POR Channel Estimation for UWB Communications

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***Abstract*— Power of R (POR) technique has been successfully applied to multiuser detection for a direct sequence code-division multiple access (CDMA) system even when multipath channel is unknown. It yields channel estimate asymptotically converged to that of the ideal subspace approach while without request of estimation of the noise subspace of the received data covariance matrix. Its applicability in multiple access ultra-wideband (UWB) systems is investigated in this paper. First, a time-hopping (TH) UWB system using pulse position modulation (PPM) is converted to a linear form similar to a multirate CDMA system, after transforming modulation delays to amplitudes of pulses and then defining a new set of virtual inputs for each user. Based on the new multirate model, POR technique is applied to estimate unknown channel parameters. Performance of the proposed channel estimator is analyzed and verified. Comparisons with other approaches are also performed.** [1]

Index Terms - **Power of R, ultra wideband, channel estimation, subspace.**

I. INTRODUCTION

Recently there emerges considerable interest in studying and deploying time-hopping (TH) ultra-wideband (UWB) communication systems due to their appealing features and recent release of the spectral mask from the Federal Communications Commission. UWB technology is an ideal candidate for secure low-power multiuser communications. It offers exceptional multipath resolvability, robustness to jamming, low probability of interception and detection [1].

In a UWB system, typically a RAKE receiver is employed to detect the information symbols. It consists of multiple waveform correlators [2]. This low-complexity implementation sacrifices performance and yields a large discrepancy from the optimal receiver. To fully capture signal energy spread over multiple paths, the receiver needs to know channel parameters when correlation is performed. In a dense multipath wireless environment, channel information is not known *a priori*. Channel parameters can be either measured or estimated. However, field test is sensitive to location and time, and not feasible for an unknown environment in general. Although maximum likelihood (ML) channel estimation methods [3], [4] provide a theoretical guidance for evaluation of other channel estimators, they are computationally prohibitive. Meanwhile, multiuser interference (MUI) is approximated as a Gaussian process which may lead to degraded performance. Low complexity channel estimators with explicit consideration of MUI are thus more desirable. They are also required by either existing RAKE receivers or other advanced detectors such as linear multiuser receivers [5].

Since modulation delay causes non-linearity of the system, which is not easy for signal processing, we thus first transform the UWB channel input/output model to a linearly modulated system following [5] at a pulse rate sampling. The new "linear" model casts the modulation delay into amplitudes of newly defined pulses. The TH sequence uniquely specifies a "code" matrix for each user that only contains zeros and ones to indicate whether contribution of the channel exists or not. Then received data is linearly dependent on amplitude, code matrix and channel in a tri-linear form. If we treat "code" matrix to be in a similar role as code matrix in a CDMA system, then the model will be shown to be similar to a multi-code multirate CDMA system [6], leading to possible application of Power of R (POR) technique [7], which outperforms a minimum variance method [8].

In this paper, we use lower case boldfaced letters for vectors, upper case boldfaced letters for matrices. Denote transpose by ^{T}, inverse by $^{-1}$, pseudo-inverse by † and determinant by $det(\cdots)$. $E\{\cdot\}$ represents expectation of a random variable, $\boldsymbol{I}_a$ an identity matrix of degree a whose ith column is denoted by $\boldsymbol{e}_{a,i}$. $\mathbf{1}_a$ is a vector of length a with all elements equal to one. $\delta(\cdot)$ is a discrete-time unit impulse function. $\lfloor\cdot\rfloor$ stands for integer floor, while $\lceil\cdot\rceil$ for integer ceiling, $\otimes$ for Kronecker product.

