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디지탈 통신 시스템을 위한 효율적인 블라인드 최대비 결합 방법

(Efficient Blind Maximal Ratio Combining Methods for Digital Communication Systems)

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요 약

본 논문에서는 ML(maximum likelihood) 원리와 디지탈 통신 시스템의 고유 특성인 유한 알파벳 특성 (FAP: finite alphabet properties)에 근거한 블라인드 최대비 결합(MRC: maximal ratio combining)을 위한 간단한 방법들을 제안한다. 이 방법들은 아주 작은 길이의 데이터를 가지고도 채널 파라미터들을 정확하게 추정할 수 있기 때문에, 이 방법들을 사용하면 거의 완벽한 최대비 결합을 수행할 수 있다. 이 방법들은 교번 투영 기법(alternating projection technique)을 이용하여 다이버시티 가지들에 대한 채널 파라미터와 데이터 시퀀스를 동시에 추정한다. 두 가지 다른 JC-DSE (joint combining and data sequence estimation) 방법과 PC-BPE (pre-combining and blind phase estimation) 방법이 제안되며, 전영역 최적화를 보장할 수 있도록 하는 효율적인 초기화 방법도 제시된다. 모의실험 결과들을 통하여, 제안된 두가지 방법의 심볼 오류율과 채널 파라미터의 추정 정확도에 관한 성능을 보여준다.

Abstract

We present simple block methods for blind maximal ratio combining (MRC) based on a maximum likelihood (ML) principle and finite alphabet properties (FAP) inherent in digital communication systems. The methods can provide accurate estimates of channel parameters even with a small subset of data, thus realizing nearly perfect combining. The channel parameters of diversity branches and the data sequence are estimated simultaneously by using an alternating projection technique. Two different methods, that is, (1) Joint combining and data sequence estimation (JC-DSE) method and (2) Pre-combining and blind phase estimation (PC-BPE) method are presented. Efficient initialization schemes that can assure the convergence to the global optimum are also presented. Simulation results demonstrate the performance of the two methods on the symbol error rate (SER) and the estimated accuracy of the channel parameters.

I. INTRODUCTION

For coherent communication systems with independent diversity branches, MRC is the optimal linear combining technique, in which the perfect knowledge on the channel parameters of respective branches is required [1],[2]. Accurate estimates of the channel parameters can be easily obtained by invoking adaptive techniques based on decision-directed methods with training preamble and pilot-symbol assisted methods [3]-[6]. However, the use of pilot signals or training sequences has a drawback of requiring a dedicated channel and/or an additional bandwidth, thus reducing throughput efficiency of the network. In addition, for systems of requiring the

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dynamic selection of combining branches[7]-[10] such as direct-sequence spread-spectrum (DS/SS) systems, these adaptive techniques using the pilot signal cannot be used directly any more since they must be reinitialized after every selection of a new set of combining branches. The number of dominant combining branches even may be varied.

In this context of dynamic selection and combining, dominant combining branches can be determined by a power-monitoring method with a threshold, and then MRC is applied to the selected branches only in order to maximize a signal-to-noise ratio (SNR) at the combiner output. This problem of the dynamic selection and combining can be solved indirectly by combining the signals from all the possible branches as in [3]. However, this requires huge computations proportional to the number of all the possible branches at every symbol instant, and its performance may be even degraded at lower SNR values due to the destructive contributions of noisy branches. Therefore, a class of blind methods that can provide reliable estimates of the channel parameters for the optimal combining, irrespective of dynamic selection of combining branches, is desirable.

In this paper, we propose two blind MRC methods based on an ML principle and FAP inherent in digital communication systems[11], which can provide accurate estimates of the channel parameters even with a small subset of data. Without invoking training models, the proposed methods estimate simultaneously the data sequence and the channel parameters by using an alternating projection technique. Two different methods are presented as follows: (1) JC-DSE method estimates iteratively the channel parameters and the data sequence from a finite observation by using the alternating projection technique; and (2) PC-BPE method firstly combines the diversity branches by using sufficiently good estimates of the channel parameters up to an unknown phase rotation, and then estimates iteratively the unknown phase and the data sequence from the combined signal by the alternating projection technique[12]. Respective initialization schemes for these two methods are presented to assure the convergence to the global optimum.

Ⅱ. PROBLEM FORMULATION

Consider a baseband digital communication system with M diversity branches. A matched-filtered output of the i-th branch can be expressed as

$$x_i(n) = a_i e^{j\theta_i} s(n) + v_i(n), \quad i = 1, \cdots, M, \qquad (1)$$

where $x_i(n)$, $v_i(n)$, a_i, and θ_i are a received signal, an additive white Gaussian noise (AWGN) with zero mean and variance of σ^2, a gain, and a phase at the i-th branch, respectively; $s(n)$ is a transmitted data sequence which is commonly carried over all the diversity branches. In what follows, we assume independent identically distributed (i.i.d.) noises at all the branches. In compact form,

$$\mathbf{x}(n) = s(n)\mathbf{c} + \mathbf{v}(n) \qquad (2)$$

where υ(n)=[$x_1(n),\cdots,x_M(n)$], υ(n)=[$v_1(n),\cdots,v_M(n)$], and υ=[$c_1,\cdots,c_M$], with channel response, c_i for the i-th branch defined as $c_i = a_i e^{j\theta_i}$. Collecting data over N symbol periods, we can rewrite (2) in matrix form

$$\mathbf{X} = \mathbf{s} \cdot \mathbf{c} + \mathbf{V}, \qquad (3)$$

where X=[x(1),$\cdots$,x(N)]^T], V=[v(1),$\cdots$,v(N)]^T], and υ=[s(1),$\cdots$,s(N)]^T] with the superscript T denoting transpose.

