RAPID DETECTION AND SUPPRESSION OF MULTI-USER INTERFERENCE IN DS-CDMA

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ABSTRACT

Minimum Mean Squared Error (MMSE) detection has been recently proposed for Direct Sequence-Code Division Multiple Access (DS-CDMA) systems. MMSE detectors are near-far resistant, and can be adapted with standard adaptive algorithms without knowledge of user parameters (i.e., spreading codes). These algorithms rely on a known training sequence for intial adaptation, and subsequently switch to decision-directed mode. After the switch, the performance of the adaptive algorithm may degrade substantially if a strong interferer suddenly appears (i.e., if power control is relaxed). We present a ‘‘rescue’’ algorithm that monitors for sudden changes in the signal space, which may be caused by the appearance of a strong interferer. If a new interferer is detected, decision-directed adaptation is suspended, and an estimate of the optimal filter coefficients is obtained without a training sequence. It is shown that in the presence of low-level background noise, a good estimate can be obtained within a few symbol intervals. A numerical example is given which illustrates the performance of the rescue algorithm in a synchronous DS-CDMA system.

1. INTRODUCTION

Direct Sequence-Code Division Multiple Access (DS-CDMA) offers a number of important benefits for multi-user wireless communications. Namely, it can be operated asynchronously, it is robust with respect to narrowband fading and interference, and it does not require frequency assignments. A disadvantage of Direct-Sequence (DS)-CDMA is the *near-far problem*: Because the transmitted waveforms are not orthogonal, a transmitter close to a base station receiver can disrupt communications from a transmitter relatively far away. Current DS-CDMA systems (e.g., IS-95) solve this problem with closed-loop power control [1]. However, because of the stringent requirements on received power for acceptable system performance, this solution adds substantially to system complexity.

Recently, Minimum Mean Squared Error (MMSE) estimation has been proposed for detecting a DS-CDMA signal in the presence of multiple-access interference [2]-[4]. The linear MMSE detector has the following properties:

- It is robust with respect to strong interference (i.e., it is near-far resistant [5]).
- It can be implemented as a single tapped-delay line for each desired user, analogous to the linear equalizer for a dispersive single-user channel.
- It can be adapted using standard adaptive filtering algorithms (i.e., stochastic gradient or least squares).
- Initial adaptation relies only on a training sequence. Knowledge of user spreading sequences, amplitudes, and relative phases is not needed.
- The performance degrades gracefully as the number of (equal power) users increases.

The linear MMSE detector is less complex and easier to adapt than many of the multi-user detectors previously proposed (i.e., see [5]). This detector might therefore help to alleviate the stringent requirements on power control in DS-CDMA. A remaining problem, however, is that after initial adaptation with a training sequence, a conventional adaptive algorithm must switch to decision-directed mode. This switch occurs once the error probability is sufficiently low. It therefore can happen that the detector adapts to an initial set of users, but once in decision-directed mode, a new strong interferer appears. This would render the decisions made by the detector unreliable, and may prevent the adaptive algorithm from converging to the new set of users. An additional problem is making sure that the adaptive algorithm can track changes in the wireless channel.

To solve the preceding problem, we present an algorithm that monitors for sudden changes in the signal space. If a significant change is detected, then decision-directed adaptation is suspended, and the tap weights of the detector are adapted blindly without a training sequence. The purpose of the blind adaptation is to find a new initial condition from which decision-directed adaptation can proceed.

In this paper we assume an ideal channel, and consider only the addition of new users (interferers). We present a blind adaptation algorithm which exploits the fact that the tap weights have converged to one set of users, and that an additional interferer (or interferers) has suddenly appeared. The blind adaptation then reduces to estimating only one parameter per new user for synchronous CDMA, and two parameters per new user for asynchronous CDMA. In the absence of noise, and assuming a single new interferer, only two symbol periods are needed to compute this parameter for synchronous CDMA, and three symbol periods are needed for asynchronous CDMA. The algorithm therefore ‘‘rescues’’ the tap weights each time a strong interferer appears. If the number of strong interferers is sufficiently small, then in the absence of noise the algorithm finds the zero-forcing solution (i.e., the contribution from the interferers is nulled out). The complexity of the algorithm is quite modest when used with a decision-directed stochastic gradient (LMS) algorithm.