II. DISCRETE-TIME UWB SYSTEM MODEL

Assume there are K users simultaneously sharing the spectrum in a multiple access (MA) TH-UWB system. The transmitted baseband UWB signal from user k can be described by [5]

$$\alpha_k(t) = \sqrt{\mathcal{P}_k} \sum_{i=-\infty}^{\infty} w(t - iT_f - c_k(i)T_c - \tau_{I_k(\lfloor i/N_f \rfloor)}) \quad (1)$$

where $\mathcal{P}_k$ is the kth user's transmission power, $w(t)$ is the baseband monopulse, T_f is the frame duration, N_f is the number of frames over which an M-ary PPM symbol repeats, $c_k(i) \in [0, N_c - 1]$ is a periodic hopping sequence with period equal to one symbol period. Each chip has duration T_c. $I_k(\lfloor i/N_f \rfloor) \in [0, M-1]$ is the kth user's information bearing symbol during the ith frame, $\tau_{I_k(\lfloor i/N_f \rfloor)} = I_k(\lfloor i/N_f \rfloor)\sigma$ is the corresponding modulation delay in a multiples of σ seconds. Assume $T_f = N_cT_c$ and $T_c = M\sigma$. Eq. (1) shows a nonlinear relationship between $\alpha_k(t)$ and the transmitted information symbol. However, a linear relationship can be obtained as shown in [5]. Let us define M virtual inputs for user k with the mth one as $s_{k,m}(\lfloor i/N_f \rfloor) = \delta\Big(I_k(\lfloor i/N_f \rfloor) - m\Big)$. Clearly, only one of the M inputs will be nonzero each time.

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Correspondingly, M pulse-rate code sequences are defined for the M virtual inputs with the mth sequence as $\boldsymbol{c}_{k,m} = \widetilde{\boldsymbol{c}}_k \otimes \boldsymbol{e}_{M,m}$, where $\widetilde{\boldsymbol{c}}_k$ is the chip-rate code sequence with its ith element defined as $\widetilde{c}_k(i) = \delta\Big(\lfloor i/N_c \rfloor N_c + c_k(\lfloor i/N_c \rfloor) - i\Big)$. Then, (1) can be equivalently expressed as

$$\alpha_k(t) = \sqrt{\mathcal{P}_k} \sum_{i=-\infty}^{\infty} \sum_{m=0}^{M-1} u_{k,m}(i) w(t - i\sigma) \tag{2}$$

where $u_{k,m}(i) = \sum_{l=-\infty}^{\infty} s_{k,m}(l) c_{k,m}(i - lP)$, $P \triangleq MN_cN_f$, and $c_{k,m}(i)$ is the ith element of $\boldsymbol{c}_{k,m}$. If we define an effective channel including effects from modulated pulse at the transmitter, propagation channel and matched filter at the receiver by $g_k(t) = \sqrt{\mathcal{P}_k} w(t) \star \bar{g}_k(t) \star w(-t)$ where $\star$ denotes convolution, then the received signal at pulse rate becomes

$$y(n) = \sum_{k,m} \sum_{i=0}^{q} u_{k,m}(n - i - d_k) g_k(i) + v(n). \tag{3}$$

where $v(n)$ and d_k denote additive white Gaussian noise (AWGN) and propagation delay of user k, respectively. The effective channel delay spread is assumed to be $q\sigma$. If we collect P samples from $y(nP+1), \ldots, y(nP+P-1)$, then the received data vector follows [8]

$$\boldsymbol{y}_n = \sum_{k,m,l} \boldsymbol{C}_{k,m,l} \boldsymbol{g}_k s_{k,m}(n+l) + \boldsymbol{v}_n \tag{4}$$

where l takes all integers from $-\lceil q/P \rceil$ to 0, $\boldsymbol{g}_k$ is an unknown channel vector for user k which contains channel coefficients at the pulse rate and power factor $\sqrt{\mathcal{P}_k}$, $\boldsymbol{C}_{k,m,l}$ is a code filtering matrix constructed from $\boldsymbol{c}_{k,m}$. This model can be compactly expressed in another form

$$\boldsymbol{y}_n = \sum_{k,l} \boldsymbol{H}_{k,l} \boldsymbol{s}_{k,n,l} + \boldsymbol{v}_n = \boldsymbol{H}\boldsymbol{s}_n + \boldsymbol{v}_n \tag{5}$$

after collecting M inputs in a vector $\boldsymbol{s}_{k,n,l} = [s_{k,0}(n+l), \cdots, s_{k,M-1}(n+l)]^T$, defining a corresponding effective channel matrix $\boldsymbol{H}_{k,l} = [\boldsymbol{C}_{k,0,l}\boldsymbol{g}_k, \cdots, \boldsymbol{C}_{k,M-1,l}\boldsymbol{g}_k]$, and successively stack such matrices (or vectors) in $\boldsymbol{H}$ (or $\boldsymbol{s}_n$).