Blind MRC problem requires the joint estimation of the channel parameters **c** and the data sequence **s** from the finite observation **X**. In this paper, we consider only symmetric QAM systems such as 4-QAM and 16-QAM, although the proposed methods can be extended directly to nonsymmetric modulations. Hence, all the phase estimates υ = [$\theta_1,\cdots,\theta_M$], obtained from any blind estimation methods may suffer the phase ambiguity of $\pi/2$.

III. MAXIMUM LIKELIHOOD ESTIMATION

Using (3) and from the AWGN assumption, we can obtain the log likelihood function as

$$\ln L = const - MN\log\sigma^2 - \frac{1}{\sigma^2}\sum_{n=1}^{N}\| \mathbf{x}(n) - s(n)\cdot\mathbf{c}\|^2 . \quad (4)$$

Neglecting constant terms, the problem of maximizing L with respect to the unknown parameters $\mathbf{c}$ and $s(n)$, $n = 1, \cdots, N$ reduces to the following least square (LS) problem:

$$\arg\min_{\mathbf{c},\mathbf{s}} \|\mathbf{X} - \mathbf{s}\cdot\mathbf{c}\|_F^2 , \quad (5)$$

where the subscript F denotes the Frobenious norm of a matrix. Since elements of $\mathbf{s}$ in digital communication systems are constrained to finite alphabets, this problem is a nonlinear separable optimization problem with mixed discrete and continuous variables. This problem can be solved in two steps as follows: Minimizing (5) with respect to $\mathbf{c}$ with $\mathbf{s}$ fixed, since $\mathbf{c}$ is unconstrained, we obtain

$$\mathbf{c} = (\mathbf{s}^*\mathbf{s})^{-1}\mathbf{s}^*\mathbf{X}, \quad (6)$$

where the asterisk denotes complex conjugate transpose. We can then obtain the ML estimate of $\mathbf{s}$ by substituting (6) back into (5) as

$$\arg.\min_{\mathbf{s}} \|(\mathbf{I} - \mathbf{s}\mathbf{s}^*(\mathbf{s}^*\mathbf{s})^{-1})\mathbf{X}\|_F^2 \quad (7)$$

Then, the channel parameters $\mathbf{c}$ are obtained by substituting $\mathbf{s}$ obtained from (7) back into (6).

The global minimization of (7) can be obtained by exhaustive two-dimensional search. However, the number of possible $\mathbf{s}$ vectors grows exponentially with both N and the number of alphabets. This exhaustive search cannot be used even for modest size problems. Hence, a class of iterative methods is desirable. In the subsequent two sections, we deal with iterative methods that give much lower computational complexity.

IV. JOINT COMBINING AND DATA SEQUENCE ESTIMATION (JC-DSE) METHOD

We propose a block method that estimates simultaneously the channel parameters and the data sequence by using finite alphabet properties and an alternating projection technique. We begin by assuming an initial estimate $\hat{c}$ of the channel parameters. An unconstrained LS estimate of data sequence, $\hat{s}_{uc}$ is obtained by minimizing (5) with respect to $\mathbf{s}$, with $\hat{c}$ fixed as

$$\hat{\mathbf{s}}_{uc} = \mathbf{X}\hat{\mathbf{c}}^*(\hat{\mathbf{c}}\hat{\mathbf{c}}^*)^{-1}.$$

The constrained estimate $\hat{s}$ is obtained by projecting $\hat{s}_{uc}$ onto finite alphabet space as

$$\hat{\mathbf{s}} = proj(\hat{\mathbf{s}}_{uc}) = proj(\mathbf{X}\hat{\mathbf{c}}^*(\hat{\mathbf{c}}\hat{\mathbf{c}}^*)^{-1}), \quad (8)$$

where $proj(\cdot)$ denotes the projection of the unconstrained estimate onto finite alphabet space associated with modulation schemes. Then, a better estimate of $\mathbf{c}$ is obtained by substituting the sequence estimate $\hat{s}$ of (8) into (6). We continue this process until $\hat{c}$ and/or $\hat{s}$ converge. This method may not converge to the global optimum with an arbitrary initial estimate $\hat{c}_0$. Hence, this requires an initialization scheme that can assure the convergence to the global optimum.

