SINGLE- AND MULTI-USER BLIND RECEIVERS FOR LONG-CODE WCDMA

Quang Hieu Dang and Alle-Jan van der Veen

Delft University of Technology
Department of Electrical Engineering
Mekelweg 4, 2628 CD Delft, The Netherlands

ABSTRACT

In previous work, Tong, Van der Veen e.a. derived a blind decorrelating receiver and channel estimation algorithm for long-code (aperiodic) wideband CDMA systems. Although its performance in the presence of multiaccess interference is usually much better than the conventional matched filter (RAKE), in heavily loaded systems its performance is degraded because the decorrelating step colors the noise. In this paper, we propose both single-user and multi-user blind source-channel estimation algorithms by making use of an iterative estimation scheme combined with a decorrelating RAKE receiver (DRR) as the initial channel estimate, which takes the noise color into account. The conventional RAKE receiver is also considered as an alternative for the initial channel estimation. The algorithm when multiple received antennas are used at the base station is also developed. Simulation results show significant improvements, even in heavily loaded systems.

1. INTRODUCTION

Current receivers for long-code (or aperiodic spreading code) wideband CDMA are typically based on RAKE receivers, i.e. banks of matched filters which correlate the received data with the desired user's code, followed by a combining of the outputs (RAKE fingers). Since multiuser interference is not completely cancelled, the performance degrades, especially when the network is heavily loaded and power control imperfect.

In [1, 2], Tong, Van der Veen et al. considered an uplink receiver algorithm (DRR) where the base station knows all codes. By constructing and inverting a code matrix, a blind decorrelating RAKE receiver was derived to estimate the channel and user symbols, based on all samples in a frame. After the decorrelating step, the users are treated independently, which is computationally advantageous but suboptimal.

In particular when the system is heavily loaded (the code matrix is almost not tall), the performance of the channel estimation step in [1, 2] is degraded. The reason seems to be that, due to the code inversion, the noise becomes correlated among symbols and users. A second reason is that the code inversion followed by the channel inversion (separate for each user) is suboptimal and gives more noise enhancement than the inversion of the product of the code and channel matrices. In this paper, we take these effects into account.

We propose to use the single-user channel estimates from the DRR as an initial point for an iterative symbol/channel estimation algorithm which also considers the noise correlations. This can be done on a per-user bases, or, with better performance, jointly in a multi-user fashion. In heavily loaded systems, this algorithm shows a significant improvement over the current decorrelating RAKE receiver and the conventional RAKE receiver even when noise is strong.

Channel estimation and multiuser detection for long code CDMA has not seen the same levels of attention as the short-code equivalent, yet has been considered by a number of other authors, see e.g., [3] and references therein. In particular, the channel estimation in [3] is non-blind and considers the transmission of training symbols for all users; they also consider sequential interference cancellation (SIC) techniques. Blind techniques based on second order moment matching have appeared in [4–8]. These rely on the convergence of time averages, which often requires hundreds to thousands of symbols. In comparison, the techniques in [1, 2] can be called *deterministic*, since no statistical model of the sources is assumed. Deterministic techniques have been considered by Weiss and Friedlander [9], but for the downlink, where users can be considered synchronous and only a single common channel is to be estimated.

2. DATA MODEL

As in [1, 2], we consider the uplink of a slotted system with K asynchronous users. In a frame, the i-th user transmits a vector $\mathbf{s}_i$ consisting of M_i symbols s_{ik}. Each symbol is spread by an aperiodic code $\mathbf{c}_{ik}$ of length G_i. After multipath propagation over a channel with length L_i chips and relative delay D_i, pulse shape matched filtering and sampling at the chiprate, the receiver stacks the received samples in a frame in a vector $\mathbf{y}$. The contribution of s_{ik} is a linear combination of the transmitted signal $\mathbf{c}_{ik}s_{ik}$, plus delays of it, properly scaled by the L_i channel coefficients collected in a vector $\mathbf{h}_i$, or

$$\mathbf{y}_{ik} = \mathbf{T}_{ik}\mathbf{h}_i s_{ik}\,, \quad k = 1, \cdots, M_i\,.$$

