An Efficient Detection Technique for Synchronous CDMA Communication Systems Based on the Expectation Maximization Algorithm

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***Abstract*—Maximum likelihood detection of superimposed signals in code-division multiple access (CDMA) communication systems has a computational complexity that is exponential in the number of users, and its implementation is practically prohibitive even for a moderate number of users. Applying the expectation maximization algorithm to this problem, we decompose the multiuser detection problem into a series of single-user problems, and thus present an iterative computationally efficient algorithm for detection of superimposed signals in synchronous direct-sequence CDMA communication systems. The resulting structure includes the well-known multistage detector as one of its special cases. With a proper choice of its parameters, the new detector can achieve the advantages of both the multistage and conventional detector and have good performance for both strong and weak users.**

***Index Terms*—Code-division multiple-access (CDMA) systems, expectation maximization (EM) algorithm, multiuser detection, spread spectrum.**

I. Introduction

In a code-division multiple access (CDMA) system, several users transmit data symbols over a common channel using preassigned signature waveforms. Here, we consider the synchronous case, in which the bit sequences of all users are aligned in time. This assumption will greatly simplify formula calculations, though its generalization to asynchronous case can be achieved by some modifications, as described in [12].

In a synchronous direct-sequence CDMA (DS-CDMA) system with binary phase-shift keying (BPSK) modulation, the received signal is

$$r(t) = \sum_{j} \sum_{k=1}^{K} b_k(j) s_k(t - jT) + z(t) \tag{1}$$

where

- $s_k(t)$ signature waveform of the kth user with energy w_k;
- $b_k(j)$ jth bit of the kth user;
- $z(t)$ white Gaussian noise with two-sided power spectral density σ^2.

Each signature waveform is zero outside $[0, T]$, and the input sequences of the various users are independent streams of independent equiprobable bits. Under these conditions, the optimum detector, which is a maximum likelihood detector for independent identically distributed data sequences, is a one-shot detector that uses only the jth bit interval to make decisions regarding the jth bit of the various users. Without loss of generality, we consider the interval $[0, T]$ and suppress the argument j.

It is well known that the set of matched-filter outputs

$$y_k = \int_0^T r(t) s_k(t)\, dt \qquad k = 1, 2, \ldots, K \tag{2}$$

is a sufficient set of statistics for the detection problem. We define the vectors $\mathbf{y} = [y_1\, y_2\, \ldots\, y_K]^T$ and $\mathbf{b} = [b_1\, b_2\, \ldots\, b_K]^T$, and note that

$$\mathbf{y} = \mathbf{H}\mathbf{b} + \mathbf{z} \tag{3}$$

where $\mathbf{H}$ is the matrix of signature waveforms cross-correlations whose klth element is

$$h_{kl} = \int_0^T s_k(t) s_l(t)\, dt \tag{4}$$

and $\mathbf{z}$ is a Gaussian vector with covariance matrix $\sigma^2 \mathbf{H}$.

The conventional detector simply sets

$$\hat{b}_k = \operatorname{sgn}(y_k) \qquad k = 1, 2, \ldots, K. \tag{5}$$

This detector is very simple, but it may perform poorly when the signature codes of different users are not orthogonal and have nonzero cross-correlations. These cross-correlations, though very small, cause severe degradations in the performance of the conventional detector when there are many users or when the user energies are substantially different.

The optimum detector chooses $\mathbf{b}$ to maximize the log-likelihood function and sets

$$\hat{\mathbf{b}} = \arg \max_{\mathbf{b} \in \{-1, 1\}^K} [2\mathbf{y}^T \mathbf{b} - \mathbf{b}^T \mathbf{H} \mathbf{b}]. \tag{6}$$

This detector performs much better than the conventional one, but its computational complexity is exponential in K and thus becomes prohibitive for even a moderate number of users.

Practical suboptimum detectors that perform much better than the conventional one have been described in [1]–[12]. Lupas and Verdu [1] describe a family of linear detectors called decorrelators whose complexity grows linearly with the number of users. These detectors eliminate multiuser interference at the expense of increased noise power. Furthermore, the linear decorrelating detectors require correlation matrix inversion, which may be difficult to perform in real time, especially for asynchronous systems. Some suboptimal approaches have been taken to implement the decorrelating detector for asynchronous

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systems [2]–[5]. The most important advantage of the decorrelating detector is that it does not require the estimation of the received amplitudes.

