Optimal Multistage Interference Cancellation for CDMA Systems using the Nonlinear MMSE Criterion

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Abstract

This paper proposes an optimal multistage interference cancellation scheme for a multiuser DS/CDMA system with linear or nonlinear modulation. The proposed canceler is optimal in terms of minimizing the energy of the difference between true and reconstructed interference due to each user. Solutions for the special cases of BPSK and M-ary orthogonal modulation are derived using the general solution and efficient architectures are proposed for implementation. A novel blind channel estimation strategy based on an adaptive filtering approach that yields unbiased channel estimates and low estimation variance is also proposed. Simulation results indicate that the proposed scheme achieves substantial capacity gains with very little additional computational complexity compared to the conventional multistage canceler.

1 Introduction

Multistage interference cancellation schemes (see, e.g., [8]) are known to be simple and effective techniques for mitigation of multiple access interference (MAI) in DS-CDMA systems. They offer key advantages over linear multiuser detection schemes [4] and decision feedback detectors for practical CDMA systems in their ability to operate with random (long) spreading codes, asynchronous reception, multipath channels, high dimensional modulation schemes etc. In addition, they fully exploit the knowledge of the spreading codes of all users at the base-station. However, the performance of conventional interference cancellation receivers is degraded due to incorrect decisions on interference that are subtracted from the received signal.

In this paper, an optimal multistage interference canceler that minimizes the power of residual cancellation error for each user is proposed to mitigate the effect of incorrect cancellation. The proposed scheme can also be viewed as an iterative solution to the nonlinear MMSE multiuser detection problem [5], in which the objective is to find unconstrained MMSE estimates of each user's signal given the received signal and the spreading codes of all users. It is shown in [5] that this is equivalent to minimum probability of error multiuser detection when BPSK or M-ary orthogonal signals are used, and that the global MMSE solution is a fixed point of the iterative solution presented in this paper.

The signal model for a single path asynchronous multiaccess channel with linear or nonlinear modulation in an observation interval $[0, T]$ can be written as

$$r(t) = r_1(t) + r_2(t) + \cdots + r_K(t) + n(t), \qquad (1)$$

where $r_k(t) = a_k m_k(t - \tau_k) c_k(t - \tau_k)$ is the signal received from the kth transmitter, and $n(t)$ is white Gaussian noise. The message signal, spreading code, complex signal amplitude and delay of the kth user are denoted by $m_k(t)$, $c_k(t)$, a_k and τ_k, respectively. A general multistage or parallel interference canceler (PIC) is shown in Figure 1. In each stage of the PIC, each user's signal is estimated and reconstructed, and the estimated interference due to all other users is sub-

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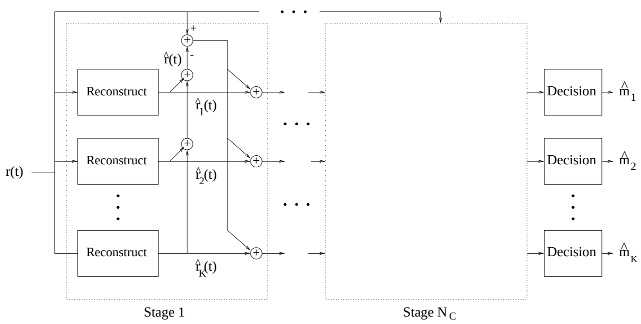

Figure 1. Multistage parallel interference canceler.

tracted from the received signal to form inputs to the following stage. The final stage is a bank of single-user detectors (hardlimited matched filters for BPSK modulation). The kth user's reconstruction operation in a conventional PIC consists of a conventional matched filter detector to make tentative hard decisions followed by respreading and complex scaling by an estimate of a_k.

The following section presents an interference canceler with an optimized reconstruction block. An efficient and accurate parameter estimation scheme is proposed in Section 3, and simulation results are presented in Section 4.