2. SYSTEM MODEL

There are K users transmitting to a single receiver. User k transmits the signal

$$s_k(t) \; = \; \sum_i b_k[i] p_k(t - iT) \tag{1}$$

where $b_k[i] \in \{\pm 1\}$ is the ith bit transmitted by user k and $p_k(t)$ is the pulse shape assigned to user k. For DS-CDMA,

$$p_k(t) \; = \; \sum_{i=0}^{N-1} a_k[i] \Psi(t - iT_c) \tag{2}$$

where $a_k[i]$, $i = 0, \ldots, N-1$, is the spreading sequence, $\Psi(t)$ is the chip waveform, T_c is the chip duration, and $N = T/T_c$ is the processing gain.

This model applies to both the uplink (mobile to base station) and downlink (base station to mobile) in a cellular system. In what follows we assume that the receiver wishes to detect a *single* user (i.e., user 1) in the presence of interference from the other users. Our discussion still applies to the uplink, since for the detector considered, minimizing total MMSE summed over all desired users is equivalent to minimizing MMSE for each user. Consequently, MMSE detection of each user is equivalent to joint MMSE detection of all users.

The problems of interest are present in both synchronous and asynchronous CDMA systems. For simplicity, we therefore consider symbol- and chip-synchronous DS-CDMA. Generalization of the following discussion to an asynchronous system is conceptually straightforward. We assume that the receiver contains a chip-matched filter followed by a chip-rate sampler. (For asynchronous CDMA, the MMSE detector requires a higher sampling rate [4].) Let $\mathbf{r}[i]$ denote the vector of samples obtained during the ith symbol interval. That is, $\mathbf{r}$ contains N elements, where N is the processing gain, and the jth element corresponds to the jth chip. For the baseband model, we can write

$$\mathbf{r}[i] \; = \; \sum_{k=1}^{K} A_k b_k[i] \mathbf{p}_k + \mathbf{n}[i] \tag{3}$$

where $b_k[i] \in \{\pm 1\}$ is the ith bit transmitted by user k, $\mathbf{p}_k$ is the unit-norm vector of N samples received from user k, A_k is the amplitude associated with user k, and $\mathbf{n}$ is the vector of noise samples.

For the synchronous system considered, the MMSE detector consists of the N-vector $\mathbf{c}$, where $\mathbf{c}$ is chosen to minimize $E\{(b_k[i] - \mathbf{c}'\mathbf{r}[i])^2\}$. The estimated symbol is $\hat{b}_k[i] = \mathrm{sgn}\,(\mathbf{c}'\mathbf{r}[i])$. In principle, any standard adaptive filtering algorithm can be used to estimate the MMSE solution for $\mathbf{c}$. However, suppose that power control is relaxed, the algorithm continues in decision-directed mode, and a new interferer (subscript $K+1$) suddenly appears. If the associated amplitude A_{K+1} is large enough, then the estimated symbols $\hat{b}_1[i]$ will be unreliable (assuming $\mathbf{p}_{K+1}{}'\mathbf{p}_1 \neq 0$), causing the adaptive algorithm to lose track of the desired user. Sudden changes in channel characteristics due to mobility might also cause an adaptive algorithm to lose track.

3. RESCUE ALGORITHM

To explain this algorithm, we neglect the noise term in (3). The numerical example which follows assumes a signal-to-background noise ratio (SNR) of 15 dB. Let $S_{l,m}$ denote the space spanned by $\{\mathbf{p}_l, \ldots, \mathbf{p}_m\}$ where $m > l$, and let $\mathbf{P}_S^{\perp}(\mathbf{x})$ denote the orthogonal projection of the vector $\mathbf{x}$ onto the space S. Before user $K+1$ appears, the sequence of received vectors $\{\mathbf{r}[i]\}$ spans $S_{1,K}$, so that $\|\mathbf{P}_{S_{1,K}}^{\perp}(\mathbf{r}[i])\| = 0$. Suppose that user $K+1$ appears at time i_0. If $\mathbf{p}_{K+1} \notin S_{1,K}$, then $\mathbf{r}[i_0] \notin S_{1,K}$, and

$$\begin{aligned} \mathbf{P}_{S_{1,K}}^{\perp}(\mathbf{r}[i_0]) \; &= \; \sum_{k=1}^{K+1} A_k b_k[i_0] \, \mathbf{P}_{S_{1,K}}^{\perp}(\mathbf{p}_k) \\ &= \; A_{K+1} b_{K+1}[i_0] \, \mathbf{P}_{S_{1,K}}^{\perp}(\mathbf{p}_{K+1}) \end{aligned} \tag{4}$$