We now develop an efficient initialization scheme by noting that a good estimate of the channel parameters $\mathbf{c}$ can be obtained by eliminating the effect of the data sequence from $\mathbf{X}$. The effect of the data sequence can be easily eliminated by constructing the covariance matrix as

$$\mathbf{R}_{XX} = E\{\mathbf{X}^*\mathbf{X}\} = p\mathbf{c}^*\mathbf{c} + \sigma^2\mathbf{I}, \quad (9)$$

where $E\{\cdot\}$ denotes the statistical expectation of $\{\cdot\}$ and p is a real constant proportional to the signal power. From (9), we see that $\mathbf{c}$ can be completely determined from the principal eigenvector of R_{xx} up to a phase rotation. That is, υ can be expressed as

$$\mathbf{c}^* = \alpha \cdot \mathbf{c}_P^* \cdot e^{j\phi}, \quad (10)$$

where α, υ and ϕ are a normalizing real constant, a phase-normalized principal eigenvector of R_{xx}, and an unknown phase after phase normalization, respectively. In this paper, we normalize c_P^* so that its modulus is equal to unity, $\|\mathbf{c}_P^*\|^2 = 1$ (amplitude normalization), and so that the strongest element defined as $c_P(i_{\max})$with $i_{\max} = \arg\max_i [|c_P(i)|, i = 1, \cdots, M]$ has zero-phase (phase normalization). In practice, a good estimate of **c** up to a phase rotation can be obtained from the principal eigenvector of the sample covariance matrix instead of the covariance matrix as

$$\mathbf{R}_{\mathbf{XX}}^S = \frac{1}{N} \cdot \mathbf{X}^* \mathbf{X} = \frac{1}{N} (\mathbf{s}^* \mathbf{s} \cdot \mathbf{c}^* \mathbf{c} + \mathbf{V}^* \mathbf{V}). \quad (11)$$

From (11), note that $1/N \cdot (s^* s)$ stands for an averaged signal power over N symbol periods.

For an initial selection of α, we can assume, without loss of generality, that the gain of the strongest branch is equal to unity. In this case, an appropriate value of α is chosen as

$$\hat{\alpha}_0 = 1 / c_P(i_{\max}). \quad (12)$$

Alternatively, without any assumption on branch gains, the normalizing constant can be estimated by using the maximum eigenvalue of $\mathbf{R}_{XX}^S$ (i.e., $\lambda_{\max}$) as

$$\hat{\alpha}_0 = \sqrt{\frac{\lambda_{\max} - \sigma^2}{PF \cdot N}}, \quad (13)$$

where PF denotes the power contribution factor associated with modulation schemes.

Given the exact c_P^*, the blind MRC requires the joint estimation problem of obtaining simultaneously the phase rotation $e^{j\phi}$ and the data sequence **s** from the finite observation **X**. Hence, this can be solved in a similar way as in the blind phase estimation method with multiple initial estimates and the post selection scheme [12]. Hence, assuming a good estimate of channel parameters, $\hat{\mathbf{c}}_P^*$, we choose a set of initial estimates, $\{\mathbf{c}_{i,0}^* = \hat{\mathbf{c}}_P^* e^{j\phi_{i,0}}, i=1,\cdots,ndiv\}$, corresponding to the *ndiv* different phases, $\{\phi_{i,0}, i = 1,\cdots,ndiv\}$. In this case, the set of initial phases must be sufficient to assure the convergence to the global optimum. After respective estimations of pairs of (**c**,**s**) with all the *ndiv* initial estimates, the pair that minimizes the LS criterion of (5), ($\hat{c}$, $\hat{s}$) is decided as the final estimates of (c, s). We summarize the JC-DSE method as follows:

Iterative JC-DSE MRC Method with Multiple Initial Estimates:

1. Compute $\hat{\mathbf{c}}_P^* = pe-vec(\mathbf{R}_{\mathbf{XX}}^S) = pe-vec(\mathbf{X}^* \mathbf{X})$
2. Determine $\hat{\alpha}_0$ from (12) or (13).
3. For $i = 1, ndiv$
   3.a) $\phi_{i,0} = \{(i-0.5)/ndiv\} \cdot (\pi/2)$, k=0
   3.b) $\mathbf{c}_{i,0}^* = \hat{\alpha}_0 \cdot \hat{\mathbf{c}}_P^* \cdot e^{i\phi_{i,0}}$
   3.c) $k = k + 1$
      . $\mathbf{s}_{i,k} = proj(\mathbf{X}\mathbf{c}_{i,k}^* \cdot (\mathbf{c}_{i,k}\mathbf{c}_{i,k}^*)^{-1})$
      . $\mathbf{c}_{i,k} = (\mathbf{s}_{i,k}^* \mathbf{s}_{i,k})^{-1} \mathbf{s}_{i,k}^* \mathbf{X}$
   3.d) Repeat 3.c) until $(\mathbf{c}_{i,k}, \mathbf{s}_{i,k}) = (\mathbf{c}_{i,k-1}, \mathbf{s}_{i,k-1})$.
   3.e) ; $(\hat{\mathbf{c}}_i, \hat{\mathbf{s}}_i) = (\mathbf{c}_{i,k}, \mathbf{s}_{i,k})$
   End;
4. $(\hat{\mathbf{c}}, \hat{\mathbf{s}}) = \arg\min_{(\hat{\mathbf{c}}_i, \hat{\mathbf{s}}_i)} \|\mathbf{X} - \hat{\mathbf{s}}_i \cdot \hat{\mathbf{c}}_i\|_F^2$, $i = 1, / \cdots, div$.