2 Optimal Multistage Interference Cancellation

Residual interference after cancellation can be minimized by designing the reconstruction operation to minimize the energy of the residual signal, $r_k(t) - \hat{r}_k(t)$, for each user. Representing each signal in the interval $[0, T]$ by a vector of its samples (possibly after chip-matched filtering), (1) can be rewritten as

$$\mathbf{r} = \mathbf{r}_1 + \mathbf{r}_2 + \cdots + \mathbf{r}_K + \mathbf{n}. \tag{2}$$

Without loss of generality, we focus on reconstructing the kth user's signal, and assume that $\tau_k = 0$ and T is one symbol interval. If spreading is assumed to be random, and we constrain the kth user's reconstruction block not to use knowledge of the spreading codes of all other users, then the matched filter output for the kth user, $\mathbf{y}_k^n$, is a sufficient statistic for $\mathbf{r}_k$ in stage n (matched filter output can be a vector in the case of nonlinear modulation). Since n is arbitrary, we omit the superscript n in the remainder of the paper. Minimizing the residual error for the kth user in the nth stage is equivalent to minimizing $E\{\|\mathbf{r}_k - \hat{\mathbf{r}}_k(\mathbf{y}_k)\|_2^2\}$. The solution to this nonlinear MMSE estimation problem is the conditional mean estimate,

$$\hat{\mathbf{r}}_k = E\{\mathbf{r}_k | \mathbf{y}_k\}. \tag{3}$$

The multistage interference canceler that uses the above MMSE reconstruction operation will henceforth be called a *nonlinear MMSE interference canceler* (NMIC) to distinguish it from the conventional PIC (CPIC). It is shown in [5] that the nonlinear MMSE signal estimates $E\{\mathbf{r}_k | \mathbf{r}, \mathbf{c}_1, \cdots, \mathbf{c}_K\}$, $k = 1, 2, \cdots, K$, form a fixed point to the NMIC.

2.1 BPSK Modulation

When BPSK modulation is used and T is one bit interval, then $m_k(t) = b_k \in \{-1, +1\}$, and hence $\mathbf{r}_k = a_k b_k \mathbf{c}_k$. The normalized matched filter output of the kth user at any stage is given by

$$y_k = a_k b_k + v_k, \tag{4}$$

where v_k is the interference plus noise at the matched filter output. If the spreading codes are random and the spreading gain and number of users are large, then v_k can be assumed to be a zero-mean complex Gaussian random variable with variance σ_k^2 in real and imaginary parts. In the first stage of cancellation, v_k is independent of b_k, and thus the MMSE signal estimate is given by the following sigmoidal nonlinearity,

$$\hat{\mathbf{r}}_k = a_k E\{b_k | y_k\} \mathbf{c}_k = a_k \tanh\left(\frac{\mathcal{R}e(a_k^* y_k)}{\sigma_k^2}\right) \mathbf{c}_k. \tag{5}$$

The above solution suggests the use of a sigmoidal nonlinearity in place of a hardlimiter in the reconstruction operation. The use of the hyperbolic tangent function in interference cancellation has also been proposed in prior works (see, e.g., [3]). In later stages, however, v_k may be correlated with b_k. In this case, the matched filter output conditioned on b_k may be treated as a Gaussian variable with mean $\tilde{a}_k b_k$, where $\tilde{a}_k$ is an *effective* gain that depends on the correlation between b_k and v_k. The optimal signal estimator is of the same form as (5) but with a_k inside the sigmoid function replaced with $\tilde{a}_k$. In the second stage of the canceler, the effective gain can be shown to be smaller in magnitude than the true channel gain. Figure 2 shows a schematic of the optimal reconstruction block for any stage.

2.2 M-ary Orthogonal Modulation

If the message signal is selected from a set of M orthogonal Walsh codes, then the kth user's received signal can be written as $\mathbf{r}_k = a_k C_k W \mathbf{i}_k$, where C_k is a

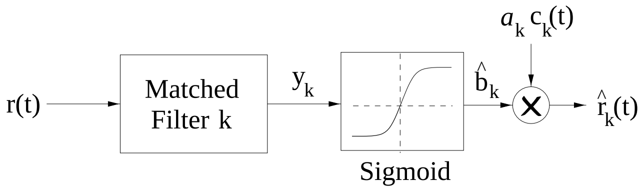

Figure 2. Optimal reconstruction for BPSK modulation.