It is desirable that the set of pulse vectors $\{\mathbf{p}_j\}$ have low cross-correlations, which means that $\|\mathbf{P}_{S_{1,K}}^{\perp}(\mathbf{p}_{K+1})\| \approx \|\mathbf{p}_{K+1}\| = 1$. Let $\boldsymbol{\delta}[i] = \mathbf{P}_{S_{1,K}}^{\perp}(\mathbf{r}[i])$. If user $K+1$ suddenly appears, and A_{K+1} is large, then the norm of $\boldsymbol{\delta}[i]$ must suddenly increase. To detect the appearance of user $K+1$ at time i we therefore use the decision rule:

$$||\boldsymbol{\delta}[i]|| \begin{array}{ll} < \eta : & K \text{ users} \\ > \eta : & K+1 \text{ users} \end{array} \tag{5}$$

where the threshold η is selected so that the error probability (or MSE) in decision-directed mode remains sufficiently low given the decision "K users". The performance of this detector is illustrated in the next section.

Note that any set of K linearly independent received vectors $\{\mathbf{r}[i_j]\}$, $j = 1, \ldots, K$ (prior to the appearance of user $K+1$ at time i_0), can serve as a set of basis vectors for the space $S_{1,K}$. However, an orthogonal basis can be obtained by replacing $\mathbf{r}[i_j]$ by the orthogonal projection of $\mathbf{r}$ onto the space spanned by the existing basis vectors. Computing the preceding orthogonal projection then becomes quite simple. The decision (5) determines when to add a new basis vector to the existing set.

In the absence of noise, the MMSE estimate for $\mathbf{c}$ given $K+1$ users is $\mathbf{P}^{\perp}_{S_{2,K+1}}(\mathbf{p}_1)$ (the zero-forcing solution), and it is easily shown that

$$\mathbf{P}^{\perp}_{S_{2,K+1}}(\mathbf{p}_1) \;=\; \kappa\left(\mathbf{P}^{\perp}_{S_{2,K}}(\mathbf{p}_1) + \alpha\boldsymbol{\delta}[i_0]\right) \tag{6}$$

where κ is a scale factor, and α is a parameter to be estimated. Note that $\mathbf{P}^{\perp}_{S_{2,K}}(\mathbf{p}_1)$ is the zero-forcing solution for $\mathbf{c}$ given K users, and lies in $S_{1,K}$. Equation (6) is therefore an orthogonal decomposition of the zero-forcing solution $\mathbf{P}^{\perp}_{S_{2,K+1}}(\mathbf{p}_1)$. Since binary symbols are assumed, the scale factor κ is unimportant. Consequently, if user $K+1$ appears at time i_0, then the new optimal vector can be written as

$$\tilde{\mathbf{c}} \;=\; \mathbf{c}[i_0 - 1] + \alpha\boldsymbol{\delta}[i_0] \tag{7}$$

Once α is determined, $\tilde{\mathbf{c}}$ is used as the initial condition for decision-directed adaptation, starting from time i_0.

The orthogonal decomposition in (7) is central to this approach, and was motivated by the minimum variance blind interference suppression technique presented in [6]. This decomposition allows the MMSE criterion to be replaced by output variance. To see this we write the MMSE as

$$E\{[A_1 b_1 - \tilde{\mathbf{c}}'\mathbf{r}]^2\} \;=\; A_1^2(1 - 2\tilde{\mathbf{c}}'\mathbf{p}_1) + E[(\tilde{\mathbf{c}}'\mathbf{r})^2], \tag{8}$$