III. Blind Channel Estimation and Symbol Detection

According to (5), $\boldsymbol{y}_n$ has nonzero mean, which will induce nonzero cross terms in its correlation matrix and is inconvenient for channel estimation. Therefore, we first obtain zero-mean data. Noticing that $E\{\boldsymbol{y}_n\}$ is given by $\bar{\boldsymbol{y}} \triangleq E\{\boldsymbol{y}_n\} = \frac{1}{M}\sum_{k,m,l} \boldsymbol{C}_{k,m,l}\boldsymbol{g}_k$, the zero mean data vector $\boldsymbol{z}_n \triangleq \boldsymbol{y}_n - \bar{\boldsymbol{y}}$ is given by

$$\boldsymbol{z}_n = \sum_{k,l,m} \boldsymbol{C}_{k,l} \boldsymbol{g}_k a_{k,m}(n+l) + \boldsymbol{v}_n = \boldsymbol{H}, \tag{6}$$

where $a_{k,m}(n+l) = s_{k,m}(n+l) - \frac{1}{M}$. For shorter notation, we denote the information symbol in $s_{k,m}(n+l)$ simply by I after ignoring its time and user dependence. It takes values $0, \cdots, M-1$ with equal probability $\frac{1}{M}$. If we define $\boldsymbol{a}_{k,n,l} = \boldsymbol{s}_{k,n,l} - \frac{1}{M}\boldsymbol{1}_M$, then

$$\boldsymbol{a}_{k,n,l} = [\delta(I), \cdots, \delta(I-(M-1))]^T - \frac{1}{M}\boldsymbol{1}_M^T. \tag{7}$$

The covariance of $\boldsymbol{a}_{k,n,l}$, denoted by $\boldsymbol{\Phi} = E\{\boldsymbol{a}_{k,n,l}\boldsymbol{a}_{k,n,l}^T\}$, can be found to be [8]

$$\boldsymbol{\Phi} = \frac{1}{M}\sum_{i=1}^{M} \widetilde{\boldsymbol{e}}_{M,i}\widetilde{\boldsymbol{e}}_{M,i}^T, \quad \widetilde{\boldsymbol{e}}_{M,i} = \boldsymbol{e}_{M,i} - \frac{1}{M}\boldsymbol{1}_M \tag{8}$$

which has rank $M-1$. Let singular value decomposition of $\boldsymbol{\Phi}$ be $\boldsymbol{\Phi} = \boldsymbol{B}_a\boldsymbol{\Lambda}_a^2\boldsymbol{B}_a$, then $\boldsymbol{a}_{k,n,l} = \boldsymbol{\Phi}\boldsymbol{\Lambda}\widetilde{\boldsymbol{a}}_{k,n,l}$ with $\widetilde{\boldsymbol{a}}_{k,n,l}$ denoting whitened input. As a result, the zero mean data vector is rewritten as

$$\boldsymbol{z}_n = \sum_{k,l,j} \boldsymbol{S}_{k,j,l}\boldsymbol{g}_k\widetilde{\boldsymbol{a}}_{k,n,l} + \boldsymbol{v}_n \tag{9}$$

where $\boldsymbol{S}_{k,j,l} = \sum_{i=1}^{M} b_{i,j}\widetilde{\lambda}_j\boldsymbol{C}_{k,i-1,l}$ for $j = 1, \ldots, M-1$ with $b_{i,j}$ and $\widetilde{\lambda}_j$ denoting the (i,j)th element of $\boldsymbol{B}_a$ and the jth diagonal element of $\boldsymbol{\Lambda}_a$, respectively. (9) resembles a multi-rate CDMA system [6], where $\boldsymbol{S}_{k,j,l}$ can be treated as a code matrix for the jth input in $\widetilde{\boldsymbol{a}}_{k,n,l}$. Let $\boldsymbol{R} \triangleq E\{\boldsymbol{z}_n\boldsymbol{z}_n^H\}$ denote the covariance matrix of the zero-mean data vector. According to (9), $\boldsymbol{R} = \sum_{k,l,j} \boldsymbol{S}_{k,j,l}\boldsymbol{g}_k\boldsymbol{g}_k^H\boldsymbol{S}_{k,j,l}^H + \sigma_v^2\boldsymbol{I}$ where σ_v^2 is noise power. Define eigen-decomposition of $\boldsymbol{R}$ as