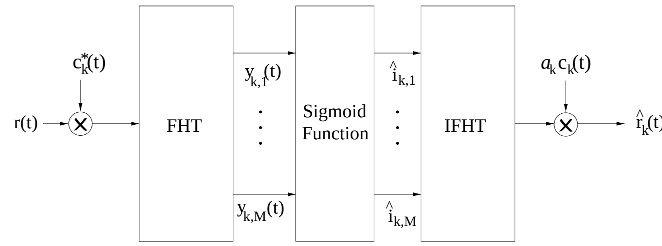

Figure 3. Optimal reconstruction for M-ary orthogonal modulation.

diagonal matrix with spreading code $\mathbf{c}_k$ on the diagonal, W is a matrix whose columns are the M orthogonal Walsh codes, and $\mathbf{i}_k$ is a unit vector that selects the transmitted column from W. The matched filter output in any stage is the vector $\mathbf{y}_k$ of normalized correlations of $\mathbf{r}$ with the columns of W. If N_s is the size of vector $\mathbf{r}$, then $\mathbf{y}_k = (C_k W)^H \mathbf{x}_k / N_s$, where $\mathbf{x}_k$ is the input to the reconstruction block. When the spreading gain and number of users are large and the spreading is random, we can again make the Gaussian assumption for the conditional density of $\mathbf{y}_k$ given $\mathbf{i}_k$, and $\mathbf{y}_k$ can be written as

$$\mathbf{y}_k = a_k \mathbf{i}_k + \mathbf{v}_k, \tag{6}$$

where $\mathbf{v}_k$ is zero-mean Gaussian. If $\mathbf{e}_m$ denotes the unit vector with a '1' at the mth position, then the MMSE signal estimate is given by

$$\hat{\mathbf{r}}_k = a_k C_k W E\{\mathbf{i}_k | \mathbf{y}_k\} = a_k C_k W \hat{\mathbf{i}}_k, \tag{7}$$

where $\hat{\mathbf{i}}_k = \sum_{m=1}^{M} \mathbf{e}_m P[\mathbf{i}_k = \mathbf{e}_m | \mathbf{y}_k]$, which implies

$$\hat{i}_{km} = \frac{\exp\{\mathcal{R}e(a_k^* y_{km})/\sigma_k^2\}}{\sum_{q=1}^{M} \exp\{\mathcal{R}e(a_k^* y_{kq})/\sigma_k^2\}}, \tag{8}$$

$\hat{i}_{km}$ and y_{km} being the mth elements of $\hat{\mathbf{i}}_k$ and $\mathbf{y}_k$, respectively.

A Fast Hadamard Transform (FHT) is usually used in receivers to compute the matched filter outputs for M-ary orthogonal signals. Noting that the remodulation operation in (7) is the inverse of the correlating operation, the Inverse FHT (IFHT) algorithm can be used to efficiently compute MMSE signal estimates, as shown in Figure 3. The IFHT operation is identical to the FHT within a scalar factor. The MMSE signal estimate is a weighted sum of all the M orthogonal signals. The optimal weighting vector $\hat{\mathbf{i}}_k$ is computed from $\mathbf{y}_k$ using a zero-memory MIMO sigmoidal function described by (8).

3 Blind Channel Estimation

The optimal multistage interference canceler, like any other multistage receiver, requires estimates of the complex channel gains, a_k. The conventional channel estimation technique for interference cancellation is called the *averaging method*. For BPSK modulation, the averaging channel estimator computes the channel gain estimate of any user as the time-average of the absolute value of that user's matched filter output. For M-ary orthogonal modulation, the averaging estimator corresponds to averaging the element of the matched filter output vector that is the largest in magnitude. This estimation procedure can be shown to yield biased estimates. Moreover, it leads to high estimation variance due to the fact that the averaging technique, instead of exploiting the known structure of MAI, treats it as unknown zero-mean additive noise. The problem is more pronounced in a fading environment since the time-varying nature of the channel prevents the use of large averaging windows to reduce estimation variance.

The channel estimation scheme proposed here is based on an adaptive filtering approach, shown in Figure 4, that exploits the MMSE property of the signal estimates. With any modulation scheme, consider an adaptive filter with input vector $\mathbf{x}(t) = [x_1(t) \cdots x_K(t)]^T$, with $x_k(t) = \hat{m}_k(t-\tau_k) c_k(t-\tau_k)$, and desired output $r(t)$ at time t (cf. equation (1)), where $\hat{m}_k(t)$ is the MMSE signal estimate of the transmitted signal, derived in Section 2. The Wiener solution to the weight vector of this adaptive filter is given by $\hat{\mathbf{a}} = R_{\mathbf{xx}}^{-1} E\{\mathbf{x}^* r\}$. Using the property of the MMSE estimates that $E\{m_k(t)\hat{m}_k(t)\} = E\{\hat{m}_k^2(t)\}$, and using the random code assumption, it follows that $\hat{\mathbf{a}} = \mathbf{a} = [a_1 \cdots a_K]^T$, the vector of true channel gains. Therefore, the adaptive filtering channel estimation scheme using MMSE signal estimates converges to the true channel gains. Since MMSE signal estimation in turn requires channel estimates, this gives us a bootstrapping technique for channel estimation. The presence of MAI is explicitly taken into account by the scheme, resulting in more reliable estimates, as evidenced by the simulation results in the following section. Also, chip-rate adaptation enhances the capability of the channel estimator to track fast channel variations.