In the above description of the method, $pe\text{-}vec(\cdot)$ denotes the principal eigenvector of $(\cdot)$.

Starting with each initial estimate, this method converges very rapidly to an extreme point. This requires about $O((2M+1)N)$ complex multiplications at every iteration, thus the computational complexity for all the iteration processes is about $ndiv*nicnv*O((2M+1)N)$ complex multiplications for estimating *ndiv* possible candidates, assuming *nicnv* iterations to convergence. Also, this method requires $(M^2 N + \varepsilon M^2)$ complex multiplications by using the power method [13] with iterations for the computation of $\hat{\mathbf{c}}_P^*$, and $ndiv^*(1.5MN)$ complex multiplications for the post selection.

V. PRE-COMBINING AND BLIND PHASE ESTIMATION (PC-BPE) METHOD

In the previous section, we have described that given the exact c_p^*, the blind MRC requires the joint estimation problem of obtaining simultaneously the phase rotation $e^{j\phi}$ and the data sequence $\mathbf{s}$ from the finite observation $\mathbf{X}$. In the JC-DSE method, both the amplitude and phase of each branch have been updated simultaneously at every iteration, thus providing optimum channel parameters. In this section, we develop a much simpler method that combines firstly the diversity branches by using the good estimate of the combining vector, $\hat{\mathbf{c}}_p^*$ instead of the true combining vector, and then estimates iteratively the phase offset and the data sequence from the combined signal by using the FAP and the alternating projection technique[12]. We begin by assuming the exact combining vector c_p^*. Substituting (10) into (3), we get

$$\mathbf{X} = \mathbf{s} \cdot \mathbf{c}_p \cdot \alpha \cdot e^{-j\phi} + \mathbf{V} \qquad (14)$$

Noting $\| \mathbf{c}_p^* \|^2 = 1$, we get the combined signal $\mathbf{X}_c$ as

$$\mathbf{X}_c = \mathbf{X}\mathbf{c}_p^* = \mathbf{s} \cdot \alpha_c + \mathbf{V}_c, \qquad (15)$$

where $\alpha_c = \alpha \cdot e^{-j\phi}$, and $\mathbf{V}_c = \mathbf{V}\mathbf{c}_p^*$ which is also a white Gaussian noise vector with zero mean and covariance of $\sigma^2 \mathbf{I}$.

Now, the blind MRC requires the joint estimation of the factor α_c and the data sequence $\mathbf{s}$ from the combined observation $\mathbf{X}_c$. This problem can be solved in a similar way as in the blind phase estimation method with multiple initial estimates and the post selection scheme[12]. Using (15) and from the Gaussian assumption of $\mathbf{V}_c$, we can obtain the pre-combined LS problem as

$$\arg \min_{\alpha_c, \mathbf{s}} \| \mathbf{X}_c - \alpha_c \cdot \mathbf{s} \|^2. \qquad (16)$$

Since elements of $\mathbf{s}$ are constrained to finite alphabets, this again is a nonlinear separable optimization problem with mixed discrete and continuous variables. This pre-combined LS problem can be solved as follows: Minimizing (16) with respect to α_c with $\mathbf{s}$ fixed, we obtain

$$\hat{\alpha}_c = (\mathbf{s}^*\mathbf{s})^{-1}\mathbf{s}^*\mathbf{X}_c. \qquad (17)$$

Substituting (17) into (16), we can obtain the ML estimate of $\mathbf{s}$ as

$$\arg \min_{\mathbf{s}} \| (\mathbf{I} - (\mathbf{s}^*\mathbf{s})^{-1} \cdot \mathbf{s}\mathbf{s}^*)\mathbf{X}_c \|^2. \qquad (18)$$

Although the global minimization of (18) can be computed by exhaustive two-dimensional search, we would develop a much simpler iterative method. To get a simpler method for the pre-combined LS problem, we develop a simple block method that estimates simultaneously the factor α_c and the data sequence by using the FAP and the alternating projection technique. We begin by assuming an initial estimate $\hat{\alpha}_c = \hat{\alpha} e^{-j\hat{\phi}}$ of α_c. An unconstrained LS estimate of data sequence $\hat{\mathbf{s}}_{uc}$ is obtained by minimizing (16) with respect to $\mathbf{s}$, with $\hat{\alpha}_c$ fixed as

$$\hat{\mathbf{s}}_{uc} = \mathbf{X}_c \hat{\alpha}_c^{-1}.$$

The constrained estimate $\hat{s}$ is then obtained by projecting $\hat{\mathbf{s}}_{uc}$ onto finite alphabet space as

$$\hat{\mathbf{s}} = proj(\hat{\mathbf{s}}_{uc}) = proj(\mathbf{X}_c \hat{\alpha}_c^{-1}) \qquad (19)$$

Then, a better estimate of α_c is obtained by substituting (19) back into (17). We continue this process until $\hat{\alpha}_c$ and/or $\hat{s}$ converge.