$$\boldsymbol{R} = \begin{bmatrix} \boldsymbol{U}_s & \boldsymbol{U}_n \end{bmatrix} \begin{bmatrix} \boldsymbol{\Lambda}_s + \sigma_v^2\boldsymbol{I} & \boldsymbol{0} \\ \boldsymbol{0} & \sigma_v^2\boldsymbol{I} \end{bmatrix} \begin{bmatrix} \boldsymbol{U}_s^H \\ \boldsymbol{U}_n^H \end{bmatrix}. \tag{10}$$

Suppose user 1 is the desired user. The subspace approach for estimating $\boldsymbol{g}_1$ has been shown to be [9]

$$\widehat{\boldsymbol{g}}_1 = \min_{||\boldsymbol{g}||=1} \sum_{j=1}^{M-1} \boldsymbol{g}^H\mathcal{S}_j^H\boldsymbol{U}_n\boldsymbol{U}_n^H\mathcal{S}_j\boldsymbol{g}$$

where $\mathcal{S}_j \triangleq \boldsymbol{S}_{1,j,0}$ for simple notation. In practice, $\boldsymbol{U}_n$ is not known *a priori*. It is usually obtained from eigenvalue decomposition of the sample covariance matrix. Due to effects of noise and finite samples, the dimension of the noise subspace may be estimated incorrectly, resulting in degraded performance of the subspace method. By contrast, power of R (POR) technique [7] has been shown to asymptotically estimate the noise subspace without rank estimation, since $\sigma_v^{2p}\boldsymbol{R}^{-p}$ can be decomposed for a positive integer p as

$$\sigma_v^{2p}\boldsymbol{R}^{-p} = \boldsymbol{U}_n\boldsymbol{U}_n^H + \boldsymbol{U}_s diag\{(\frac{\sigma_v^2}{\lambda_i^2 + \sigma_v^2})^p\}\boldsymbol{U}_s^H. \tag{11}$$

Clearly, each null basis has a unity weight, while the ith signal basis has a weight of $(\frac{\sigma_v^2}{(\lambda_i^2+\sigma_v^2})^p$, which is less than 1, irrespective of the noise power. $(\frac{\sigma_v^2}{\lambda_i^2+\sigma_v^2})^p$ can converge to zero for sufficiently large p. If $\boldsymbol{R}^{-p}$ is used to replace the noise subspace component, and noticing that scalar σ_v^{2p} will not affect eigenvector of a matrix, then POR based channel estimation method is readily obtained as

$$\widehat{\boldsymbol{g}}_1 = arg \min_{||\boldsymbol{g}||=1} \sum_j \boldsymbol{g}^H\mathcal{S}_j^H\boldsymbol{R}^{-p}\mathcal{S}_j\boldsymbol{g}. \tag{12}$$

$\widehat{\boldsymbol{g}}_1$ is the minimum eigenvector of $\mathcal{S}_j^H\boldsymbol{R}^{-p}\mathcal{S}_j$ corresponding to minimum eigenvalue γ_{por}. It is clear that as $p \to \infty$, the proposed channel estimate in (12) converges to the subspace one. On the other hand, although asymptotic convergence is established for $p \to \infty$, $p = 2$ is sufficient for satisfactory performance in practice, as shown by our simulation examples.

A. Symbol Detection

RAKE receiver can be readily constructed based on the estimated channel to detect the information symbols. Note that input symbol corresponds to the position of the only one maximum value in $\boldsymbol{a}_{k,n,l}$. Therefore, we need to design M receivers $\boldsymbol{f}_i$ $(i = 1, \cdots, M)$ with each one corresponding to each element in $\boldsymbol{a}_{k,n,l}$. Then outputs of M receivers are compared and the index of the maximum element is determined. Considering that I takes values $0, \cdots, M-1$, our symbol detection criterion can be described as follows

$$I = \arg \max_{i \in \{1, \cdots, M\}} Re\{\boldsymbol{f}_i^H \boldsymbol{z}_n\} - 1.$$

The M RAKE receivers can be shown to be $\boldsymbol{F}_{k,RAKE} = \boldsymbol{H}_{k,0}$.

