n) = a_1,\ A_{2k+1}(n) = a_2|\mathbf{R}, \mathbf{G}^{(i)}\Big), \qquad \mu = 1, 2 \tag{13}$$

where S_k denotes the alphabet set taken by the kth OFDM symbol.

A truncated expansion $\mathbf{G}_{\mu,r}$ can be formed by selecting r orthonormal basis vectors among all the basis vectors that satisfy $\mathbf{C}_{\mathbf{H}_\mu}\boldsymbol{\Psi} = \boldsymbol{\Psi}\boldsymbol{\Lambda}$. The optimal one that yields the smallest average mean-squared truncation error $1/(N_c/2)\ E[\boldsymbol{\epsilon}_r^\dagger \boldsymbol{\epsilon}_r]$ is the one expanded with the orthonormal basis vectors associated with the first largest r eigenvalues given by

$$\frac{1}{\frac{N_c}{2}-r} E\left[\boldsymbol{\epsilon}_r^\dagger \boldsymbol{\epsilon}_r\right] = \frac{1}{\frac{N_c}{2}-r} \sum_{i=r}^{\frac{N_c}{2}-1} \lambda_i \tag{14}$$

where $\boldsymbol{\epsilon}_r = \mathbf{G}_\mu - \mathbf{G}_{\mu,r}$. For the problem at hand, the truncation property of the KL expansion results in a low-rank approximation. Thus, a rank-r approximation of $\boldsymbol{\Lambda}_r$ is defined as $\boldsymbol{\Lambda}_r = \mathrm{diag}\{\lambda_0, \lambda_1, \ldots, \lambda_{r-1}, 0, \ldots, 0\}$. Since the trailing $N_c/2 - r$ variances $\{\lambda_l\}_{l=r}^{N_c/2-1}$ are small compared to the leading r variances $\{\lambda_l\}_{l=0}^{r-1}$, then the trailing $N_c/2 - r$ variances are set to zero to produce the approximation. However, the pattern of eigenvalues for $\boldsymbol{\Lambda}$ typically splits the eigenvectors into dominant and subdominant sets. Then, the choice of r is more or less obvious. The optimal truncated KL (rank-r) estimator of (11) can easily be obtained by replacing $\boldsymbol{\Lambda}_r$ with $\boldsymbol{\Lambda}$ in (11).

A. *Initialization*

In order to choose good initial values for the unknown channel parameters, the N_{PS} data symbols $\{A_k(n)\}$ for $k \in S_{PS}$ in each OFDM frame are inserted as pilot symbols known by the receiver. Corresponding to the pilot symbols, we focus on an under-sampled signal model and employ the least squares (LS) estimate to obtain under-sampled channel parameters. Then, the complete initial channel gains can easily be determined using an interpolation technique, i.e., a lowpass interpolation algorithm [16]. Finally, the initial values of $\mathbf{G}_\mu^{(0)}$ are used in the iterative EM algorithm to avoid divergence. The details of the initialization process is presented in [17] and [18].

B. *Computation of $\Gamma_\mu^{(i)}(k)$ for QPSK*

As the details are given in Appendix II, $\boldsymbol{\Gamma}_\mu^{(i)} = [\Gamma_\mu^{(i)}(0), \ldots, \Gamma_\mu^{(i)}((N_c/2)-1)]^T$ can be computed for QPSK signaling as follows:

$$\boldsymbol{\Gamma}_\mu^{(i)} = \frac{1}{2}\tanh\left[\frac{1}{\sigma^2}\mathrm{Re}\left(\mathbf{Z}_\mu^{(i)}\right)\right] + \frac{j}{2}\tanh\left[\frac{1}{\sigma^2}\mathrm{Im}\left(\mathbf{Z}_\mu^{(i)}\right)\right] \tag{15}$$

where

$$\mathbf{Z}_1^{(i)} = \mathcal{R}_e \boldsymbol{\Psi}^* \mathbf{G}_1^{*(i)} + \mathcal{R}_o^* \boldsymbol{\Psi} \mathbf{G}_2^{(i)}$$
$$\mathbf{Z}_2^{(i)} = \mathcal{R}_e \boldsymbol{\Psi}^* \mathbf{G}_2^{*(i)} - \mathcal{R}_o^* \boldsymbol{\Psi} \mathbf{G}_1^{(i)}$$

and $\mathcal{R}_e$ and $\mathcal{R}_o$ are $N_c/2 \times N_c/2$ diagonal matrices whose elements are $\mathbf{R}_e$ and $\mathbf{R}_o$, respectively.