This method may not converge to the global optimum with an arbitrary initial estimate. Hence, it uses *ndiv* different initial estimates $\{\hat{\alpha}_{c,0,i} = \hat{\alpha}_0 \cdot e^{-j\phi_{0,i}},\ i = 1 \cdots, ndiv\}$ corresponding to a set of *ndiv* different initial phases to assure the convergence to the global optimum as done in the JC-DSE method. After respective estimations of a pair of (α_c, $\mathbf{s}$) with all the *ndiv* initial estimates, the pair that minimizes the pre-combined LS criterion of (16), ($\hat{\alpha}_c$, $\hat{\mathbf{s}}$), is decided as the final estimates of (α_c, $\mathbf{s}$). We summarize the PC-BPE method as follows:

Pre-Combining and Iterative Phase Estimation Method with Multiple Initial Estimates:

1. Compute $\hat{\mathbf{c}}_P^* = pe - vec(\mathbf{R}_{\mathbf{XX}}^S) = pe - vec(\mathbf{X} * \mathbf{X})$
2. Determine $\hat{\alpha}_0$ from (12) or (13).
3. $\mathbf{X}_c = \mathbf{X} \cdot \hat{\mathbf{c}}_P^*$
4. For i = 1, *ndiv*
   - 4.a) $\phi_{i,0} = \{(i-0.5)/ndiv\} \cdot (\pi/2)$, $k = 0$
   - 4.b) $\alpha_{c,i,0} = \alpha_0 \cdot e^{-j\phi_{i,0}}$
   - 4.c) $k = k + 1$
     - $\mathbf{s}_{i,k} = proj(\mathbf{X}_c \cdot \alpha^{-1}_{c,i,k-1})$
     - $\alpha_{c,i,k} = (\mathbf{s}^*_{i,k}\mathbf{s}_{i,k})^{-1}\mathbf{s}^*_{i,k}\mathbf{X}_c$
   - 4.d) Repeat 4.c) until$(\alpha_{c,i,k}, \mathbf{s}_{i,k}) = (\alpha_{c,i,k-1}, \mathbf{s}_{i,k-1})$.
   - 4.e) $(\hat{\alpha}_{c,i}, \hat{s}_i) = (\alpha_{c,k,i}, S_{k,i})$.

   End;
5. $(\hat{\alpha}_c, \hat{\mathbf{s}}) = \arg \min_{(\hat{\alpha}_{c,i}, \hat{\mathbf{s}}_i)} \|\mathbf{X}_c - \hat{\alpha}_{c,i} \cdot \hat{\mathbf{s}}_i\|^2$, $i = 1, \cdots ndiv$.

Starting with each initial estimate, this method also converges very rapidly to an extreme point. This requires about *O(2.5N)* complex multiplications at each iteration, thus the computational complexity for all the iteration processes is about $ndiv^*nicnv^*O(2.5N)$ complex multiplications for estimating *ndiv* possible candidates, assuming *nicnv* iterations to convergence. Therefore, this method can reduce the computational complexity by a factor of above M as compared to that of the JC-DSE method in Section IV for estimating *ndiv* possible candidates. Also, this method requires $(M^2N + \varepsilon M^2)$ complex multiplications by using the power method with ε iterations for $\mathbf{c}^*_P$, and MN complex multiplications for $\mathbf{X}_c$, and $ndiv^*N$ complex multiplications for the post selection.

VI. SIMULATION RESULTS AND DISCUSSIONS

We present several simulation results to demonstrate the performance of the two proposed methods on the SER and the estimated accuracy of the channel parameters. For comparison, we also present the symbol error performance obtained using the exact channel parameters (It will be marked as ideal performance in figures.) and Cramer-Rao bounds (CRBs).

In our simulations, we consider two symmetric modulations such as 4-QAM and 16-QAM, and consider 2 and 4 as appropriate *ndiv* values for 4-QAM and 16-QAM modulations, respectively. In every experiment, a total of $1\text{x}10^6$ symbols are used to obtain the SER as a function of SNR_b (i.e., SNR per bit at the strongest branch, branch #1 in all our experiments) with N as a parameter. Also, the means and variances of the channel parameters are computed using the same set of symbols. We consider N=4, 8, 16, 32, and 64 for 4-QAM, and N=10, 16, 32 and 64 for 16-QAM. We use 3 diversity branches (M=3) which have (1.0, 0°), (0.5, 140°), and (0.866, -90°) pairs of the amplitudes and phases, respectively. The above combination of amplitudes and phases gives the largest phase deviation from the selected initial phases for both the modulations considered.

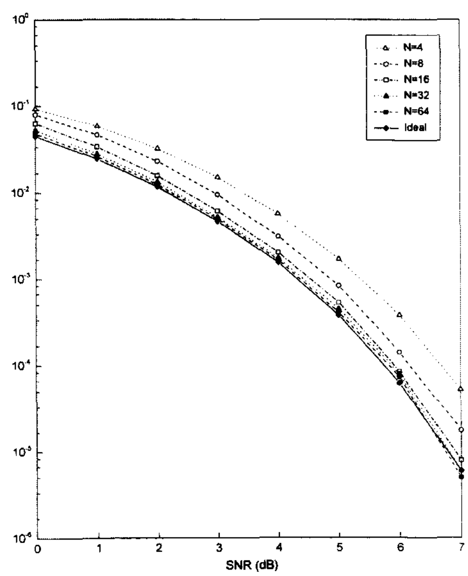


그림 1. 4-QAM 방식에서 JC-DSE 방법의 매개변수 N에 따른 SNR_b에 대한 심볼 오류율

Fig. 1. Symbol error rate of the JC-DSE method as a function of SNR_b with N as a parameter in the 4-QAM case.

