New Semi-Blind Algorithms for Space-Time Rake Receivers in WCDMA Systems

Claudio J. Bordin Jr., Luiz A. Baccalá and Silvio E. Barbin

***Abstract*— In this work, we examine the problem of multichannel equalization/identification for W-CDMA systems employing long codes. We develop new semi-blind algorithms and compare their performance with that exhibited by the most common approaches. We verify through numerical simulations, employing the COST-259 channel propagation model, that classical pilot-based approaches do not allow W-CDMA systems to achieve satisfactory capacity, specially in the presence of high data rate users, and that the proposed semi-blind approaches performed robustly, leading in general to much smaller error rates.**

***Index Terms*— WCDMA, long coded systems, space-time rake receiver, COST-259**

I. Introduction

Multichannel equalization algorithms have long been proposed as one of the most promising techniques for increasing the capacity of CDMA systems. The use of such algorithms coupled with antenna arrays result in the so-called "smart antennas" systems, which allow the joint exploitation of both temporal and spatial diversities as induced by multipath propagation channels. In this work, we evaluate the performance of several different multichannel algorithms for uplink W-CDMA reception.

We focused our attention on algorithms capable of operating with long-coded systems. In fact, despite the academic community bias towards the development of algorithms for short-coded systems, the default operation modes of all practical 3G systems are based on long-codes, making most of the literature inapplicable in practice (see, e.g., [1], [2]). Regardless of the claim that short codes ease the implementation of multiuser detection schemes, their utilization does not guarantee that all users achieve the same mean performance [3]: this poses issues that must be well investigated before these systems are used in practice.

The W-CDMA uplink signal carries a code-multiplexed pilot signal that allows the receiver to perform trained equalization. However, classical estimation theory results guarantee that much better performance may be achieved if the random portion of the signal is also exploited, by means of so-called "semi-blind" algorithms. Nevertheless, the development of blind or trained channel equalization/identification algorithms suitable for long-coded CDMA systems is not an easy task, since the equivalent transfer function at bit level (considering the spread and despread processes) varies over each bit interval, which remains true even if the transmission channel is not time-varying.

Perhaps due to this difficulty, the first long-code suited channel identification approaches [4] [5] appeared in the literature no more than a few years ago. Following the pioneer approaches, a few others were proposed: in [6] and [7], multiuser detection algorithms based on iterative maximum-likelihood techniques were proposed. In [8] and [9], in turn, some methods based on subspaces were introduced. These methods, in addition to their enormous complexity, exhibit severe robustness problems, being thus hardly suited for practical implementations.

Some other identification methods, in spite of their complexity, are robust enough to be considered for practical implementations. The channel identification method proposed in [4], for instance, performs channel parameter identification exploiting the interference randomization induced by long-code scrambling. Some methods based on the MSNIR (maximum signal to noise and interference ratio) criterion [10] allow direct determination of steering vectors, at the cost of performing the generalized eigenvalue decomposition of two matrices (namely, the covariance matrices of the signal from the user of interest and from the interferers jointly).

In this work, we implement new semi-blind multichannel equalization methods suitable for long-coded CDMA systems. This report is organized as follows: in Section II, we describe the W-CDMA signal model and in Section III the algorithms we employed in our simulations. In Section IV, we present some simulation results and, finally, in Section V, we draw some conclusions.

II. W-CDMA Signal Model

The W-CDMA system physical layer specifications ([11], [12], [13]) are defined by the TSG-RAN WG1 technical specification group, being available for download from the 3GPP web site. The WCDMA signal model is very complex, in the sense that for a given transmission data rate, several radio configurations are possible, e.g, one can choose between short or long spreading codes, having a single-coded or a multi-coded system, etc. In this work, we restricted ourselves to signal model described in Fig.s 1 and 2, which constitutes a subset of the standard specifications.

According to this model, the user data stream s_k is spread by the DPDCH (dedicated physical data channel) channelization code, with processing gain G. The control bit stream b_k (which includes the pilot symbols), in turn, is spread by the DPCCH (dedicated physical control channel) channelization

The authors are with the Telecommunications and Control Department - Escola Politécnica - Universidade de São Paulo - Av. Prof. Luciano Gualberto, trav. 3, 158 - São Paulo - CEP 05508-900 - Brazil. E-mail: {bordin, baccala, barbin}@lcs.poli.usp.br. Funding for this study was provided by Ericsson Research via Ericsson/USP-13 project entitled Smart Antennas for 3G Systems.