Madhow *et al.* [6] and Xie *et al.* [2] describe a minimum mean-squared error (MMSE) linear detector, which minimizes the mean-squared error between the actual data and the conventional detector soft outputs. Because of taking the background noise into account, the MMSE detector generally performs better than the decorrelating detector and converges to the decorrelating detector as the background noise goes to zero.

Duel-Hallen in [7] presents a nonlinear multiuser detector called a decorrelating decision-feedback detector (DDFD), in which the users are ranked according to their signal strengths from the strongest one to the weakest one. This detector is based on a white-noise channel model whose noise-whitening filter is obtained by the Cholesky decomposition of the cross-correlation matrix $\mathbf{H}$. The detector performs successive interference cancellation at the output of the noise-whitening filter using past decisions. For the strongest user, this detector performs similar to the decorrelator, but as the user's power decreases compared to the power of interferers, the detector outperforms the decorrelator and its performance approaches the single user bound. However, its important difficulty is the need for computing the Cholesky decomposition. The other successive interference cancellation detectors are described in [9] and [10].

In [8], Varanasi *et al.* describe a parallel interference cancellation detector called a multistage detector, in which the tentative decisions obtained from the previous stage are used to estimate and subtract the multiuser interference. The first stage decisions are usually obtained from the conventional detector. This detector, like the DDFD of [7], outperforms the decorrelator when interfering users are stronger than the user under consideration, but its performance degrades as the energies of the interfering users decrease.

In Section II using the expectation maximization (EM) algorithm, we develop a new multistage detector that outperforms the original multistage detector of [8] for stronger users. The resultant structure includes the multistage detector [8] as a special extreme case. We present simulation results in Section III and offer conclusions in Section IV.

II. New Algorithm

The EM algorithm has been used for estimating the channel parameters in CDMA systems by some investigators [13], [14]. Here, by applying the EM algorithm, we decompose the K-dimensional maximization problem in (6) into K one-dimensional maximization problems, and thus strikingly reduce the computational complexity of the optimum detector. The resultant detector will have a computational complexity that is linear in K.

First, as in [14], we define the complete data set $x_k(t)$

$$x_k(t) = b_k s_k(t) + z_k(t) \qquad k = 1, 2, \ldots, K \tag{7}$$

where $z_k(t)$ is white Gaussian noise with zero mean and power spectral density σ_k^2 and

$$\sum_{k=1}^{K} \sigma_k^2 = \sigma^2. \tag{8}$$

Thus, the received signal can be written as

$$r(t) = \sum_{k=1}^{K} x_k(t). \tag{9}$$

It is easily shown [15] that the maximization of the log-likelihood function

$$L(\mathbf{b}) = \frac{-1}{2\sigma^2} \int_0^T \left| r(t) - \sum_{k=1}^{K} b_k s_k(t) \right|^2 dt \tag{10}$$

is equivalent to the maximization of the function $U(\mathbf{b}, \mathbf{b}')$, which is defined as follows:

$$U(\mathbf{b}, \mathbf{b}') = \mathrm{E}\left\{\log_e \left(f_{\mathbf{X}}(\mathbf{x}(t); \mathbf{b})\right) | r(t), \mathbf{b} = \mathbf{b}'\right\} \tag{11}$$

where

$$f_{\mathbf{X}}(\mathbf{x}(t); \mathbf{b}) = \frac{1}{(2\pi)^{K/2} \prod_{k=1}^{K} \sigma_k} \cdot \exp\left(\sum_{k=1}^{K} \frac{-1}{2\sigma_k^2} \int_0^T |x_k(t) - b_k s_k(t)|^2 \, dt \right).$$

That is, if $U(\mathbf{b}, \mathbf{b}') > U(\mathbf{b}', \mathbf{b}')$, then $L(\mathbf{b}) > L(\mathbf{b}')$. In this equation, $\mathbf{x}(t)$ is the waveform vector defined as $\mathbf{x}(t) = [x_1(t)\, x_2(t) \ldots, x_K(t)]^T$ and $\mathbf{b}'$ is the vector of initial estimates of data bits. Based on the above discussion, an iterative multistage algorithm for detection of the transmitted symbols of the users can be developed. First, $U(\mathbf{b}, \mathbf{b}^{(n)})$ is calculated according to the nth stage estimates of data bits $\mathbf{b}^{(n)}$. Then the $(n+1)$st stage estimate of data bits $\mathbf{b}^{(n+1)}$ is chosen such that $U(\mathbf{b}^{(n+1)}, \mathbf{b}^{(n)})$ is the maximum of $U(\mathbf{b}, \mathbf{b}^{(n)})$ for all $\mathbf{b}$. In the rest of this section, we show that the K-dimensional maximization problem of (11) can be reduced into K one-dimensional maximization problems.