$\mathbf{T}_{ik}$ is a Toeplitz matrix whose L_i columns consist of shifts of the code $\mathbf{c}_{ik}$. Including all users and the noise, we have

$$\begin{aligned} \mathbf{y} &= \mathbf{T}\mathbf{H}\mathbf{s} + \mathbf{w} \qquad (1)\\ \mathbf{T} &:= [\mathbf{T}_1, \cdots, \mathbf{T}_K] \\ \mathbf{H} &:= \text{ diag } (\mathbf{I}_{M_1} \otimes \mathbf{h}_1, \cdots, \mathbf{I}_{M_K} \otimes \mathbf{h}_K)\,, \end{aligned}$$

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where the i-th user's code matrix is $\mathbf{T}_i := [\mathbf{T}_{i1}, \cdots, \mathbf{T}_{iK}]$, the channel matrix $\mathbf{H}$ is block diagonal with $\mathbf{I} \otimes \mathbf{h}_i$ as the i-th block, vector $\mathbf{s}$ is a stacking of all symbol vectors of all users, and $\mathbf{w}$ is a vector representing the additive Gaussian noise.

We will assume that the code matrix $\mathbf{T}$ is known, "tall" and has full column rank. This implies that the receiver knows the codes, the delay offsets D_i, and the number of paths L_i of all users. We also assume that the noise $\mathbf{w}$ is white Gaussian, with variance σ^2.

The problem we consider is, given the code matrix $\mathbf{T}$ and the received data vector $\mathbf{y}$, to find good estimates of all users' source symbols $\mathbf{s}$ and all channel coefficients $\mathbf{h}$, where

$$\mathbf{h} = [\mathbf{h}_1^H, \cdots, \mathbf{h}_K^H]^H$$

is the stacking of all users' channels $\mathbf{h}_i$.

3. DECORRELATING RAKE RECEIVER ALGORITHM (DRR)

As introduced in [1, 2], the Decorrelating RAKE Receiver (DRR) algorithm first applies a decorrelating matched filter, or $\mathbf{T}^\dagger = (\mathbf{T}^H\mathbf{T})^{-1}\mathbf{T}^H$, to the vector of received data $\mathbf{y}$. This removes all multi-user interference. The output of the decorrelating matched filter is given by

$$\mathbf{u} = \mathbf{T}^\dagger \mathbf{y} = \mathbf{H}\mathbf{s} + \mathbf{n}\,, \tag{2}$$

where $\mathbf{n} = \mathbf{T}^\dagger \mathbf{w}$ is a colored noise vector. The new noise covariance matrix is

$$\begin{aligned}\mathbf{R}_n := \ \mathrm{E}\ (\mathbf{n}\mathbf{n}^H) &= \sigma^2 \mathbf{T}^\dagger \mathbf{T}^{\dagger H} \\ &= \sigma^2 (\mathbf{T}^H\mathbf{T})^{-1}\,.\end{aligned} \tag{3}$$

Since $\mathbf{H}$ is block diagonal, the filter output can be separated into individual user contributions. Split $\mathbf{u}$ into K segments $\mathbf{u}_i$, one for each user, then

$$\mathbf{u}_i = (\mathbf{I} \otimes \mathbf{h}_i)\mathbf{s}_i + \mathbf{n}_i, \quad i = 1, \cdots, K\,. \tag{4}$$

By unstacking the vector $\mathbf{u}_i$ into a matrix $\mathbf{U}_i$, we obtain the model

$$\mathbf{U}_i = \mathbf{h}_i \mathbf{s}_i^T + \mathbf{N}_i, \quad i = 1, \cdots, K\,. \tag{5}$$