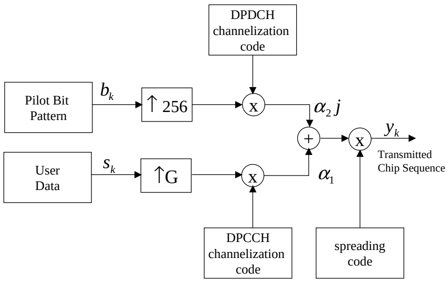

Fig. 1. WCDMA uplink transmitter model used in the simulations; here G is the interest user processing gain (which is restricted to be a power of 2) and α_1 and α_2 are constants adjusted by higher protocol layers (these constants are restricted to be multiples of $1/15$). DPDCH and DPCCH stand respectively for Dedicated Physical Data Channel and Dedicated Physical Control Channel.

code, now with processing gain 256. Both signals are added, and the result is scrambled with a long complex pseudo-noise code, whose generation is described in [13]. The resulting complex discrete-time y_k signal is transmitted as an ordinary QPSK signal $y(t)$: the real part of y_k modulates the in-phase component of $y(t)$ and its imaginary part modulates the quadrature component (Fig. 2).

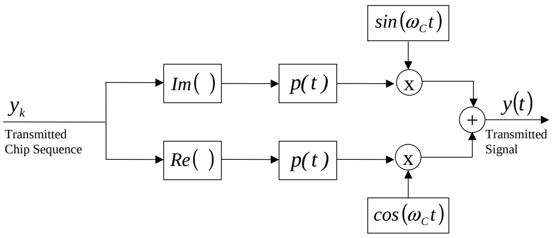

Fig. 2. WCDMA uplink modulator: real and imaginary parts of y_k are mapped respectively onto the in-phase and the quadrature components of $y(t)$; the standardized pulse shaping filter $p(t)$ has a square-root raised cosine response with .22 roll-off factor. Here, ω_C is the carrier frequency.

The transmitted signal $y(t)$ then propagates through the wireless medium between the mobile unit and the base station, where it is received by an L element sensor array. Assuming that the transmission medium is linear and slowly time-varying, the i−th element received signal $r^{(i)}(t)$ can be given by the model described in Fig. 3. There, $h^{(i)}(t)$ models the impulse response of the channel between the transmitter and the i−th receiver input, which is assumed to have finite support. In turn, $n^{(i)}(t)$ models the additive noise contribution to the i−th receiver output signal. The additive noise is assumed white, gaussian and spatially uniform.

III. Space-Time Rake Receivers

The concept of Rake receivers was developed in the early sixties in the context of analog communications as a way of exploiting the time diversity provided by multipath communication channels [14]. This concept was later extended to the spread spectrum communications context, where it refers to any receiver which obtains transmitted symbols estimates combining components of the received signal despread at different delays.

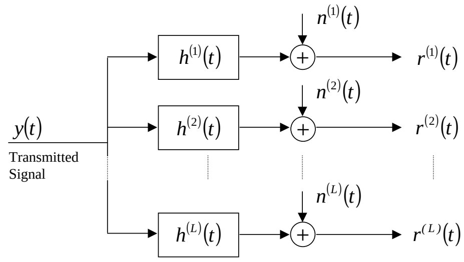

Fig. 3. SIMO system resulting from multi-antenna reception; here, $h^{(i)}(t)$ is the impulse response of the channel between the transmitter and the i−th receiver output, $r^{(i)}(t)$ is the i−th receiver output signal and, $n^{(i)}(t)$ is the additive noise contribution to the i−th receiver output signal.

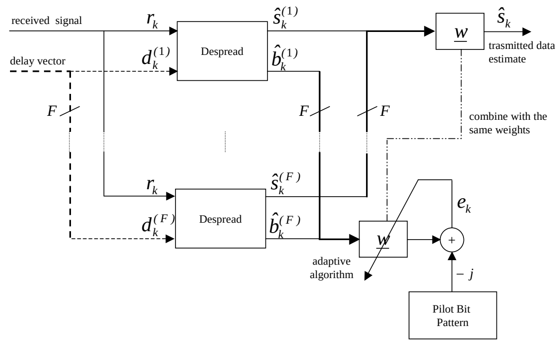

Fig. 4. Discrete time 1-D (time only) rake MMSE receiver with F fingers. The weight vector $\underline{w}$ is adapted in order to minimize the error e_k.