It can be easily observed that

$$\log_e \left(f_{\mathbf{X}}(\mathbf{x}(t); \mathbf{b})\right) = A + \sum_{k=1}^{K} \cdot \left[\frac{1}{\sigma_k^2} \int_0^T x_k(t) b_k s_k(t)\, dt - \frac{1}{2} \int_0^T b_k^2 s_k^2(t)\, dt \right] \tag{12}$$

where A is a constant. Since $b_k^2 = 1$, the second integral does not depend on $\mathbf{b}$, and (12) can be simplified to

$$\log_e \left(f_{\mathbf{X}}(\mathbf{x}(t); \mathbf{b})\right) = g(\mathbf{x}) + \sum_{k=1}^{K} \frac{1}{\sigma_k^2} \int_0^T x_k(t) b_k s_k(t)\, dt. \tag{13}$$

Ignoring the first term, which has no effect on the maximization process, and changing the order of integration and summation, we will have

$$\log_e \left(f_{\mathbf{X}}(\mathbf{x}(t); \mathbf{b})\right) = \int_0^T \mathbf{C}^T(t) \mathbf{x}(t)\, dt \tag{14}$$

where

$$\mathbf{C}(t) = \left[b_1 \sigma_1^{-2} s_1(t)\, b_2 \sigma_2^{-2} s_2(t) \ldots, b_K \sigma_K^{-2} s_K(t)\right]^T.$$

Substituting (14) into (11), we have

$$U(\mathbf{b}, \mathbf{b}^{(n)}) = \int_0^T \mathbf{C}^T(t) \mathrm{E}\left\{\mathbf{x}(t) | r(t), \mathbf{b}^{(n)}\right\} dt. \tag{15}$$

In Appendix I, we will show that the above equation can be written as

$$U(\mathbf{b}, \mathbf{b}^{(n)}) = \sum_{k=1}^{K} \frac{b_k}{\sigma_k^2} \int_0^T s_k(t) \cdot \left[b_k^{(n)} s_k(t) + \frac{\sigma_k^2}{\sigma^2} \left\{ r(t) - \sum_{j=1}^{K} b_j^{(n)} s_j(t) \right\} \right] dt. \tag{16}$$

Since each term in the above sum contains only one of the b_ks, for maximizing the whole sum, it is sufficient to maximize each term separately. Thus, the problem is reduced as follows:

$$\max_{\mathbf{b} \in \{-1,1\}^K} U\left(\mathbf{b}, \mathbf{b}^{(n)}\right) \Updownarrow \left\{ \max_{b_k \in \{-1,\,1\}} U_k(b_k, \mathbf{b}^{(n)}) \qquad k = 1, 2, \ldots, K \right\} \tag{17}$$

where we have

$$U_k(b_k, \mathbf{b}^{(n)}) = b_k \left\{ b_k^{(n)} \int_0^T s_k^2(t)\, dt + \frac{\sigma_k^2}{\sigma^2} \cdot \left[\int_0^T s_k(t) r(t)\, dt - \sum_{j=1}^{K} b_j^{(n)} \int_0^T s_k(t) s_j(t)\, dt \right] \right\}. \tag{18}$$

Substituting the values of integrals and dividing the equation by the kth user's energy (which has no effect in maximization process), we have

$$U_k(b_k, \mathbf{b}^{(n)}) = b_k \left\{ b_k^{(n)} + \frac{\sigma_k^2}{\sigma^2 w_k} \left[y_k - \sum_{j=1}^{K} b_j^{(n)} h_{kj} \right] \right\}. \tag{19}$$

Since b_k can only take the values $+1$ and -1, it is clear that the following choice for b_k maximizes the above equation:

$$b_k^{(n+1)} = \operatorname{sgn} \left\{ (1 - \beta_k) b_k^{(n)} + \frac{\beta_k}{w_k} \left[y_k - \sum_{j \neq k} b_j^{(n)} h_{kj} \right] \right\} \tag{20}$$

where $\beta_k = (\sigma_k^2/\sigma^2)$.