which says that the MMSE and output variance $E[(\tilde{\mathbf{c}}'\mathbf{r})^2]$ differ by a constant. Consequently, choosing α to minimize the output variance also minimizes the MMSE. Minimizing output variance does not require a training sequence. Furthermore, the output variance is a quadratic function of α with a unique minimum. Consequently, we choose α to minimize

$$\sum_{i=i_0}^{i_1}\left(\tilde{\mathbf{c}}'\mathbf{r}[i]\right)^2,$$

where $i_1 - i_0$ is large enough to obtain a good estimate for α. In the absence of noise, the α which gives the (scaled) zero-forcing solution $\tilde{\mathbf{c}} = \kappa^{-1}\mathbf{P}^{\perp}_{S_{2,K+1}}(\mathbf{p}_1)$ can be obtained from just two received vectors, $\mathbf{r}[i_0]$ and $\mathbf{r}[i_0+1]$, provided that they are linearly independent.

Remarks

(i) Extension of this algorithm to asynchronous DS-CDMA is straightforward. However, because each interferer contributes two linearly independent vectors to the received vector $\mathbf{r}[i]$, when a new user appears two parameters must be estimated, instead of the single parameter α in (7). In the absence of noise, these parameters can be computed from three linearly independent received vectors $\mathbf{r}[i_0]$, $\mathbf{r}[i_0+1]$, and $\mathbf{r}[i_0+2]$. Also, unlike the synchronous case considered here, the performance can be improved by increasing the size (number of dimensions) of $\mathbf{c}$.

(ii) If a user disappears, then the error probability can only improve. This implies that the decisions $\hat{b}_1[i]$ remain reliable, and that decision-directed adaptation can continue.

(iii) As the level of background noise (or low-power interference) increases, it becomes more difficult to obtain basis vectors for the space $S_{1,K}$. Averaging techniques may prove useful for obtaining better estimates of the basis vectors. Also, the estimate $\tilde{\mathbf{c}}$ deviates further from the zero-forcing solution as the noise increases.

4. NUMERICAL RESULTS

The performance of the rescue algorithm is illustrated in Figure 1, which shows estimated Signal-to-Interference Ratio (SIR) vs. time for a synchronous CDMA system with processing gain $N = 10$, $K = 6$ users (initially), and a signal-to-background (Gaussian) noise level (SNR) of 15 dB. The SIR was computed as $E[(\mathbf{c}'[i]\mathbf{p}_1)^2]/E\{[\mathbf{c}'[i](\mathbf{r}[i] - b_1[i]\mathbf{p}_1)]^2\}$, where the expectation is replaced by an average over 200 runs. The interfering amplitudes satisfy $A_k/A_1 = 3$, $k = 2, \ldots, 6$, and the new interferer has amplitude $A_7/A_1 = 15$. The LMS algorithm is used for the first 200 iterations with a training sequence, and then switches to decision-directed mode. At iteration 300 a new user appears. Without the rescue operation, the new user is strong enough to cause the adaptive algorithm to lose track of the desired user. However, the rescue operation (which in this case uses three received vectors to compute α in (7)) is able to maintain positive SIR.

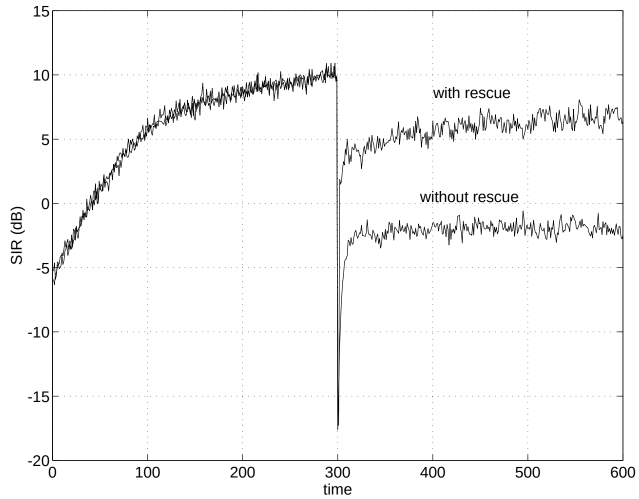

Figure 1. SIR vs. time for for the LMS algorithm, and the LMS algorithm with a rescue at time iteration 300. $N = 10$, $K = 6$, SNR = 15 dB, $A_k/A_1 = 3$, $k = 2, \ldots, 6$, $A_7/A_1 = 15$