The despread components can be combined in different manners, the most common being equal ratio combining (where the despread components as simply added up without any weighting), maximum ratio combing (the components are weighted proportionally to their individual signal-to-noise ratios) and minimum-mean square error (MMSE) combining. This last approach provides optimum performance, but is computationally more demanding. It can be also shown that this structure is indeed a chip-level equalizer, in which only some selected "taps" are used [4]. The combining vector can be estimated in batch or using traditional RLS or LMS adaptive algorithms.

In Fig. 4, we depict the structure of an F finger MMSE rake receiver. This approach has the additional advantage of automatically solving the carrier phase estimation problem.

Preferably, the F fingers must be chosen among the ones of largest power. However, specially for rapidly varying channels, one must cope with phase estimation problem: each despread component cannot be combined while its phase is not effectively estimated. In our simulations, we addressed this issue by employing the following algorithm: a total of C, $C > F$ fingers are initially selected for the "candidate set". Once one of the fingers belonging to the candidate set becomes one of the F most powerful fingers, it enters the "active set" of the F fingers effectively combined, remaining there until it becomes weaker than the C most powerful fingers. In our simulations, we made $C = 5$ and $F = 3$ respectively.

The concept of rake combining can be easily extended to the space-time case, as shown in Fig. 5. In this case, a total of LF fingers are combined, being F fingers for each of the L an

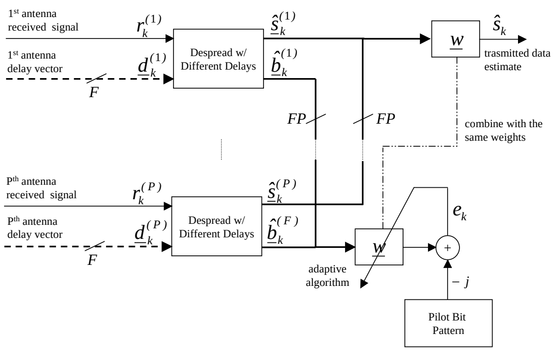

Fig. 5. Discrete time 2-D rake MMSE receiver with F fingers. The weight vector $\underline{w}$ is adapted in order to minimize the error e_k.

In addition to the MMSE 2-D rake combiner, we also developed another scheme based on fixed beamforming, where the outputs of F fixed beamformers (each despreading the signal at a different delay) are equal-ratio combined (added up). The performance of both schemes is presented in Section IV.

A. Semi-Blind Approaches

The MMSE spatial and spatio-temporal beamforming algorithms presented in Section III rely on known pilot symbols for steering vectors estimation. In a practical situation, it is desirable for the sake of power efficiency to maintain the pilot (control channel) power as low as possible. This makes steering vector estimation a hard task, since adaptive algorithms will have to operate at very low signal-to-noise ratios.

If both data and control channel bits are used in the steering vector estimation, it can be easily shown that the estimation procedure becomes statistically more efficient, that is, these vectors could be estimated with smaller variance (see e.g. [15]). In the next sections, we describe three semi-blind spatio-temporal beamforming approaches, which are later implemented for performance evaluation under realistic situations.

1) MSINR criterion based algorithm: Several multiuser detection algorithms known in the literature are based on the MSINR (Maximum Signal to Interference and Noise Ratio) optimization criterion. According to this criterion, the weights $\underline{w}$ are determined in order to maximize the ratio of the desired signal power by the interference plus noise after rake combining:

$$\hat{\underline{w}} = \arg\max_{\underline{w}} \frac{\underline{w}^H R_S \underline{w}}{\underline{w}^H R_F \underline{w}} \tag{1}$$

where $R_S \triangleq Ess^H$ and $R_F \triangleq Eff^H$ are respectively the covariance matrices of the desired signal (user data estimates) and the undesired signal (interference and noise) and $\underline{w}$ is a vector which groups the 2-D rake receiver weights:

$$r = \begin{bmatrix} \underline{r}_k^{(1)} \\ \vdots \\ \underline{r}_k^{(L)} \end{bmatrix} \quad f = \begin{bmatrix} \hat{\underline{f}}_k^{(1)} \\ \vdots \\ \hat{\underline{f}}_k^{(L)} \end{bmatrix} \quad r, f \in \mathbb{C}^{LF\times 1} \tag{2}$$

where L is the number of sensors, F is the number of rake receiver fingers, vectors $\hat{\underline{s}}_k^{(i)}$ is defined in Fig. 5, and $\hat{\underline{f}}_k^{(i)}$ collects the noise plus interference estimates.