The channel estimation proceeds by taking a rank-1 decomposition of $\mathbf{U}_i$. As shown in [1, 2], this can be improved by computing $\mathbf{U}_i\mathbf{U}_i^H$ and taking the non-white noise covariance into account. This led to the computation

$$\begin{aligned}\mathbf{g}_* &= \arg \max_{\|\mathbf{g}\|=1} \mathbf{g}^H (\mathbf{\Delta}_i^{-1/2} \hat{\mathbf{R}}_i \mathbf{\Delta}_i^{-H/2})\mathbf{g}\,, \\ \hat{\mathbf{h}}_i &= \mathbf{\Delta}^{1/2}\mathbf{g}_*\,.\end{aligned} \tag{6}$$

where

$$\hat{\mathbf{R}}_i := \frac{1}{M_i} \sum_{k=1}^{M_i} \mathbf{u}_{ik}\mathbf{u}_{ik}^H$$

$$\mathbf{\Delta}_i := \frac{1}{M_i} \sum_{k=1}^{M_i} (\mathbf{R}_n)_{ik}$$

and where $(\mathbf{R}_n)_{ik}$ is a submatrix on the main diagonal of $\mathbf{R}_n$ corresponding to the noise covariance of s_{ik}, the k-th symbol of the i-th user.

The above derivation from [1, 2] was (without making this explicit) making two assumptions on the noise:

1. Instead of considering the global noise covariance matrix $\mathbf{R}_n$, take only the block-diagonal

   $$\mathrm{diag}\ ((\mathbf{R}_n)_1, \cdots, (\mathbf{R}_n)_K)$$

   into account, which implies that the correlations between the noise of different users are ignored. Therefore, we could make the step of the multi-user model (2) into the partitioning into single-user equations (4).
2. Instead of considering the temporal correlations of the columns of the noise matrix $\mathbf{N}_i$, consider them independent, which means that from each block $(\mathbf{R}_n)_i$, only the block-diagonals $(\mathbf{R}_n)_{ik}$ are considered. This simplification helps to partition each single-user equation into symbol-level equations,

   $$\mathbf{u}_{ik} = \mathbf{h}_i s_{ik} + \mathbf{n}_{ik}\,, \tag{7}$$

   which eventually led to the algorithm in (6).

The two assumptions above certainly ignore much information in the noise covariance matrix $\mathbf{R}_n$ but they do simplify the initial estimation of the channel. Our aim will be to improve the estimation by taking the complete noise model into account. As it turns out, the elegant rank-1 channel estimation property is hard to generalize. However, using the DRR to obtain an initial channel estimate, we can improve the estimate by a simple iteration, discussed next.

4. JOINT SOURCE-CHANNEL ESTIMATION

4.1. Multi-user estimation

Consider the data model in (1). We can formulate the channel/data estimation problem as a typical Least Squares problem: find $\mathbf{h}$ and $\mathbf{s}$ to minimize $f(\mathbf{h}, \mathbf{s}) := \|\mathbf{y} - \mathbf{T}\mathbf{H}\mathbf{s}\|^2$. With a good initial channel estimate, $\mathbf{h}^{(0)}$ say, we can use the following (not unfamiliar) Alternating Least Squares iteration to improve the estimate. For iteration index $k = 1, 2, \cdots$ until convergence, do

1. Keeping the channel $\mathbf{h}^{(k-1)}$ fixed, find the source symbols $\mathbf{s}^{(k)}$ as the solution to the Least Square problem

   $$\mathbf{s}^{(k)} = \arg\min_{\mathbf{s}}\ f(\mathbf{h}^{(k-1)}, \mathbf{s})\,. \tag{8}$$

2. Keeping the source symbols $\mathbf{s}^{(k)}$ fixed, find $\mathbf{h}^{(k)}$ as

   $$\mathbf{h}^{(k)} = \arg\min_{\mathbf{h}}\ f(\mathbf{h}, \mathbf{s}^{(k)})\,. \tag{9}$$

After the iterations, step 1 is repeated once more to get the final estimate of the source symbols.