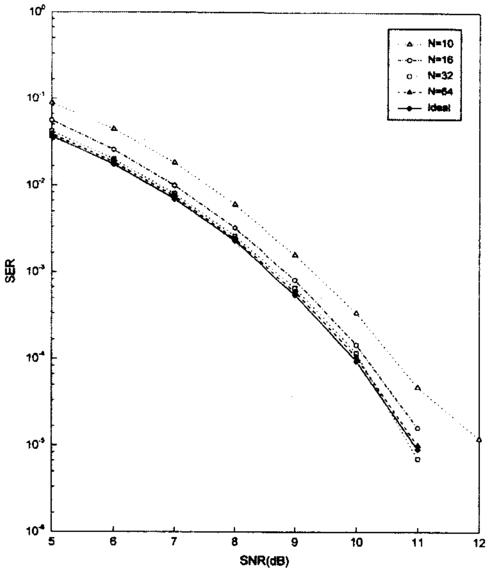


그림 2. 16-QAM 방식에서 JC-DSE 방법의 매개변수 N에 따른 SNR_b에 대한 심볼 오류율

Fig. 2. Symbol error rate of the JC-DSE method as a function of SNR_b with N as a parameter in the 16-QAM case.

Figs. 1 and 2 show SERs of the JC-DSE method as a function of SNR_b with N as a parameter for 4-QAM and 16-QAM, respectively. From these figures, we see that the JC-DSE method has almost the same performance as the ideal performance (using exact parameters) with all N considered, irrespective of modulation types. The degradation with a quite small N (e.g., N=4 for 4-QAM and N=10 for 16-QAM) is still tolerable. The performance gets improved as N increases. Fig. 3 shows the root-mean-squared (RMS) errors of the channel parameters for 4-QAM. From this, we see that the RMS errors for both the amplitude and the phase angle are very close to the corresponding CRBs, thus concluding the estimates obtained by the JC-DSE method to be very efficient. However, the RMS errors of the phase estimates diverge rapidly from the corresponding CRBs as SNR decreases. With smaller N, the degree of divergence gets severer.

Figs. 4 and 5 show SERs of the PC-BPE method as a function of SNR_b with N as a parameter for 4-QAM and 16-QAM, respectively.

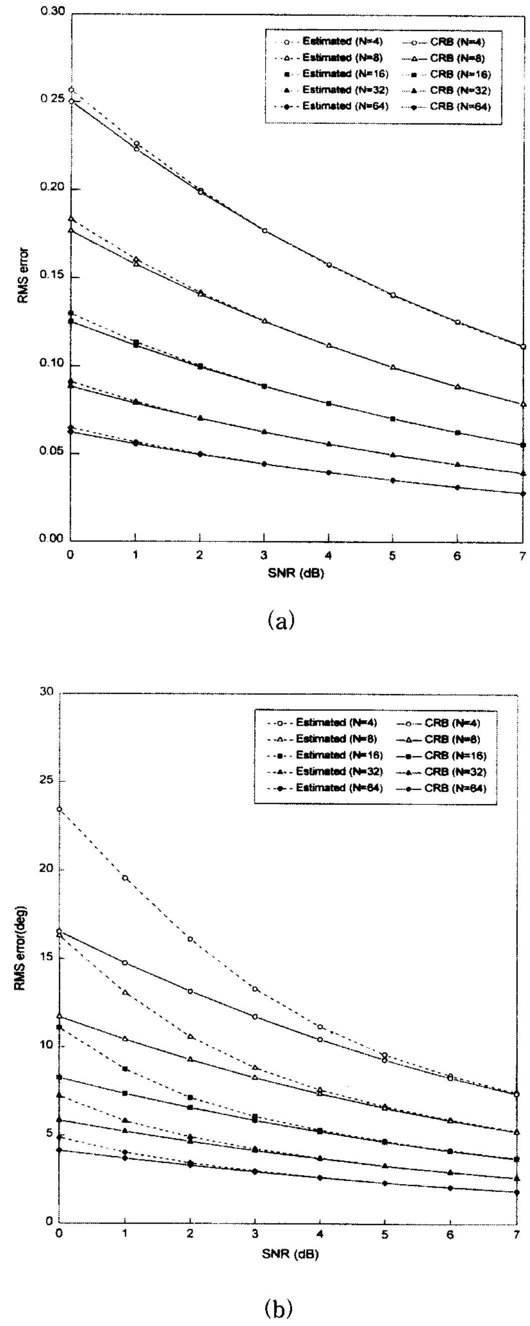


그림 3. 4-QAM 방식에서 JC-DSE 방법의 매개변수 N에 따른 채널 파라미터의 RMS 오차
(a) 세기 (b) 위상각

Fig. 3. RMS errors of the channel parameters estimated by the JC-DSE method as a function of SNR_b with N as a parameter in the 4-QAM case.
(a) Amplitude (b) Phase angle