IV. Performance of Channel Estimation

Channel estimation mean-square-error will be derived in the presence of nontrivial noise and finite data samples in this section.

A. Noise Induced Channel Estimation Error

We first study effect of noise. Let

$$\boldsymbol{A} = \sum_{j=1}^{M-1} \mathcal{S}_j^H \boldsymbol{R}^{-p} \mathcal{S}_j, \ \boldsymbol{A}_0 = \sum_{j=1}^{M-1} \mathcal{S}_j^H \boldsymbol{U}_n \boldsymbol{U}_n^H \mathcal{S}_j,$$
$$\boldsymbol{A}_p = \sum_{j=1}^{M-1} \mathcal{S}_j^H \boldsymbol{U}_s \boldsymbol{\Lambda}_s^{-p} \boldsymbol{U}_s \mathcal{S}_j. \quad (13)$$

Since by (12) the estimated channel vector is the eigenvector of matrix $\boldsymbol{A}$ corresponding to its minimum eigenvalue (for convenience, we call it minimum eigenvector). Applying (11), $\boldsymbol{A}$ can be decomposed as

$$\sigma_v^{2p} \boldsymbol{A} = \boldsymbol{A}_0 + \sum_{j=1}^{M-1} \mathcal{S}_j^H \boldsymbol{U}_s diag\{(\frac{\sigma_v^2}{\lambda_i^2 + \sigma_v^2})^p\} \boldsymbol{U}_s^H \mathcal{S}_j. \quad (14)$$

Note that the minimum eigenvector of $\boldsymbol{A}_0$ is exactly the desired channel $\boldsymbol{g}_1$. If we view the second term on the right-hand-side of (14) as a perturbation to $\boldsymbol{A}_0$ due to noise and denote it by $\delta \boldsymbol{A}_0$, then perturbation of the minimum eigenvector, or equivalently the channel estimation error is given by [10]

$$\delta \boldsymbol{g}_1 \approx -\boldsymbol{A}_0^\dagger \delta \boldsymbol{A}_0 \boldsymbol{g}_1. \quad (15)$$

We observe that channel estimation error is related to ratio $(\frac{\sigma_v^2}{\lambda_i^2 + \sigma_v^2})^p$ in $\delta \boldsymbol{A}_0$. At low signal to noise ratio (SNR), larger p is necessary to achieve smaller channel estimation error. Since the ratio is a fractional number, theoretically speaking, good channel estimation performance can be expected for sufficiently large p, irrespective of noise power. At high SNR, we can assume that $\sigma_v^2 \ll [\boldsymbol{\Lambda}_s]_{i,i}$, then the factional term $(\frac{\sigma_v^2}{\lambda_i^2 + \sigma_v^2})^p$ can be expanded by Taylor series, resulting the following channel estimation error

$$\delta \boldsymbol{g}_1 \approx -\sigma_v^{2p} \boldsymbol{A}_0^\dagger \boldsymbol{A}_p \boldsymbol{g}_1 + \boldsymbol{O}(\sigma_v^{2p+2}) \quad (16)$$

which shows that $\delta \boldsymbol{g}_1$ is at the order of $O(\sigma_v^{2p})$, much smaller than that obtained in the minimum variance method [8].

B. Perturbation Error from Finite Data Length

Next we turn to effect of data length N on channel mean-square-error (MSE). Perturbation arises in the estimated data correlation matrix when it is estimated from N data vectors [10]

$$\widehat{\boldsymbol{R}} = \frac{1}{N} \sum_{n=1}^{N} (\boldsymbol{y}_n - \frac{1}{N} \sum_{n=1}^{N} \boldsymbol{y}_n)(\boldsymbol{y}_n - \frac{1}{N} \sum_{n=1}^{N} \boldsymbol{y}_n)^H. \quad (17)$$