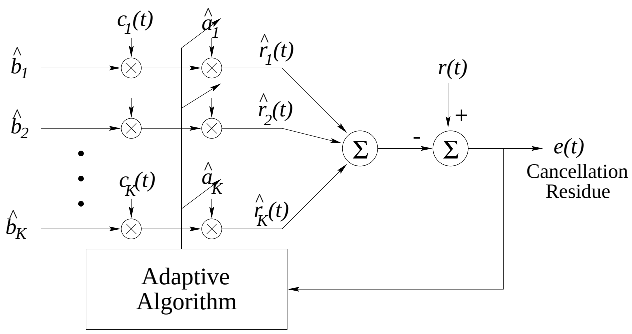

Figure 4. Adaptive filtering approach to channel estimation.

Any linear adaptive filter algorithm such as recursive least-squares (RLS), least mean-squares (LMS), or adaptive SMF algorithms can be used to train the adaptive channel estimator. However, conventional least-squares algorithms are not practically feasible due to their high computational complexity per update, combined with need to update at the chip rate. On the other hand, SMF algorithms, such as the SM-NLMS algorithm [6], BEACON algorithm [7] and DH/OBE algorithm [2], are attractive alternatives both in terms of performance and complexity. Reduction in complexity is achieved by SMF algorithms primarily due to a selective update strategy.

To estimate σ_k^2 for BPSK modulation, we note that (cf. 4) $E\{|y_k|^2 - |a_k|^2\} = 2\sigma_k^2$. Therefore, σ_k^2 can be estimated as a time-average of $(|y_k|^2 - |\hat{a}_k|^2)/2$, where $\hat{a}_k$ is an estimate of a_k. Similarly for M-ary modulation, (6) implies that σ_k^2 can be estimated by averaging $(\mathbf{y}_k^H \mathbf{y}_k - |\hat{a}_k|^2)/2$.

4 Simulation Results

This section compares the performance of the proposed technique with that of the conventional PIC and matched filter receivers. Random quadrature spreading and a single path multiaccess AWGN channel was used for the simulations. Estimation of channel gains and σ_k^2 followed the algorithms presented in Section 3. Although the proposed algorithms do not require user synchronism, the multiaccess channel was assumed to be synchronous, which represents the worst-case interference scenario. A spreading gain of 60 chips per bit was used for the BPSK case. The E_b/N_o of any user with respect to thermal noise (no interference) was set at 15 dB. Perfect power control was assumed, so that the relative powers of all users were identical. The simulation results show bit error rates (BER) estimated via Monte Carlo simulations over 5×10^6 bits, and averaged over all users.

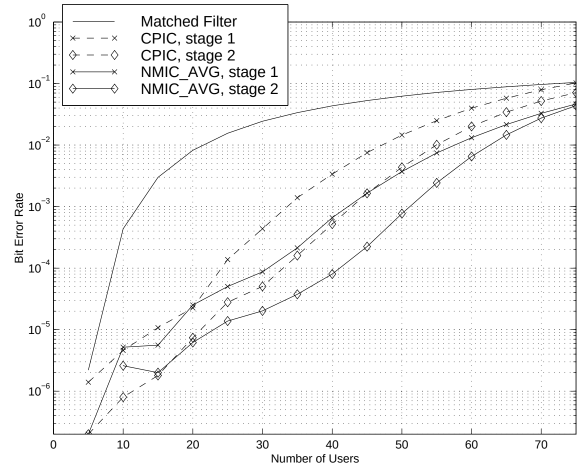

Figure 5. BPSK signaling: Bit Error Rates of NMIC/AVG, compared with the conventional interference canceler (CPIC).