Note that $h_{kk} = w_k$, and that in the derivation of (20) from (19), the term corresponding to $j = k$ is removed from the summation and is combined with the first term in the sgn function. The decisions for all users at stage $(n+1)$ can be written in the following vector form:

$$\mathbf{b}^{(n+1)} = \operatorname{sgn}\left\{ \mathbf{b}^{(n)} + \beta \mathbf{w}^{-1} \left(\mathbf{y} - \mathbf{H}\mathbf{b}^{(n)} \right) \right\} \tag{21}$$

where $\mathbf{w} = \operatorname{diag}(w_1, w_2, \ldots, w_K)$ and $\beta = \operatorname{diag}(\beta_1, \beta_2, \ldots, \beta_K)$. The block diagram of the new detector, assuming that the conventional detector is used for the first stage, is illustrated in Fig. 1.

For $\beta_k = 1$, the detector will be the multistage detector of [8], and for $\beta_k = 0$, the detector will lose its iterative function and will reduce to the one used in the first stage to obtain the initial value of decision. The proper value for β_k, for a fast convergence of the iterative algorithm or a good performance in a limited number of stages, depends on the energy of the signal and the multiuser interference (MUI). For high signal-to-MUI ratios, β_k should be chosen small; thus the detector approaches to the conventional detector. For low signal-to-MUI ratios, however, β_k should be larger, and the detector approaches the multistage detector of [8]. We expect that with suitable choice of β_k, we can achieve the advantages of both conventional and multistage detectors. The simulation results in the next section verify these expectations.

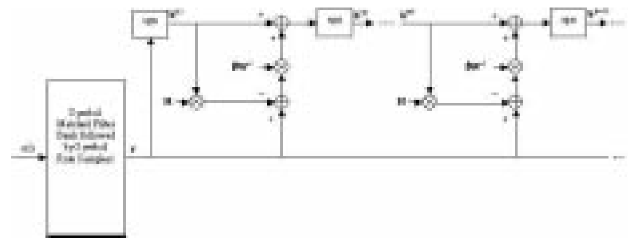

Fig. 1. Block diagram of the new detector using vector notation

According to the above discussion, the parameters β_k should be chosen in such a way that for a very strong user β_k is about zero, and for a very weak user β_k is about one. Many functions of the relative MUI can be considered that satisfy the above requirements. Here we will consider the category of the following simple hyperbolic functions for choosing these parameters:

$$\beta_k = \frac{\mathrm{ISR}_k}{c + \mathrm{ISR}_k} \tag{22}$$

in which ISR denotes the interference-to-signal ratio, calculated as follows:

$$\mathrm{ISR}_k = \frac{\displaystyle\sum_{i \neq k} |h_{ik}| w_i}{w_k} \tag{23}$$

and c is a constant. Simulation results show that the best value for c is about 0.5. We do not claim that the above formula for computing the parameters β_ks is the best one. The simulation results, however, show that this heuristic simple formula provides good performance.

Note that according to (8), the values of parameters β_ks are constrained so that their sum should be equal to one. In this sense, the above values for β_k have to be normalized, or some other formula should be chosen (e.g., the ratio of the ISR of each user to the sum of the ISRs of all users). Simulation results, however, show that for a two- or three-stage implementation, if β_ks are chosen according to (21), better performance can be achieved. If β_ks are chosen so that the mentioned constraint is satisfied, more stages will probably be needed to achieve similar performance.

III. Simulation Results

We implemented and simulated the new multistage detector described in Section II for two sets of signature waveforms derived from gold sequences of length seven [8]. For purposes of comparison, we also simulated the conventional detector and the multistage detector of [8]. In multistage detection algorithms, two- and three-stage detectors with a conventional detector in the first stage have been used. In the first two examples (Figs. 2–4), users are assumed to be of equal energies, and the parameters β_k

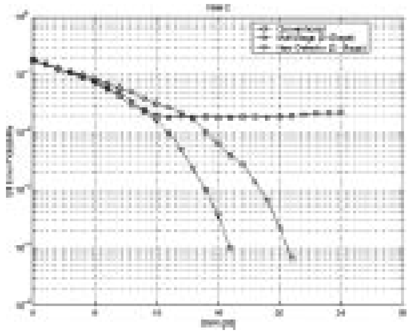

Fig. 2. Plots of bit error probability versus SNR for User 2 ($\beta_2 = 0.7$) (four-user case).