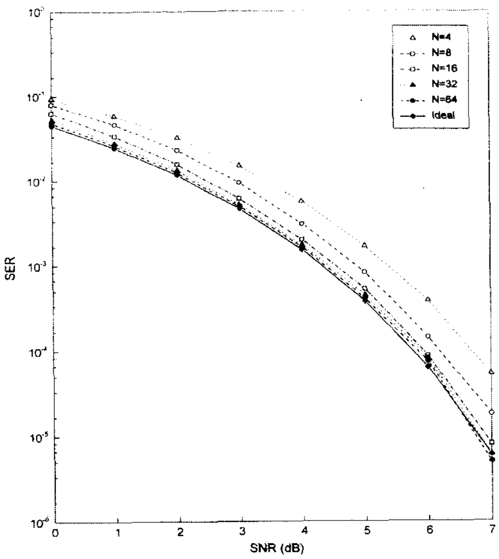


그림 4. 4-QAM 방식에서 PC-BPE 방법의 매개변수 N에 따른 SNR_b에 대한 심볼 오류율

Fig. 4. Symbol error rate of the PC-BPE method as a function of SNR_b with N as a parameter in the 4-QAM case.

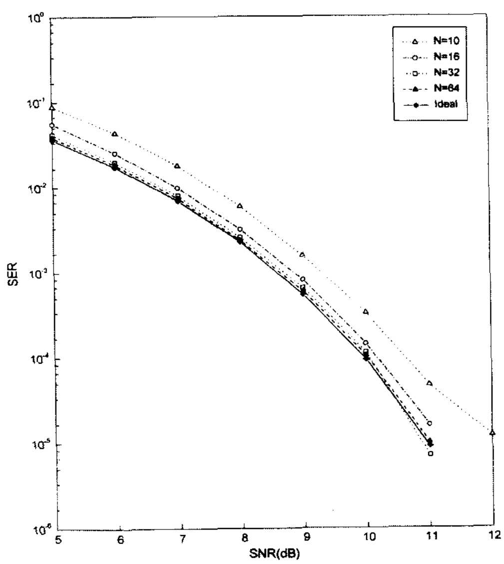
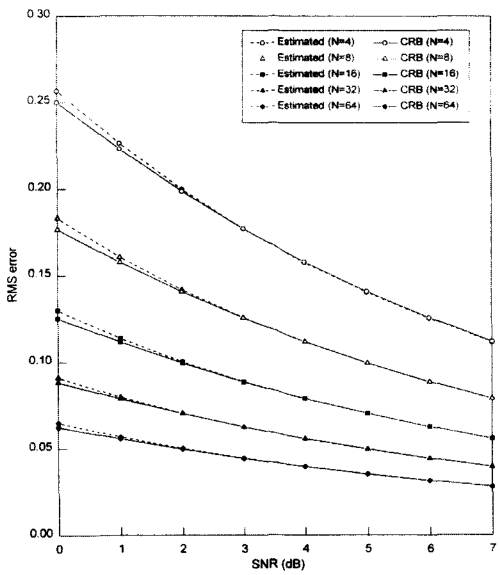


그림 5. 16-QAM 방식에서 PC-BPE방법의 매개변수 N에 따른 SNR_b에 대한 심볼 오류율

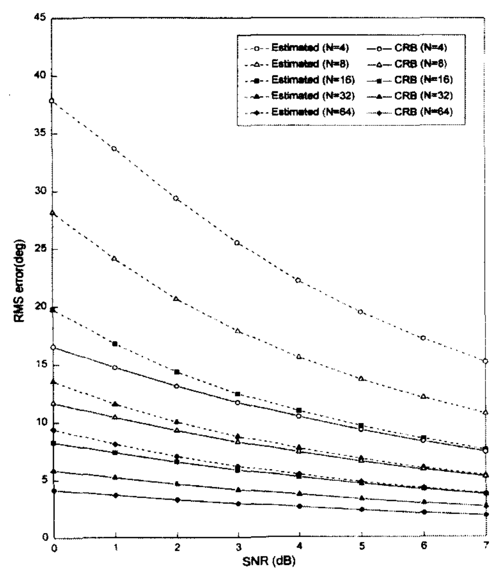
Fig. 5. Symbol error rate of the PC-BPE method as a function of SNR_b with N as a parameter in the 16-QAM case.

From these, we see that the PC-BPE method also has almost the same performance as the ideal performance with all N considered, irrespective of modulation types. From Figs. 1, 2, 4 and 5, we can not see any noticeable difference in the SER performance between the proposed two methods. By intensive computer simulations, however, we have found that the performance of the JC-DSE method is quite slightly better than that of the PC-BPE method. Also, from Fig. 6, we see that the RMS errors of the amplitude estimates obtained by the PC-BPE method are very close to the corresponding CRBs, and do not show any noticeable difference as compared to those by the JC-DSE method. However, the RMS errors of the phase estimates diverge largely from the corresponding CRBs over various values of SNR and N. This large deviation is due to the inaccuracy of the initial estimate of the channel parameter vector. Again, from Figs. 1, 2, 4 and 5, we note that the SER performance is not severely affected in spite of relatively large deviations in phase angles. This shows the relative importance of the amplitude in the combining performance rather than the phase. Finally, Fig. 7 shows the RMS errors of the phase estimates obtained by a modified PC-BPE method that performs additionally Steps 3.c) and 3.d) only of the JC-DSE method using the estimated sequence after the completion of the PC-BPE method. From this figure, we see that the RMS errors of the phase estimates by the modified method have been improved largely over those by the PC-BPE method and are almost same as those by the JC-DSE method. The SER performance and RMS errors of the amplitude estimates of the modified method are almost same as those of the above two methods.