The solution to (8) is directly given by

$$\begin{aligned}\mathbf{s}^{(k)} &= (\mathbf{T}\mathbf{H}^{(k-1)})^\dagger \mathbf{y} \\ &= (\mathbf{H}^{(k-1)^H}\mathbf{T}^H\mathbf{T}\mathbf{H}^{(k-1)})^{-1}\mathbf{H}^{(k-1)^H}\mathbf{T}^H\mathbf{y}\,,\end{aligned} \tag{10}$$

where $\mathbf{H}^{(k-1)} = \ \mathrm{diag}\ (\mathbf{I}_{M_1} \otimes \mathbf{h}_1^{(k-1)}, \cdots, \mathbf{I}_{M_K} \otimes \mathbf{h}_K^{(k-1)})$.

However, to solve (9), we must rewrite the expression of the function f as a function of $\mathbf{h}$, i.e. $f(\mathbf{h}) = \|\mathbf{y} - \mathbf{T}\mathbf{S}\mathbf{h}\|^2$, where $\mathbf{S}$ is a certain matrix structured by the source symbol vector $\mathbf{s}$.

Lemma 4.1 *Let* $\mathbf{h}$ *and* $\mathbf{s}$ *be vectors of length* L *and* M*, respectively. Then*

$$(\mathbf{I}_M \otimes \mathbf{h})\mathbf{s} = (\mathbf{s} \otimes \mathbf{I}_L)\mathbf{h} \tag{11}$$

*Proof:*Using the multiplicative property of Kronecker products, $(\mathbf{A}\otimes\mathbf{B})(\mathbf{C}\otimes\mathbf{D}) = (\mathbf{AC}\otimes\mathbf{BD})$, we immediately obtain

$$\begin{aligned}(\mathbf{I}_M \otimes \mathbf{h})\mathbf{s} &= (\mathbf{I}_M \otimes \mathbf{h})(\mathbf{s}\otimes 1) = \mathbf{s}\otimes\mathbf{h} \\ &= (\mathbf{s}\otimes\mathbf{I}_L)(1\otimes\mathbf{h}) = (\mathbf{s}\otimes\mathbf{I}_L)\mathbf{h}\,.\end{aligned}$$

□

Applying this lemma, it can be easily shown that

$$\begin{aligned}&\text{diag}\,(\mathbf{I}_{M_1}\otimes\mathbf{h}_1,\cdots,\mathbf{I}_{M_K}\otimes\mathbf{h}_K)\mathbf{s} = \\ &\quad\text{diag}\,(\mathbf{s}_1\otimes\mathbf{I}_{L_1},\cdots,\mathbf{s}_K\otimes\mathbf{I}_{L_K})\mathbf{h}\,.\end{aligned}$$

Therefore, the solution to (9) is

$$\begin{aligned}\mathbf{h}^{(k)} &= (\mathbf{T}\mathbf{S}^{(k)})^\dagger\mathbf{y} \\ &= (\mathbf{S}^{(k)H}\mathbf{T}^H\mathbf{T}\mathbf{S}^{(k)})^{-1}\mathbf{S}^{(k)H}\mathbf{T}^H\mathbf{y}\,,\end{aligned} \tag{12}$$

where $\mathbf{S}^{(k)} = \text{diag}\,(\mathbf{s}_1^{(k)}\otimes\mathbf{I}_{L_1},\cdots,\mathbf{s}_K^{(k)}\otimes\mathbf{I}_{L_K})$. This estimation step is of course similar to batch training-based techniques, cf. e.g., [3].