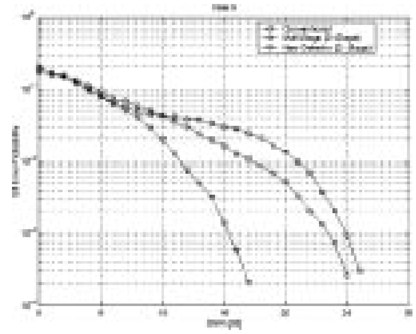

Fig. 4. Plots of bit error probability versus SNR for User 3 ($\beta_3 = 0.7$) (five-user case).

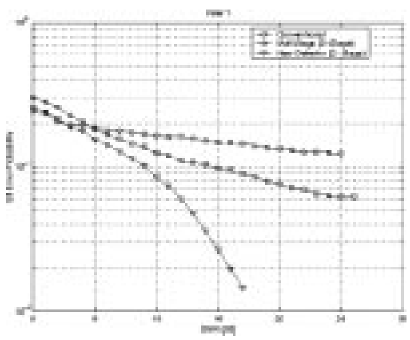

Fig. 3. Plots of bit error probability versus SNR for User 1 ($\beta_1 = 0.6$) (five-user case).

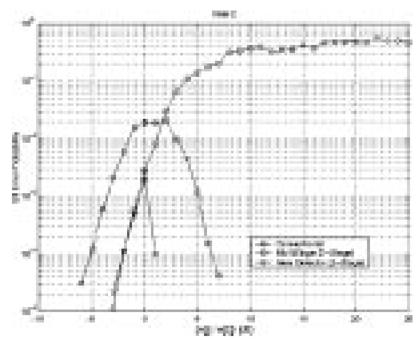

Fig. 5. Plots of bit error probability versus energies ratio for User 2 ($w_2 = 14$ dB) (four-user case).

of the new detector were initially found by simulation for the best performance. In the rest of the simulations (Figs. 5–7), where near–far effects are considered and the users are no longer assumed to be of equal energies, these parameters are calculated using (21).

In the first example, we simulated a four-user system with

$$\mathbf{H} = \frac{1}{7}\begin{bmatrix} +7 & -1 & +3 & +3 \\ -1 & +7 & +3 & -1 \\ +3 & +3 & +7 & -1 \\ +3 & -1 & -1 & +7 \end{bmatrix}$$

where $\mathbf{H}$ is the signature cross-correlation matrix. The values obtained for β_1 to β_4 in the current example were 1, 0.7, 1, and 0.7, respectively. Thus, for Users 1 and 3, the new detector reduces to the multistage detector of [8]. Fig. 2 shows the plots of the bit-error probabilities of User 2 versus the signal-to-noise ratio (SNR), with equal energies for all users. Since the results for User 4 were very similar to those for User 2, we did not include them in this paper. As can be observed, the new detector achieves a substantial improvement relative to the multistage detector of [8]. The multistage detector presents a poor performance, even worse than the conventional one. It can be explained as follows. For Users 1 and 3, the interfering signals are strong (off-diagonal elements of the cross-correlation matrix $\mathbf{H}$ for rows 1 and 3 are greater than those for rows 2 and 4), thus the multistage detector, as expected, presents good performance. For Users 2 and 4, however, the interfering signals are not so strong, and because of error propagation, the multistage detector presents an unacceptable performance. Using the decorrelator [1] in the first stage will improve the performance of the multistage detector, at the price of increased complexity.

In the second example, we considered a five-user system with

$$\mathbf{H} = \frac{1}{7}\begin{bmatrix} +7 & -1 & +3 & +3 & -5 \\ -1 & +7 & -1 & +3 & -1 \\ +3 & -1 & +7 & -1 & -1 \\ +3 & +3 & -1 & +7 & -1 \\ -5 & -1 & -1 & -1 & +7 \end{bmatrix}.$$

Figs. 3 and 4 present plots of the bit-error probabilities for Users 1 and 3, respectively. For all users, the new detector achieves a substantial improvement compared to the multistage detector of [8]. The improvement in SNR at bit-error probability 10^{-3} for Users 2 and 4 is about 8 and 2 dB, respectively.