IV. Modified Cramer–Rao Bound

In this section, we turn our attention to the analytical performance results and study the performance of the MAP channel estimator based on the evaluation of the modified CRB.

The mean-squared estimation error for the unbiased estimation of a nonrandom parameter has a lower bound, the CRB, which defines the ultimate accuracy of the unbiased estimation procedure. Suppose $\hat{\mathbf{G}}$ is an unbiased estimator of a vector of unknown parameters $\mathbf{G}$ (i.e., $E\{\hat{\mathbf{G}}\} = \mathbf{G}$), then the mse matrix is lower bounded by the inverse of the Fisher information matrix (FIM) $E\{(\mathbf{G} - \hat{\mathbf{G}})(\mathbf{G} - \hat{\mathbf{G}})^\dagger\} \geq \mathbf{J}^{-1}(\mathbf{G})$.

Since the estimation of unknown random parameters $\mathbf{G}'$ via the MAP approach is considered in this paper, the modified FIM needs to be taken into account in the derivation of the stochastic CRB [24]. Fortunately, the modified FIM can be obtained by a straightforward modification of the FIM as

$$\mathbf{J}_M(\mathbf{G}) \triangleq \mathbf{J}(\mathbf{G}) + \mathbf{J}_P(\mathbf{G}) \tag{16}$$

where $\mathbf{J}_P(\mathbf{G})$ represents the *a priori* information.

Under the assumption that $\mathbf{G}$ and $\mathbf{W}(n)$ are independent of each other and $\mathbf{W}(n)$ is a zero-mean, the A_k's are adopting finite complex values, from [24] and (9), the conditional PDF is given by

$$p(\mathbf{R}|\mathbf{G}) = E_{\mathcal{A}}\left\{p(\mathbf{R}|\mathcal{A}, \mathbf{G})\right\}$$
$$\sim \frac{1}{\sigma^2} E_{\mathcal{A}}\left\{(\mathbf{R} - \mathcal{A}\widetilde{\boldsymbol{\Psi}}\mathbf{G})^\dagger(\mathbf{R} - \mathcal{A}\widetilde{\boldsymbol{\Psi}}\mathbf{G})\right\}. \tag{17}$$

Since $\ln p(\mathbf{R}|\mathbf{G})$ is required for the computation of $\mathbf{J}(\mathbf{G})$, it is unfortunately computationally intensive. However, an approximate of $\ln p(\mathbf{R}|\mathbf{G})$ can still be obtained from $\ln p(\mathbf{R}|\mathcal{A}, \mathbf{G})$. Since the logarithmic function is a concave, by Jensen's inequality, we have

$$\ln p(\mathbf{R}|\mathbf{G}) \leq E_{\mathcal{A}} \ln\left\{p(\mathbf{R}|\mathcal{A}, \mathbf{G})\right\}. \tag{18}$$

Therefore, we get a valid $\mathbf{J}(\mathbf{G})$ from $E_{\mathbf{A}}\{\ln p(\mathbf{R}|\mathcal{A}, \mathbf{G})\}$ which may not be tight, but is much easier to compute. From (17), the derivatives follow as

$$\frac{\partial \ln p(\mathbf{R}|\mathbf{G})}{\partial \mathbf{G}^T} = \frac{1}{\sigma^2}(\mathbf{R} - \mathcal{A}\widetilde{\boldsymbol{\Psi}}\mathbf{G})^\dagger \mathcal{A}\widetilde{\boldsymbol{\Psi}} \tag{19}$$

$$\frac{\partial^2 \ln p(\tilde{\mathbf{R}}|\mathbf{G})}{\partial \mathbf{G}^* \partial \mathbf{G}^T} = -\frac{1}{\sigma^2}\widetilde{\boldsymbol{\Psi}}^\dagger \mathcal{A}^\dagger \mathcal{A}\widetilde{\boldsymbol{\Psi}}. \tag{20}$$