The performance of the rescue algorithm depends critically on the performance of the decision (5). The probabilities of a false detect (detecting a user not actually present) and a miss, given that a new user is present, are difficult to compute in general. However, an optimistic performance evaluation can be obtained by assuming that $K = 1$ (no interferers). Figure 2 shows the probability of a miss (P_m) vs. the probability of a false detect (P_{fd}) for $K = 1$ with the power of the new user as a parameter. These results were obtained by choosing different values of η and approximating $\|\mathbf{n}\|^2$ as a Gaussian random variable. As in Figure 1, $N = 10$ and the SNR is 15 dB. The new user's power varies from 0 to 6 dB above the desired user. Of course, the performance of the detector degrades as the background noise level increases, and as the number of users increases. It is, of course, possible to improve upon the performance of the decision (5) by making use of more than one received vector. We leave this for future work.

5. CONCLUSIONS

A technique has been presented for detecting the onset of a new interferer in DS-CDMA, and rapidly adapting the filter coefficients of a tapped-delay line to suppress this interferer. This rescue technique does not require a training sequence. The numerical example presented here is preliminary in that the channel is assumed to be ideal, and there are relatively few interferers. In a cellular system, there are likely to be many (i.e., more than N) low-level interferers, along with time-varying multipath, which may cause rapid fades. It is important to determine how robust this technique is (used in conjunction with either stochastic gradient or least squares estimates for $\mathbf{c}$) with respect to these impairments.

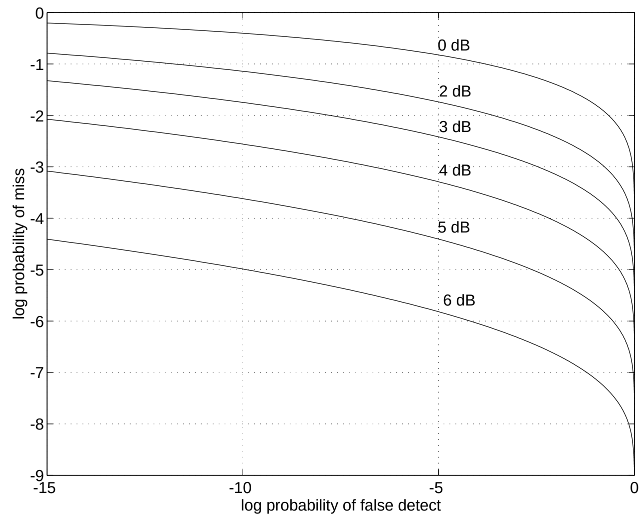

Figure 2. $\log_{10} P_m$ vs. $\log_{10} P_{fd}$ for the decision rule (5) assuming $K = 1$, $N = 10$, and SNR = 15 dB. Each plot corresponds to a different power level for the new interferer.

REFERENCES

1. "An Overview of the Application of Code Division Multiple Access (CDMA) to Digital Cellular Systems and Personal Cellular Networks", Qualcomm Document Number EX60-10010, May 1992.
2. M. Abdulrahman, A. U. H. Sheikh, and D. D. Falconer, "Decision Feedback Equalization for CDMA in Indoor Wireless Communications", *IEEE JSAC",* vol. 12, no. 4, pp. 698-704, May 1994.
3. P. B. Rapajic and B. S. Vucetic, "Adaptive Receiver Structures for Asynchronous CDMA Systems", *IEEE JSAC,* vol. 12, no. 4, pp. 685-697, May 1994
4. U. Madhow and M. L. Honig, "MMSE interference suppression for DS/SS CDMA", *IEEE Trans. on Communications,* Dec. 1994.
5. S. Verdu´, "Multiuser Detection", in *Advances in Statistical Signal Processing, Volume 2,* JAI Press Inc., pp. 369-409.
6. M. L. Honig, U. Madhow, and S. Verdu´, "Blind Adaptive Interference Suppression for Near-Far Resistant CDMA", *Proceedings Globecom '94,* San Francisco, CA, Dec. 1994.