We also investigated the near–far resistance of the new detector by simulation. We again considered the above examples. Fig. 5 shows the bit-error probability for User 2 in the four-user example versus the energies ratio in dB. The energy of User 2 was kept fixed and equal to 14 dB, and the energies of the other users were varied. The noise variance was fixed at $\sigma^2 = 0.5$. The values of the parameters β_k were chosen according to (21) and (22). Again, the results for User 4 were very similar to those for User 2, and we did not include them in this paper. Figs. 6 and 7 present the same results for Users 1 and 3 in the five-user example, respectively. As can be observed from these plots, the new detector achieves a substantial improvement relative to the multistage detector.

IV. CONCLUSION

We have presented a new multistage detector for CDMA communication systems. This detector includes the original multistage detector of [8] as one of its special cases. With a suitable choice of its parameters, this detector can achieve the ad-

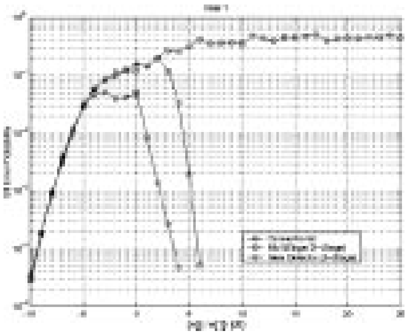

Fig. 6. Plots of bit error probability versus energies ratio for User 1 ($w_1 = 14$ dB) (five-user case).

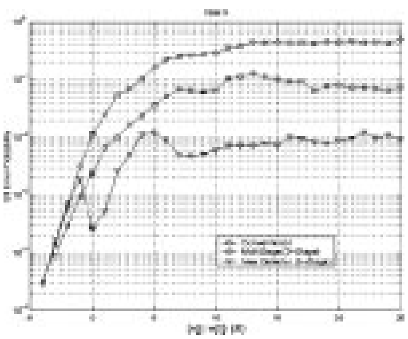

Fig. 7. Plots of bit error probability versus energies ratio for User 3 ($w_3 = 14$ dB) (five-user case).

vantages of both the multistage [8] and the conventional detectors and have a good performance for both strong and weak users. The new detector was shown, by computer simulation, to present a substantial improvement compared to the original multistage detector in most cases.

Extension of the proposed algorithm to an asynchronous case, using the method described in [12], is straightforward. Applying the algorithm to multipath fading channels is under investigation. We expect, however, that some diversity combining techniques (e.g., RAKE receivers) should be used in the first stage instead of the matched filters. Multiuser detection algorithms are then applied to the output of this stage.

APPENDIX

In this Appendix, we prove (16). Since both $\mathbf{x}(t)$ and $r(t)$ given $\mathbf{b}^{(n)}$ are Gaussian, we can write

$$\mathrm{E}\left\{\mathbf{x}(t)|r(t),\,\mathbf{b}^{(n)}\right\} = \mathrm{E}\left\{\mathbf{x}(t)|\mathbf{b}^{(n)}\right\} + \mathbf{C}_{\mathbf{x}r}C_{rr}^{-1}\left[r(t) - \mathrm{E}\left\{r(t)|\mathbf{b}^{(n)}\right\}\right] \quad (24)$$

where

$$\begin{aligned}\mathbf{C}_{\mathbf{x}r} &= \mathrm{E}\left\{\left[\mathbf{x}(t) - \mathrm{E}\left\{\mathbf{x}(t)|\mathbf{b}^{(n)}\right\}\right] \cdot \left[r(t) - \mathrm{E}\left\{r(t)|\mathbf{b}^{(n)}\right\}\right] |\mathbf{b}^{(n)}\right\},\\ C_{rr} &= \mathrm{E}\left\{\left(r(t) - \mathrm{E}\left\{r(t)|\mathbf{b}^{(n)}\right\}\right)^2 |\mathbf{b}^{(n)}\right\},\\ \mathrm{E}\left\{r(t)|\mathbf{b}^{(n)}\right\} &= \sum_{k=1}^{K} b_k^{(n)} s_k(t). \end{aligned} \quad (25)$$

It can be easily shown that

$$\begin{aligned}\mathrm{E}\left\{\mathbf{x}(t)|\mathbf{b}^{(n)}\right\} &= \left[b_1^{(n)}s_1(t)\, b_2^{(n)}s_2(t)\, \ldots,\, b_K^{(n)}s_K(t)\right]^T,\\ \mathbf{C}_{\mathbf{x}r} &= \left[\sigma_1^2\,\sigma_2^2\,\ldots,\,\sigma_K^2\right]^T. \end{aligned} \quad (26)$$