Although $\widehat{\boldsymbol{R}}$ converges to $\boldsymbol{R}$ as $N \to \infty$, a perturbation $\delta \boldsymbol{R}$ due to finite N will cause $\boldsymbol{A}$ perturbed and finally our POR solution. Here, we are interested in a perturbed eigenvector of $\boldsymbol{A}$ after $\boldsymbol{R}$ is perturbed, and investigate how $\delta \boldsymbol{R}$ affects the performance of the channel estimator. Let $\boldsymbol{g}_{por}$ denote the ideal channel estimate in the case of $N \to \infty$. Under small perturbation assumption (large N) and using Taylor's expansion up to the first order, we have $\delta \boldsymbol{A} = -\sum_{j=1}^{M-1} \mathcal{S}_j^H \sum_{k=1}^{p} \boldsymbol{R}^{-k} \delta \boldsymbol{R} \boldsymbol{R}^{-(p-k)} \boldsymbol{R}^{-1} \mathcal{S}_j$. Due to $\delta \boldsymbol{A}$, $\boldsymbol{g}_{por}$ is perturbed as $\widetilde{\boldsymbol{g}}$, resulting in a perturbation error $\delta \boldsymbol{g} = \widetilde{\boldsymbol{g}} - \boldsymbol{g}_{por}$ as the following [10],

$$\delta \boldsymbol{g} \approx -(\boldsymbol{A} - \gamma_{por} \boldsymbol{I})^\dagger \delta \boldsymbol{A} \boldsymbol{g}_{por} \approx \sum_{j=1}^{M-1} \sum_{k=1}^{p} \boldsymbol{T}_{j,k} \delta \boldsymbol{R} \boldsymbol{t}_{j,k}. \quad (18)$$

where $\boldsymbol{T}_{j,k}$ and $\boldsymbol{t}_{j,k}$ are deterministic quantities given by $\boldsymbol{T}_{j,k} = (\boldsymbol{A} - \gamma_{por} \boldsymbol{I})^\dagger \mathcal{S}_j^H \boldsymbol{R}^{-k}$, $\boldsymbol{t}_{j,k} = \boldsymbol{R}^{-(p-k)} \boldsymbol{R}^{-1} \mathcal{S}_j \boldsymbol{g}_{por}$. Therefore the covariance of $\delta \boldsymbol{g}$ becomes

$$\mathrm{Cov}_g \approx \sum_{j=1}^{M-1} \sum_{k_1, k_2=1}^{p} \boldsymbol{T}_{j,k_1} E\{\delta \boldsymbol{R} \boldsymbol{t}_{j,k_1} \boldsymbol{t}_{j,k_2}^H \delta \boldsymbol{R}\} \boldsymbol{T}_{j,k_2}^H, \quad (19)$$

and the mean-square-error is equal to the trace of Cov_g. Both are dependent on the weighted covariance of $\delta \boldsymbol{R}$ for non-white inputs, which have been derived in [9], [11].

C. Channel Estimation Error Due to Noise and Finite N

Based on the above analysis, total channel estimation error due to both noise and finite N can be computed as in the following *Lemma*.

Lemma: For small σ_v^2 and large N, channel estimation error $E\{||\widetilde{\boldsymbol{g}} - \boldsymbol{g}_1||^2\}$ is approximated by $||\boldsymbol{g}_{por} - \boldsymbol{g}_1||^2 + E\{||\widetilde{\boldsymbol{g}} - \boldsymbol{g}_{por}||^2\}$, where the first term is obtained from (16) and the second term by the trace of (19).

Proof: Noticing that $(\widetilde{\boldsymbol{g}} - \boldsymbol{g}_1) = (\boldsymbol{g}_{por} - \boldsymbol{g}_1) + (\widetilde{\boldsymbol{g}} - \boldsymbol{g}_{por})$, $E\{||\widetilde{\boldsymbol{g}} - \boldsymbol{g}_1||^2\}$ is expanded to three terms. The cross term can be neglected because $E\{\delta \boldsymbol{R}\} = \boldsymbol{0}$ leads to $E\{\widetilde{\boldsymbol{g}} - \boldsymbol{g}_{por}\} \approx \boldsymbol{0}$ according to (18). Then the lemma immediately follows. □