As an alternating projection algorithm, it is known that it will converge monotonically to a local optimum of f. Generally, the algorithm only completely converges after a number of iterations. However, with an initial estimate of the channel provided by the decorrelating RAKE receiver algorithm (or even the ordinary RAKE receiver following the same scheme for channel estimation) discussed in section 3, the algorithm rapidly converges with only 1 iteration. Because in the multi-user LS formulation, the noise is not colored, the final estimates can be much better than that of initial single-user algorithms that have to work with incomplete noise models.

Apart from this, a second reason why this algorithm is expected to have better performance is that it uses inverses $(\mathbf{TH})^\dagger$ and $(\mathbf{TS})^\dagger$ of tall matrices, whereas the previous algorithm implicitly worked with $\mathbf{H}^\dagger\mathbf{T}^\dagger$ for computing the symbol estimates. While $\mathbf{H}^\dagger\mathbf{T}^\dagger$ is a valid left inverse of $\mathbf{TH}$, it is not the minimum-norm left inverse, hence it can give unnecessary noise enhancement.

The performance of the iterative algorithm can be improved further by making decisions on the symbols after they are estimated in the first step of the iteration. This is similar to the ILSP algorithm [10]. Assuming the decisions are correct, the algorithm would approach the multi-user Linear MMSE solution with the channel estimated from completely known symbols.

4.2. Single-user estimation

When the number of users is large, the complexity of the multi-user estimator might be too large. In that case, we propose a similar iteration for each user separately, which ignores the information in the correlations of the noise between the various users.

Consider again (4). The covariance of the noise $\mathbf{n}_i$ is $(\mathbf{R}_n)_i$, and known. First whiten the noise,

$$\tilde{\mathbf{u}}_i := (\mathbf{R}_n)_i^{-1/2}\mathbf{u}_i = (\mathbf{R}_n)_i^{-1/2}(\mathbf{I}\otimes\mathbf{h}_i)\mathbf{s}_i + \tilde{\mathbf{n}}_i\,.$$

At this point, we can introduce a similar Alternating LS algorithm to estimate $\mathbf{s}_i$ and $\mathbf{h}_i$ in turns, now for each user i separately:

1. Given $\mathbf{h}_i^{(k-1)}$, solve
$$\begin{aligned}\mathbf{s}_i^{(k)} &= \arg\min_{\mathbf{s}_i}\ \|\tilde{\mathbf{u}}_i - (\mathbf{R}_n)_i^{-1/2}(\mathbf{I}\otimes\mathbf{h}_i^{(k-1)})\mathbf{s}_i\|^2 \\ &= \left((\mathbf{R}_n)_i^{-1/2}(\mathbf{I}\otimes\mathbf{h}_i^{(k-1)})\right)^\dagger\tilde{\mathbf{u}}_i\,.\end{aligned}$$
2. Keeping $\mathbf{s}_i^{(k)}$ fixed, solve
$$\begin{aligned}\mathbf{h}_i^{(k)} &= \arg\min_{\mathbf{h}_i}\ \|\tilde{\mathbf{u}}_i - (\mathbf{R}_n)_i^{-1/2}(\mathbf{s}_i^{(k)}\otimes\mathbf{I})\mathbf{h}_i\|^2 \\ &= \left((\mathbf{R}_n)_i^{-1/2}(\mathbf{s}_i^{(k)}\otimes\mathbf{I})\right)^\dagger\tilde{\mathbf{u}}_i\,.\end{aligned}$$

In comparison to the iterative multi-user algorithm in section 4.1, the performance is expected to be less, since the correlations of the noise vector $\tilde{\mathbf{n}}_i$ with the noise vectors of other users are ignored, and also the noise enhancement due to working with $\mathbf{T}^\dagger$ is not avoided. Nonetheless, the performance is expected to be better than that of the original DRR algorithm, since the complete noise covariance matrix $(\mathbf{R}_n)_i$ is used, rather than just its block diagonal entries as in (6).