Fig. 8 shows the average *nicnv* per respective estimation with different initial estimates of the JC-DSE method and the PC-BPE method. From this, we see that *nicnv* increases as N increases and SNR decreases. The increased *nicnv* with increased N is due that the number of parameters to be updated at each iteration is increased. Again, we see no noticeable difference between the two methods.



(a)



(b)

그림 6. 4-QAM 방식에서 PC-BPE 방법의 매개변수 N에 따른 채널 파라미터의 RMS오차
(a) 세기 (b) 위상각

Fig. 6. RMS errors of the channel parameters estimated by the PC-BPE method as a function of SNR_b with N as a parameter in the 4-QAM case.
(a) Amplitude (b) Phase angle

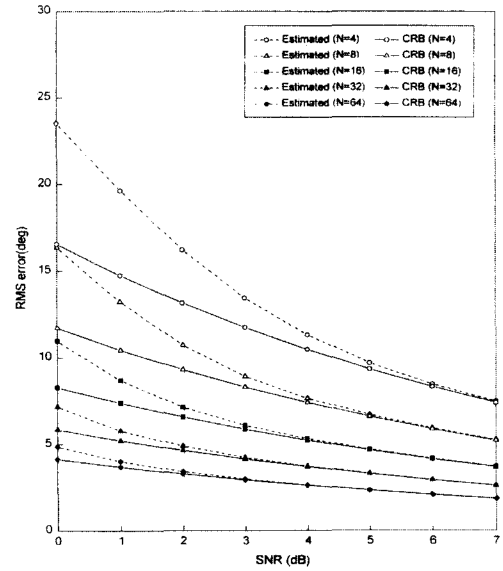


그림 7. 4-QAM 방식에서 변형된 PC-BPE 방법의 매개변수 N에 따른 위상각의 RMS오차

Fig. 7. RMS errors of the phase angles estimated by the modified PC-BPE method as a function of SNR_b with N as a parameter in the 4-QAM case.

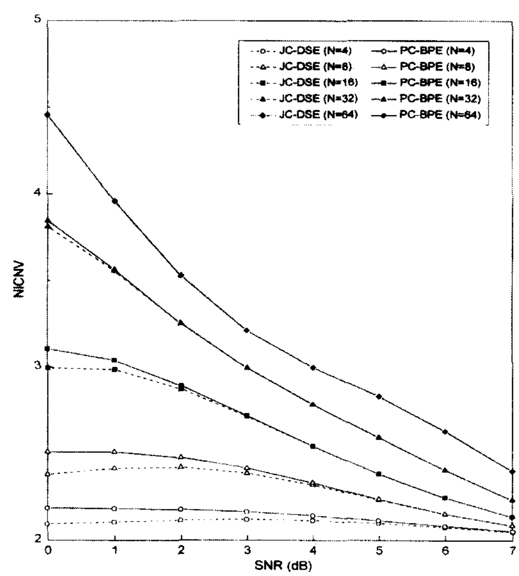


그림 8. 4-QAM 방식에서 제안된 두가지 방법의 매개변수 N에 따른 각 초기치마다 수렴에 걸리는 평균 반복 횟수

Fig. 8. Number of iterations to convergence per respective initial estimate (*nicnv*) of the proposed two methods as a function of SNR_b with N as a parameter in the 4-QAM case.

Now, we can conclude that the proposed two methods can estimate accurately the channel parameters for MRC combining even with a quite small subset of data (e.g., N=4, 8, 16). These blind MRC methods based on FAP can be used effectively in the system of requiring the dynamic selection of combining branches. The PC-BPE method can be used successfully to combine the diversity branches simply instead of the relatively complex JC-DSE method. To reduce further the computational complexity, efficient initialization schemes which can assure the global convergence should be developed.

Ⅶ. CONCLUSIONS

We have presented two block methods for blind MRC based on the ML principle and the FAP inherent in digital communication systems. We showed that the methods can provide accurate estimates of channel parameters even with a small subset of data, thus realizing nearly perfect combining. The channel parameters of selected diversity branches and the data sequence were estimated simultaneously by using the alternating projection technique. We developed two methods: (1) JC-DSE method, and (2) PC-BPE method that is much simpler than the JC-DSE method in terms of the computational complexity. Efficient initialization schemes for the two methods, that can assure the convergence to the global optimum were also presented.

Now, we can conclude that the proposed two methods can estimate accurately the channel parameters for MRC even with a quite small subset of data (e.g., N=4, 8, 16). These blind MRC methods based on FAP can be used effectively in the system of requiring the dynamic selection of combining branches. To reduce further the computational complexity, efficient initialization schemes that can assure the global convergence should be developed. The PC-BPE method reduces the computational complexity for estimating *ndiv* possible candidates by about a factor of M as compared to that of the JC-DSE method without showing a noticeable performance degradation.

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