Since the Alamouti's scheme imposes an orthogonal structure on the transmitted symbols $\mathcal{A}^\dagger\mathcal{A} = \mathbf{I}$ and using $\widetilde{\boldsymbol{\Psi}}^\dagger\widetilde{\boldsymbol{\Psi}} = \mathbf{I}$ and taking the expected values yields the simple form

$$\mathbf{J}(\mathbf{G}) = -E\left[\frac{\partial^2 \ln p(\tilde{\mathbf{R}}|\mathbf{G})}{\partial \mathbf{G}^* \partial \mathbf{G}^T}\right] = \frac{1}{\sigma^2}\mathbf{I}. \tag{21}$$

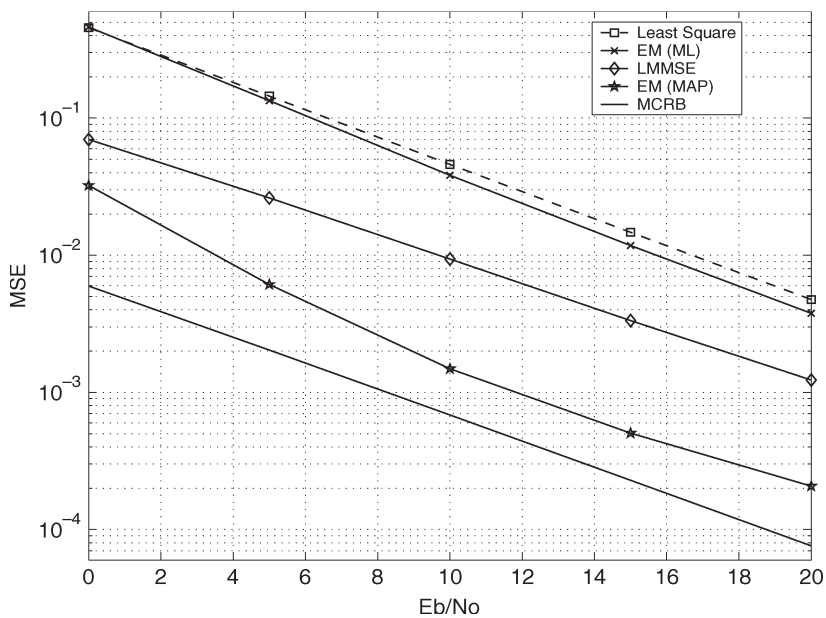

Fig. 2. Channel-estimation mse as a function of the average E_b/N_0.

The second term in (16) is easily obtained as follows. Consider the prior PDF $p(\mathbf{G}) \sim \exp[(-\mathbf{G}^\dagger \widetilde{\mathbf{\Lambda}}^{-1}\mathbf{G})]$. The respective derivatives are found as

$$\frac{\partial \ln p(\mathbf{G})}{\partial \mathbf{G}^T} = -\mathbf{G}^\dagger \mathbf{\Lambda}^{-1}, \qquad \frac{\partial^2 \ln p(\mathbf{G})}{\partial \mathbf{G}^* \partial \mathbf{G}^T} = -\mathbf{\Lambda}^{-1}. \tag{22}$$

Upon taking the negative expectations, the second term in (16) becomes $\mathbf{J}_P(\mathbf{G}) = \mathbf{\Lambda}^{-1}$. Substituting $\mathbf{J}(\mathbf{G})$ and $\mathbf{J}_P(\mathbf{G})$ in (16) produces the modified FIM as follows:

$$\begin{aligned}\mathbf{J}_M(\mathbf{G}) &= \mathbf{J}(\mathbf{G}) + \mathbf{J}_P(\mathbf{G}) \\ &= \frac{1}{\sigma^2}\mathbf{I} + \mathbf{\Lambda}^{-1}.\end{aligned} \tag{23}$$