The BER curves of NMIC with averaging channel estimator and CPIC are shown in Figure 5. Figure 6 shows the dramatic performance improvement that is achieved using the new adaptive filtering technique with the SM-NLMS algorithm. The SM-NLMS algorithm requires only a small fraction of the computational complexity of the LMS algorithm, and the average complexity of the SM-NLMS algorithm was observed to decrease with each stage. With 50 users, the average complexity of SM-NLMS was typically 1/5th of that of LMS in the first stage, and around 1/80th of that of LMS in the second stage. The complexity of channel estimation in the second stage is for most cases smaller than even the complexity of the averaging technique, which updates at symbol rate. This is in addition to the large difference in the performance of the averaging estimate and the SM-NLMS estimator. Simulation results for an M-ary orthogonal modulation system with $M = 64$ and 64 spreading chips per information bit are shown in Figures 7 and 8. Audio demonstrations of the performance of NMIC and conventional PIC can be viewed at the world wide web site [1].

5 Conclusions

This paper presented an optimal multistage parallel interference cancellation scheme based on the nonlinear MMSE criterion. Simulation results show the large performance gains that the proposed receiver can yield compared to traditional receivers. Further work is in progress to extend the scheme to CDMA systems with multiple receive antennas and convolutional coding.

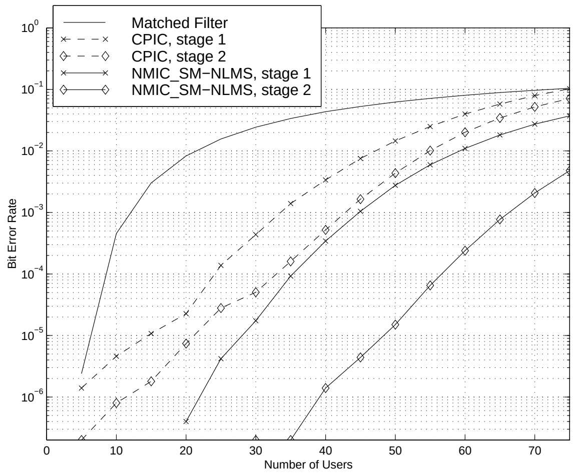

Figure 6. BPSK signaling: Bit Error Rates of NMIC/SM-NLMS, compared with the conventional interference canceler (CPIC).

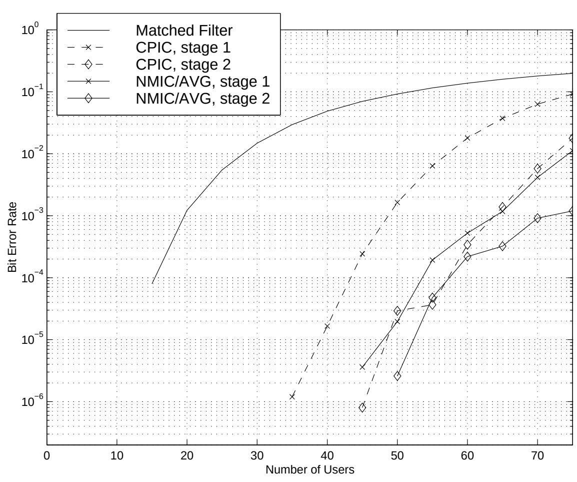

Figure 7. M-ary orthogonal signaling: Bit Error Rates of NMIC/AVG, compared with the conventional interference canceler (CPIC).

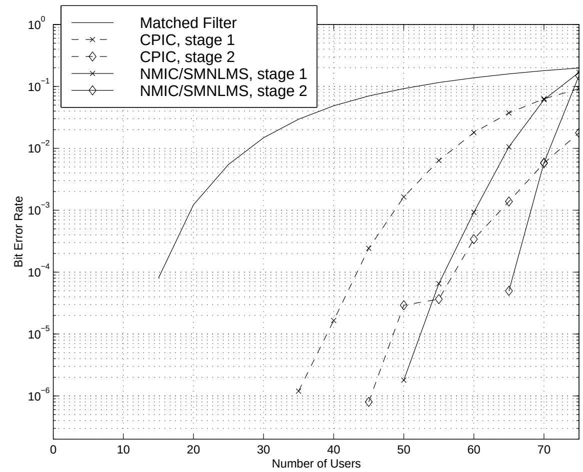

Figure 8. M-ary orthogonal signaling: Bit Error Rates of NMIC/SM-NLMS, compared with the conventional interference canceler (CPIC).

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