5. MULTIPLE ANTENNAS

Consider a case where d received antennas are used at the base station. No structure is imposed on this antenna array. The data model becomes

$$\begin{bmatrix}\mathbf{y}_1\\\mathbf{y}_2\\\vdots\\\mathbf{y}_d\end{bmatrix} = \begin{bmatrix}\mathbf{TH}_1\\\mathbf{TH}_2\\\vdots\\\mathbf{TH}_d\end{bmatrix}\mathbf{s} + \begin{bmatrix}\mathbf{w}_1\\\mathbf{w}_2\\\vdots\\\mathbf{w}_d\end{bmatrix} \tag{13}$$

where $\mathbf{y}_j$, $\mathbf{H}_j$ and $\mathbf{w}_j$ are the received vector, channel matrix and noise vector for the j-th antenna.

First, the multiple antenna version of the DRR must be available as the initial channel estimate for the iterative algorithm.

5.1. DRR for multiple antenna case

For simplicity, only an un-weighted channel estimation algorithm is developed for the multiple antenna version of DRR. From (5), all $\mathbf{U}_i$ matrices of the i-th user from each antenna are stacked into much taller matrices as follows

$$\begin{bmatrix}\mathbf{U}_{i,1}\\\mathbf{U}_{i,2}\\\vdots\\\mathbf{U}_{i,d}\end{bmatrix} = \begin{bmatrix}\mathbf{h}_{i,1}\\\mathbf{h}_{i,2}\\\vdots\\\mathbf{h}_{i,d}\end{bmatrix}\mathbf{s}_i^T + \begin{bmatrix}\mathbf{N}_{i,1}\\\mathbf{N}_{i,2}\\\vdots\\\mathbf{N}_{i,d}\end{bmatrix},\ i = 1,2,\cdots,K.$$

Ignoring the colored noise in the $\mathbf{N}_{i,j}$ matrices, channels are estimated by taking a rank-1 decomposition of the new data matrix $[\mathbf{U}_{i,1}^T\mathbf{U}_{i,2}^T\cdots\mathbf{U}_{i,d}^T]^T$, $i = 1,2,\cdots,K$.

5.2. Joint source channel estimation for multiple antenna case

In order to implement the iterative algorithm for this multiple antennas case, another form of the data model must be developed. Applying the same trick as in section 4.1, i.e. $\mathbf{TH}_j\mathbf{s} = \mathbf{TSh}_j$, we have

$$\begin{bmatrix}\mathbf{y}_1\\\mathbf{y}_2\\\vdots\\\mathbf{y}_d\end{bmatrix} = (\mathbf{I}_d\otimes(\mathbf{TS}))\begin{bmatrix}\mathbf{h}_1\\\mathbf{h}_2\\\vdots\\\mathbf{h}_d\end{bmatrix} + \begin{bmatrix}\mathbf{w}_1\\\mathbf{w}_2\\\vdots\\\mathbf{w}_d\end{bmatrix} \tag{14}$$