Inverting the matrix $\mathbf{J}_M(\mathbf{G})$ yields $\text{CRB}(\hat{\mathbf{G}}) = \mathbf{J}_M^{-1}(\mathbf{G})$. $\text{CRB}(\hat{\mathbf{G}})$ is a diagonal matrix with the elements on the main diagonal equaling the reciprocal of that of the $\mathbf{J}(\mathbf{G})$ matrix. Because of the zero-valued off-diagonal entries in the FIM, the errors between the corresponding estimates are not independent.

V. SIMULATIONS

In this section, we present some simulation results in order to verify the performance of the channel estimation via the EM algorithm for SFBC-OFDM systems. The diversity scheme with two transmit and one receive antenna is considered. The channels between the transmitter and receiver are generated according to the doubly-selective fading channel model. In this model, $H_\mu(k)$'s are with an exponentially decaying power delay profile $\theta(\tau_\mu) = C\exp(-\tau_\mu/\tau_{\rm rms})$ and delays τ_μ that are uniformly and independently distributed over the length of the cyclic prefix. C is a normalizing constant. Note that the normalized discrete channel correlations for different subcarriers and blocks of this channel model were presented in [17] as follows:

$$r_1(k,k') = \frac{1-\exp\left[-L\left[\frac{1}{\tau_{\rm rms}} + \frac{2\pi j(k-k')}{N_c}\right)\right]}{\tau_{\rm rms}\left(1-\exp\left(\frac{-L}{\tau_{\rm rms}}\right)\right)\left(\frac{1}{\tau_{\rm rms}} + \frac{j2\pi(k-k')}{N_c}\right)}.$$

The scenario for the SFBC-OFDM simulation study consists of a wireless QPSK-OFDM system. The system has a 2.28-MHz bandwith (for the pulse roll-off factor $\alpha = 0.2$) and is divided into $N_c = 512$ tones with a total period Ts of 136 μs, of which 1.052 μs constitutes the cyclic prefix $(L = 4)$. The uncoded data rate is 7.6 Mb/s. We assume that the rms width is $\tau_{\rm rms} = 1$ sample (0.263 μs) for the power-delay profile.

The proposed EM-based iterative channel estimator of (11) is implemented and compared with the previously reported SFBC-OFDM channel estimator [13] in terms of average mse for a wide range of signal-to-noise ratio (E_b/N_0) levels. The average mse is defined as the norm of the difference between the vectors $\mathbf{G} = [\mathbf{G}_1^T, \mathbf{G}_2^T]$ and $\widehat{\mathbf{G}}_{\rm map}$, representing the true and the estimated values of the channel parameters, respectively. Namely, mse $= 1/2N_c\|\mathbf{G} - \widehat{\mathbf{G}}_{\rm map}\|^2$. In order to obtain good initial values for the unknown channel parameters, $N_{PS} = 64$ equally spaced pilot tones are inserted into the data symbols. Corresponding to the pilot symbols, we employed the LS estimate to obtain under-sampled channel parameters. Then, the complete initial channel gains are determined using a lowpass interpolation technique [16]. Finally, the initial values of $\mathbf{G}_\mu^{(0)}$ are used in the iterative EM algorithm to avoid divergence.