V. Numerical Examples

We test performance of the proposed method by simulations in this section. Second derivative of Gaussian function with pulse width equal to $0.7ns$ is assumed for the received signal [2]. All simulation results are based on 100 independent realizations, and each user's time hopping codes are randomly generated in each realization. We first consider a UWB system with $N_c = 10$, $N_f = 4$, $M = 2$, $K = 8$. Fig. 1 (a) shows effect of noise with $N \to \infty$ and Fig. 1 (b) shows effect of data length N with $SNR = 15dB$. As expected, experimental results are very close to analytical ones in both figures, verifying our analysis. On the other hand, it is observed that the POR method with $p = 2$ has similiar performance as $p = 4$, since perturbation error is the dominant error for the POR receivers with $p = 2,\ 4$ when N is not very large. Therefore, in practice it is sufficient to apply POR with $p = 2$ for less complexity. Comparisons with nondata aided (NDA) and data aided (DA) methods in [4] are also performed with channel MSE plotted in Fig. 2 and BER in Fig. 3, respectively. The system parameters including channels are taken from [4] without repetition here. $N = 600$ is used for channel estimation. It can be observed that the proposed method, though a blind method, converges to the DA in a single user situation, while outperforms DA at most SNRs in the presence of multiuser interference. Compared with NDA method [4], the proposed method shows much better performance. [2]

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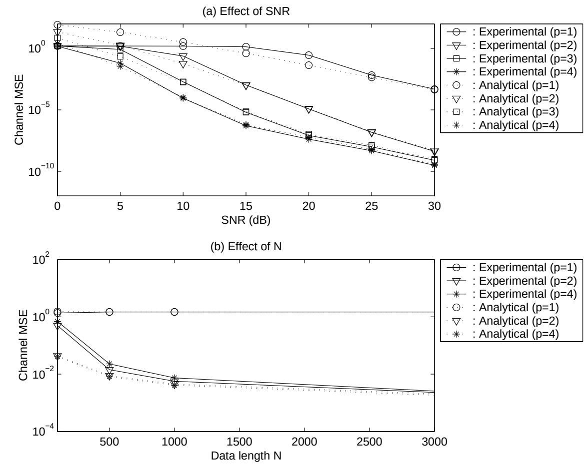

Fig. 1. Analysis verification.

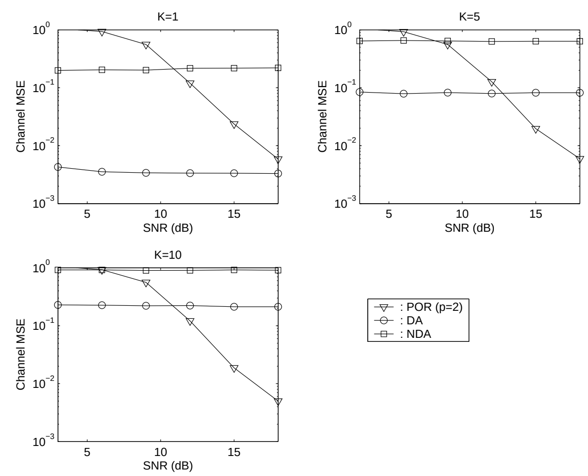

Fig. 2. MSE comparison.

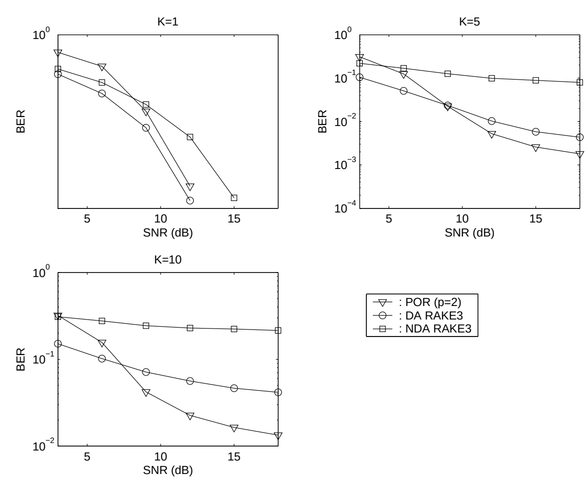

Fig. 3. BER comparison.