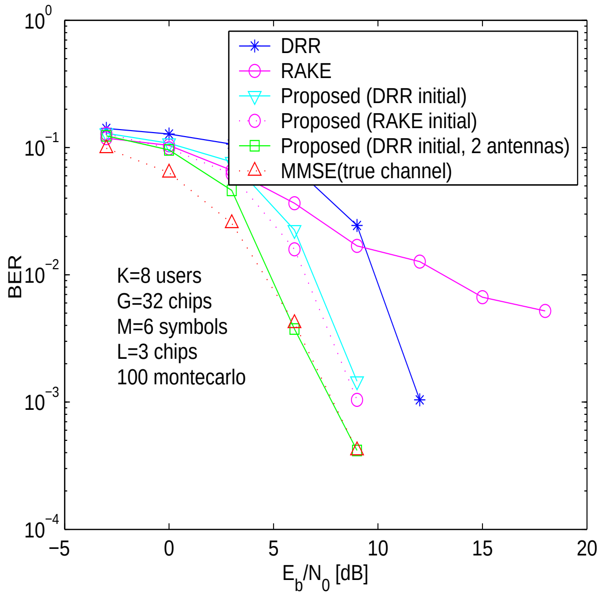

Figure 1: BER vs. SNR

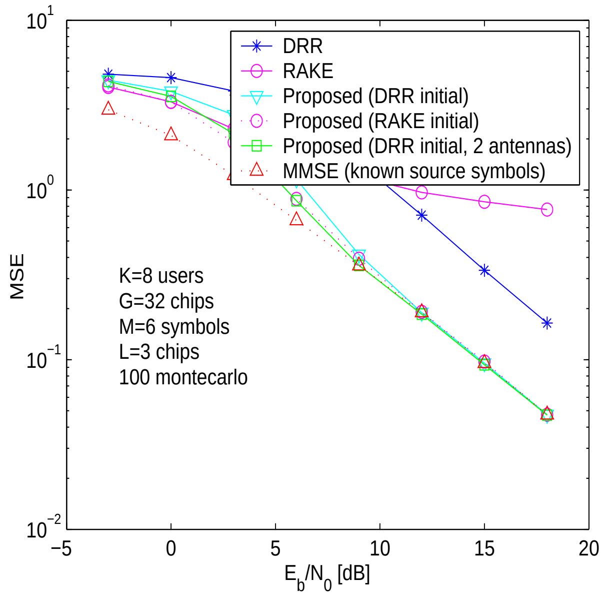

Figure 2: Channel estimation error (MSE) vs. SNR

where $\mathbf{h}_j$ is the stacking of all channel vectors for the j-th antenna.

In the first step of the iterative algorithm, where source symbols are estimated from known channel vectors using (13), the benefit comes from the inversion of a much taller matrix $[(\mathbf{TH}_1)^T(\mathbf{TH}_2)^T\cdots(\mathbf{TH}_d)^T]^T$. In the second step, estimating the channels from known source symbols using (14), the new matrix $\mathbf{I}_d\otimes(\mathbf{TS})$ is exactly as tall as the matrix $(\mathbf{TS})$ in the single-antenna case. Actually, the channels are estimated independently from the source symbols, which means no gain is available in this step. However, the overall performance improvement over the single antenna case, after only one iteration, is significant.

6. SIMULATION RESULTS

In this section, some simulation results of the multi-user iterative joint source-channel estimation algorithm are discussed. We consider a case with $K = 8$ asynchronous users with equal power and randomly generated spreading codes with gain $G = 32$. Each user's channel has $L = 3$ fingers with a random delay spread. Consequently, the system is heavily loaded (the code matrix $\mathbf{T}$ is barely tall). Each user transmits symbols in frames of length $M = 6$. The remaining phase ambiguity after blind channel estimation can be removed by using a single training pilot symbol per user per frame or by differential encoding. Source symbol decision is employed to enhance the iterative estimation steps in the algorithm. Monte Carlo runs are used to simulate the algorithm. The resulting plots of channel mean square error (MSE) and the bit error rate (BER) versus signal-to-noise ratio (SNR) are used as the performance criteria.

6.1. Bit error rate (BER) comparison

The BERs of the different algorithms are compared for varying SNR. The reference curve "MMSE (true channel)" indicates the performance of a linear MMSE receiver based on the true channel coefficients. It is shown in Fig. 1 that the (DRR, 1 iteration) improves the BER performance about 3 dB when BER is 10^{-2}. The distances slightly increase when BER increases. Compared with the conventional RAKE receiver, the proposed algorithms (DRR) outperforms the RAKE receiver when SNR is around 5 dB.

The proposed algorithm -(RAKE, 1 iteration) is much better than the conventional RAKE receiver. It has the same behavior and only 2dB worse than the reference curve. The floor effect of RAKE receivers is completely removed in the (RAKE, 1 iteration). Thus, the gaps between RAKE and the proposed curves become arbitrarily large when the BER increases.