Fig. 2 compares the performance of the proposed EM-MAP channel-estimation approach with an EM-ML [13] which is the modified version of [12] and both used LS for initialization. The proposed EM-based approach is also compared to other widely

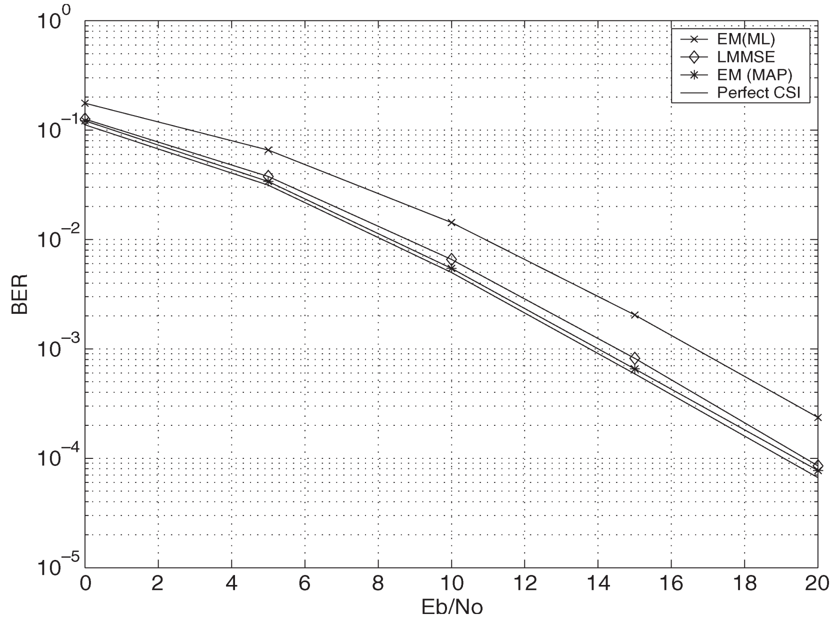

Fig. 3. BER performance of the EM algorithms as a function of the average E_b/N_0.

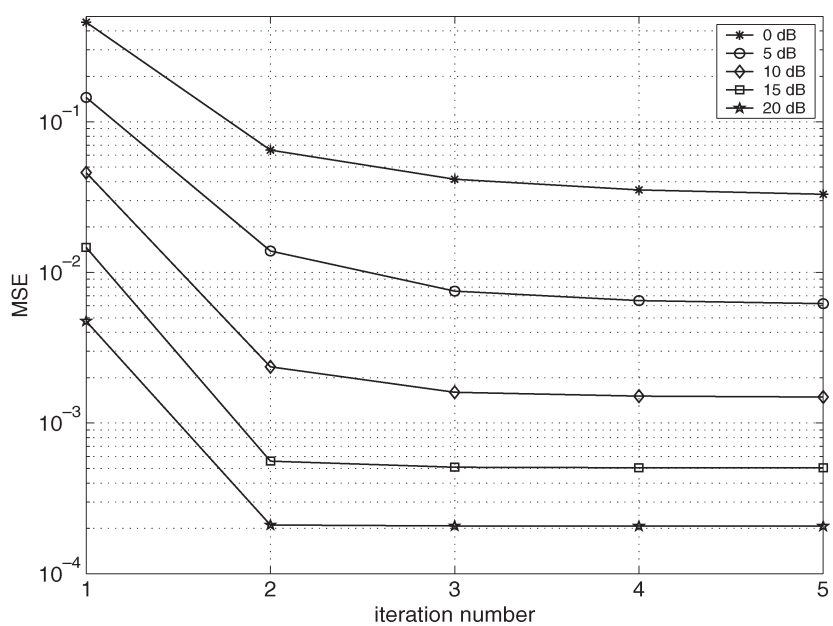

Fig. 4. Convergence of the mse with respect to the number of iterations.

used linear mmse (Lmmse) and LSE pilot symbol assisted modulation (PSAM) channel-estimation techniques [23]. It can be seen that the proposed EM-MAP significantly outperforms the EM ML as well as the PSAM techniques.

Assuming the channel parameters are estimated accurately, the SF block constructs the decision estimate vector in [14]. Therefore, we used channel estimates for symbol decoding and compared the bit error rate (BER) performance of the proposed iterative EM-MAP estimator with the EM-ML and the Lmmse ones. Fig. 3 shows the average results of 1000 Monte Carlo runs. We observe from the BER performance simulation results that the EM-MAP BER performance still outperforms the EM-ML and the Lmmse approaches, especially for high SNRs.