Substituting (25) and (26) into (24), we will have

$$\mathrm{E}\left\{\mathbf{x}(t)|r(t),\,\mathbf{b}^{(n)}\right\} = \begin{bmatrix} b_1^{(n)}s_1(t)\\ b_2^{(n)}s_2(t)\\ \vdots\\ b_K^{(n)}s_K(t)\end{bmatrix} + \begin{bmatrix}\sigma_1^2\\ \sigma_2^2\\ \vdots\\ \sigma_K^2\end{bmatrix} \cdot \frac{1}{\sigma^2}\left\{r(t) - \sum_{k=1}^{K} b_k^{(n)}s_k(t)\right\}. \quad (27)$$

Substituting (27) into (15) results in (16).

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REFERENCES

[1] R. Lupas and S. Verdu, "Linear multiuser detectors for synchronous code-division multiple-access channels," *IEEE Trans. Inform. Theory*, vol. 35, pp. 123–136, Jan. 1989.

[2] Z. Xie, *et al.*, "A family of suboptimum detectors for coherent multi-user communications," *IEEE J. Select. Areas Commun.*, vol. 8, pp. 683–690, May 1990.

[3] S. S. H. Wijayasuriya, *et al.*, "A near–far resistant sliding window decorrelating algorithm for multi-user detectors in DS-CDMA systems," in *Proc. IEEE Globecom'92*, Dec. 1992, pp. 1331–1338.

[4] A. Kajiwara *et al.*, "Micorcellular CDMA systems with a linear multi-user interference canceller," *IEEE J. Select. Areas Commun.*, vol. 12, pp. 605–611, May 1994.

[5] F. Zheng and S. K. Barton, "Near–far resistant detection of CDMA signals via isolation bit insertion," *IEEE Trans. Commun.*, vol. 43, pp. 1313–1317, Feb./Mar./Apr. 1995.

[6] U. Madhow and M. L. Honig, "MMSE interference suppression for direct-sequence spread-spectrum CDMA," *IEEE Trans. Commun.*, vol. 42, pp. 3178–3188, Dec. 1994.

[7] A. Duel-Hallen, "Decorrelating decision-feedback multiuser detector for synchronous code-division multiple-access channels," *IEEE Trans. Commun.*, vol. 41, pp. 285–290, Feb. 1993.

[8] M. K. Varanasi and B. Aazhang, "Near-optimum detection in synchronous code-division multiple-access systems," *IEEE Trans. Commun.*, vol. 39, pp. 725–736, May 1991.

[9] A. J. Viterbi, "Very low rate convolutional codes for maximum theoretical performance of spread-spectrum multiple-access channels," *IEEE J. Select. Areas Commun.*, vol. 8, pp. 641–649, May 1990.

[10] J. M. Holtzman, "DS/CDMA successive interference cancellation," in *Proc. IEEE ISSSTA'94*, July 1994, pp. 69–78.

[11] M. Nasiri-Kenari, R. P. Sylvester, and C. K. Rushforth, "An efficient soft-in-soft-out multiuser detector for synchronous CDMA with error-control coding," *IEEE Trans. Veh. Technol.*, vol. 47, pp. 947–953, Aug. 1998.

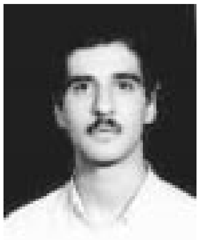
[12] R. Lupas and S. Verdu, "Near–far resistance of multiuser detectors in asynchronous channels," *IEEE Trans. Commun.*, vol. 38, pp. 496–508, Apr. 1990.

[13] H. V. Poor, "On parameter estimation in DS/SSMA formats," in *Lecture Notes in Control and Information Sciences—Advances in Communications and Signal Processing*. Berlin, Germany: Springer-Verlag, 1989.

[14] M. Feder and E. Weinstein, "Parameter estimation of superimposed signals using the EM algorithm," *IEEE Trans. Acoust., Speech, Signal Processing*, vol. 36, pp. 477–489, Apr. 1988.

[15] S. M. Kay, *Fundamentals of Signal Processing: Estimation Theory*. Englewood Cliffs, NJ: Prentice-Hall, 1993.

[16] M. J. Borran and M. Nasiri-Kenari, "An efficient decoding technique for CDMA communication systems based on the expectation maximization algorithm," in *Proc. IEEE ISSSTA'96*, Sept. 1996, pp. 1305–1309.



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