It can also be shown from this figure that the BER performance of the proposed algorithm in the multiple antenna case ($d = 2$ antennas, 1 iteration) is comparable to the linear MMSE receiver even when noise is moderate (when SNR is more than 6 dB).

6.2. Channel estimation mean square error comparison

Fig. 2 shows plots of channel MSE of the DRR, conventional RAKE receivers compared to those of the proposed multi-user algorithms with only one iteration using DRR or RAKE as the initial channel estimate. The reference curve is the channel MSE vs. SNR plot of the linear MMSE receiver when the source symbols are known. The plot of the multiple antenna case (with $d = 2$, DRR initial, 1 iteration) is also shown in this figure.

The gain of the (DRR, 1 iteration) over DRR is about

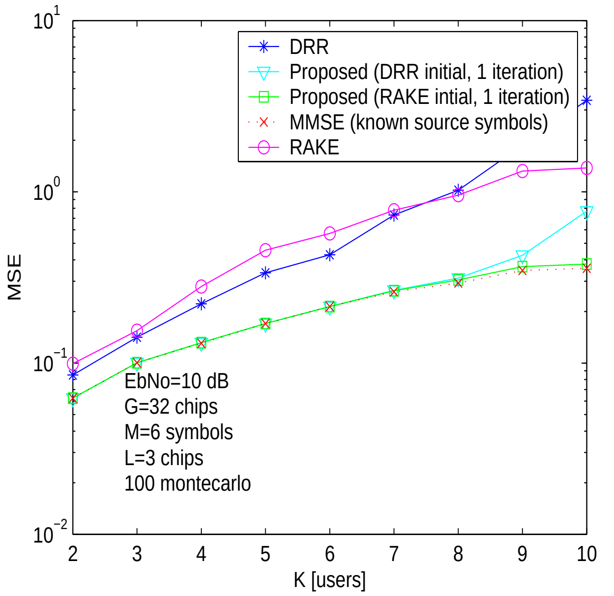

Figure 3: Channel estimation error (MSE) vs. number of users (K)

3-4 dB when noise is strong. It gradually increases when SNR increases. The two curves are parallel with the gain of about 7 dB since SNR is more than 10 dB. The curve for the multiple antenna case is slightly better than its single antenna version when the noise is strong.

The curve of (RAKE, 1 iteration) is also slightly better than (DRR, 1 iteration), the gap reduces quickly when SNR increases. The difference between these two curves, which will be shown in Fig. 3, is very small when the system is not too heavily loaded.

For more detailed understanding of the performance of the proposed algorithm, we study the channel MSE performance with respect to the number of users (K) while keeping SNR fixed at a certain level.

In Fig. 3, the curves of the proposed algorithms, when SNR is 10 dB, are still nearly identical to that of the linear MMSE receiver (with known source symbols), especially when number of users (K) is small, which makes the code matrix $\mathbf{T}$ becomes very tall. Although these curves slightly detache from the MMSE curve when K increases, the gains over the DRR or conventional RAKE receiver still increase. When the number of users reaches the upper limit ($K = 10$ in this case), which makes the matrix $\mathbf{T}$ barely square, the performance of the algorithm with DRR as the initial channel estimate will degrade in comparison to the one with RAKE.

It can be concluded, from simulation results discussed above, that the algorithm converges rapidly with the current initial estimates, and that a single iteration can have a very significant improvement in channel estimation. It is comparable to the linear MMSE receiver.

7. CONCLUSION

In this paper, we have derived a new joint source-channel estimation, which is the combination of the decorrelating RAKE receiver with an iterative symbol/channel estimation algorithm. The multiple antenna version is also developed. The use of the conventional RAKE receiver as the initial channel estimate is considered in the simulation as well. This algorithm shows a significant improvement over the current decorrelating RAKE receiver and the conventional RAKE receiver. In heavily loaded systems, the gain becomes more impressive even when noise is strong.

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