In Fig. 4, the average mse performance of the EM-MAP algorithm is presented as a function of the number of iterations. It is concluded from these curves that the mse performance of the EM-based algorithm converges within 2–4 iterations, depending on the average SNR.

Apart from the simulated BER performance, the truncated estimator performance is also studied as a function of the number of KL coefficients. Fig. 5 presents the mse result of the truncated EM-MAP estimator. If only a few expansion coefficients are employed to reduce the complexity of the proposed estimator, then the mse between channel parameters becomes large. However, if the number of parameters in the expansion is increased to include the dominant eigenvalues, we

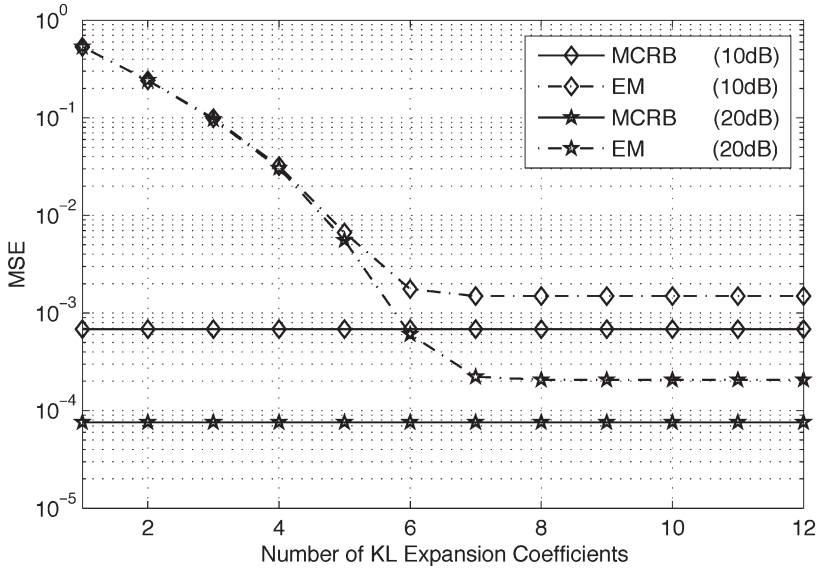

Fig. 5. Truncated EM algorithm mse performance.

are able to obtain a good approximation with a relatively small number of KL coefficients. For instance, by replacing 256 × 256 diagonal $\mathbf{\Lambda}$ in (11) with a 8 × 8 diagonal, $\mathbf{\Lambda}_r$ decreases the computational complexity enormously.

VI. Conclusion

In this paper, we proposed an efficient nondata-aided EM-based channel-estimation algorithm for SFBC-OFDM systems, which is crucial for the decoding of SF codes. This algorithm performs an iterative estimation of the channel according to the MAP criterion, using the EM algorithm employing the M-PSK modulation scheme with additive Gaussian noise. The likelihood ratio is properly averaged out over the data sequence so that the resulting algorithm does not need a training sequence to acquire the channel; thus, the throughput of the system improves substantially compared to the existing channel-estimation algorithms based on the data-aided schemes in literature. The performance of our channel-estimation algorithm is confirmed by corroborating simulations and is compared with existing EM-ML alternatives. It has been shown that the EM-MAP estimator performs well over the EM-ML. Moreover, the truncation property of the KL expansion significantly reduces the complexity of the EM-based algorithms.

Appendix I
Derivation of (11)

In (10), the term $\log p(\mathbf{R}, \mathcal{A}, \mathbf{G})$ can be expressed as

$$\log p(\mathbf{R}, \mathcal{A}, \mathbf{G}) \sim \log p(\mathcal{A}, \mathbf{G}) + \log p(\mathbf{R}|\mathcal{A}, \mathbf{G}) + \log p(\mathbf{G}). \tag{24}$$

The first term in (24) is constant, since the data sequences $\mathcal{A}$ have an equal *a priori* probability and $\mathcal{A}$ and $\mathbf{G}$ are independent of each other. Also, since the noise samples are independent, from (3) and (9), the second and third terms in (24) can be written as

$$\begin{aligned}\log p(\mathbf{R}|\mathcal{A}, \mathbf{G}) \sim & -\left[\mathbf{R}_e(n) - \mathbf{A}_e(n)\mathbf{H}_1 - \mathbf{A}_o(n)\mathbf{H}_2\right]^\dagger \\ & \times \mathbf{\Sigma}^{-1}\left[\mathbf{R}_e(n) - \mathbf{A}_e(n)\mathbf{H}_1 - \mathbf{A}_o(n)\mathbf{H}_2\right] \\ & - \left[\mathbf{R}_o(n) + \mathbf{A}_o^\dagger(n)\mathbf{H}_1 - \mathbf{A}_e^\dagger(n)\mathbf{H}_2\right]^\dagger \\ & \times \mathbf{\Sigma}^{-1}\left[\mathbf{R}_o(n) + \mathbf{A}_o^\dagger(n)\mathbf{H}_1 - \mathbf{A}_e^\dagger(n)\mathbf{H}_2\right] \\ \log p(\mathbf{G}) \sim & -\mathbf{G}_1^\dagger \mathbf{\Lambda}^{-1}\mathbf{G}_1 - \mathbf{G}_2^\dagger \mathbf{\Lambda}^{-1}\mathbf{G}_2.\end{aligned} \tag{25}$$

Taking the derivatives in (10) with respect to $\mathbf{G}_1$ and $\mathbf{G}_2$, along with the fact that $\|\mathbf{A}_e(n)\|^2 = |\mathbf{A}_o(n)|^2 = (1/2)\mathbf{I}$, and equating the resulting equations to zero, we have

$$\begin{aligned}\frac{\partial Q}{\partial \mathbf{G}_1} = & \sum_{\mathcal{A}} p\left(\mathbf{R}, \mathcal{A}, \mathbf{G}^{(i)}\right) \\ & \times \left[\mathbf{\Sigma}^{-1}\mathbf{\Psi}^\dagger\left(\mathbf{A}_e^\dagger(n)\mathbf{R}_e(n) \right.\right. \\ & \left.\left. - \mathbf{A}_o(n)\mathbf{R}_o(n) - \mathbf{H}_1\right) - \mathbf{\Lambda}^{-1}\mathbf{G}_1\right] = 0 \\ \frac{\partial Q}{\partial \mathbf{G}_1} = & \sum_{\mathcal{A}} p\left(\mathbf{R}, \mathcal{A}, \mathbf{G}^{(i)}\right) \\ & \times \left[\mathbf{\Sigma}^{-1}\mathbf{\Psi}^\dagger\left(\mathbf{A}_o^\dagger(n)\mathbf{R}_e(n) \right.\right. \\ & \left.\left. + \mathbf{A}_e(n)\mathbf{R}_o(n) - \mathbf{H}_2\right) - \mathbf{\Lambda}^{-1}\mathbf{G}_2\right] = 0.\end{aligned} \tag{26}$$

Since $p(\mathbf{R}, \mathcal{A}, \mathbf{G}^{(i)})$ may be replaced by $p(\mathcal{A}|\mathbf{R}, \mathbf{G}^{(i)})$ without violating the equalities in (26), defining the conditional probabilities as

$$\begin{aligned}\Gamma_\mu^{(i)}(k) = & \sum_{a_1}\sum_{a_2 \in S_k} a_\mu P \\ & \times \left(A_{2k}(n) = a_1, A_{2k+1}(n) = a_2 | \mathbf{R}, \mathbf{G}^{(i)}\right)\end{aligned} \tag{27}$$

$$\Gamma_{\mu}^{(i)}(k) = \frac{\sum_{a_1,a_2\in S_k} a_{\mu} p\left(\mathbf{R}|A_{2k}(n)=a_1, A_{2k+1}(n)=a_2, \mathbf{G}^{(i)}\right) P\left(A_{2k}(n)=a_1, A_{2k+1}=a_2\right)}{\sum_{a_1,a_2\in S_k} p\left(\mathbf{R}|A_{2k}(n)=a_1, A_{2k+1}(n)=a_2, \mathbf{G}^{(i)}\right) P\left(A_{2k}(n)=a_1, A_{2k+1}=a_2\right)} \tag{30}$$

and the $N_c/2 \times N_c/2$ diagonal matrix

$$\mathbf{\Gamma}_{\mu}^{(i)} = \mathrm{diag}\left(\Gamma_{\mu}^{(i)}(0), \ldots, \Gamma_{\mu}^{(i)}\left(\frac{N_c}{2}-1\right)\right) \tag{28}$$

the equations in (26) can be expressed as

$$\begin{aligned} \mathbf{\Sigma}^{-1}\mathbf{\Psi}^{\dagger}\left(\mathbf{\Gamma}_1^{(i)\dagger}\mathbf{R}_e(n) - \mathbf{\Gamma}_2^{(i)}\mathbf{R}_o(n) - \mathbf{H}_1\right) &= \mathbf{\Lambda}^{-1}\mathbf{G}_1 \\ \mathbf{\Sigma}^{-1}\mathbf{\Psi}^{\dagger}\left(\mathbf{\Gamma}_2^{(i)\dagger}\mathbf{R}_e(n) + \mathbf{\Gamma}_1^{(i)}\mathbf{R}_o(n) - \mathbf{H}_2\right) &= \mathbf{\Lambda}^{-1}\mathbf{G}_2 \end{aligned} \tag{29}$$

from which, the final expression for $\mathbf{G}_{\mu}^{(i+1)}$, $\mu = 1, 2$, given by (11) easily follows.

APPENDIX II
EXACT COMPUTATION OF $\Gamma_{\mu}^{(i)}(k)$ FOR QPSK SIGNALING

Let $a = (\pm 1 \pm j)/2$ represent the unit power and the independent and identically distributed data sequence modulating the QPSK carrier, $\Gamma_{\mu}^{(i)}(k)$ in (13) can be expressed (30), shown at the top of the page. From (9), it follows that

$$\Gamma_{\mu}^{(i)}(k) = \frac{\sum_{a_1,a_2\in S_k} a_{\mu} \exp\left(\frac{1}{\sigma^2}\mathrm{Re}\left[a_{\mu}^{*} Z_{\mu}^{(i)}(k)\right]\right)}{\sum_{a_1,a_2\in S_k} \exp\left(\frac{1}{\sigma^2}\mathrm{Re}\left[a^{*} Z_{\mu}^{(i)}(k)\right]\right)} \tag{31}$$

where

$$\begin{aligned} Z_1^{(i)}(k) &= R_{e,k}\sum_m G_1^{(i)*}(m)\psi_m^{*}(k) \\ &\quad + R_{o,k}^{*}\sum_m G_2^{(i)}(m)\psi_m(k) \\ Z_2^{(i)}(k) &= R_{e,k}\sum_m G_2^{(i)*}(m)\psi_m^{*}(k) \\ &\quad - R_{o,k}^{*}\sum_m G_1^{(i)}(m)\psi_m(k) \end{aligned}$$

Then, taking summations in the numerator and the denominator of (31) over the values of the QPSK symbols a, we have the final result as follows:

$$\begin{aligned} \Gamma_{\mu}^{(i)}(k) &= \frac{1}{2}\tanh\left[\frac{1}{\sigma^2}\mathrm{Re}\left(Z_{\mu}^{(i)}(k)\right)\right] \\ &\quad + \frac{j}{2}\tanh\left[\frac{1}{\sigma^2}\mathrm{Im}\left(Z_{\mu}^{(i)}(k)\right)\right]. \end{aligned} \tag{32}$$

ACKNOWLEDGMENT

The authors would like to thank the anonymous reviewers for their insightful comments and suggestions that improved the quality of this paper.

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