In our simulations, we estimated the interference plus noise component through a slight modification of the "code gated" procedure [10]. The solution to the problem given in Eq. 1 can be determined by solving the so-called generalized eigenvector problem. In particular, one must select among the vectors $\underline{w}$ that satisfy

$$R_S \underline{w} = \lambda R_F \underline{w} \ , \tag{3}$$

the one which maximizes λ.

As one may notice, the weight vector $\underline{w}$ is determined blindly, since the knowledge about the pilot bits was not exploited. These weights are thus insensitive to carrier phase rotations. Therefore, the carrier phase must be determined using the pilot symbols. Fortunately, this is a simple task, which can be accomplished by a single-tap adaptive filter.

2) Identification based approach: Scanning the literature, one can find very few blind identification approaches which are applicable to CDMA systems with long-coded spreading sequences. Among these algorithms, the one presented in [4] exhibits at least two favorable qualities:

- Parameter estimation variance is not affected by mismatches between the real and the assumed channel order.
- There are no identifiability conditions, that is, there is no particular channel parameter set which makes the estimated parameters biased.

The algorithm proposed in [4] makes three restrictive assumptions:

- The spreading sequence is well approximated by an i.i.d (independent and identically distributed) sequence.
- The system noise is zero-mean and white, both temporally and spatially.
- The transmitted data is i.i.d.

Under these assumptions, a vector r proportional to the channel parameters vector can be estimated as the principal eigenvector of $R_S - R_R$, where $R_R \triangleq Err^H$ is the received signal covariance matrix and $R_S \triangleq Ess^H$ is the despread signal covariance matrix:

$$r = \begin{bmatrix} \underline{r}_k^{(1)} \\ \vdots \\ \underline{r}_k^{(L)} \end{bmatrix} \quad s = \begin{bmatrix} \hat{\underline{s}}_k^{(1)} \\ \vdots \\ \hat{\underline{s}}_k^{(L)} \end{bmatrix} \quad r, s \in \mathbb{C}^{LF\times 1} \tag{4}$$

where L is the number of sensors, F is the number of rake receiver fingers and the vectors $\hat{\underline{s}}_k^{(i)}$ and $\underline{r}_k^{(i)}$ are defined in Fig. 5.

From r, an estimate of the optimal weights $\underline{w}$ can be readily obtained as $w = R_R^{-1} r$. Again, the weight vector $\underline{w}$ is determined blindly, and one must determine and compensate for carrier phase rotations using the pilot symbols.

3) Combined cost function (CCF) approach: As previously mentioned, W-CDMA receivers cannot be "blind", since the phase ambiguity inherent to blind identification or equalization processes precludes coherent detection. However, a good receiver must exploit all available channel information in order to enhance channel or equalizer estimates. To this aim, several approaches can be taken: in this and in the following sections, we propose two different cost functions for the determination of the rake weights $\underline{w}$ which do not rely exclusively on pilot bits.

In a first approach, the weights $\underline{w}$ are determined so that:

$$\underline{\hat{w}} = \arg\min_{\underline{w}} \ E\left\{|\underline{w}^H b - b_k|^2 + \alpha|\underline{w}^H f|^2\right\} \tag{5}$$

where α is a positive constant, f the vector collecting the noise plus interference estimates (Eq. 2), b_k is the pilot bit at the instant k, and b is defined as:

$$b = \begin{bmatrix} \underline{b}_k^{(1)} \\ \vdots \\ \underline{b}_k^{(L)} \end{bmatrix} \quad b \in \mathbb{C}^{LF\times 1} \tag{6}$$

and the vectors $\underline{b}_k^{(i)}$ are defined in Fig. 5.

The cost function defined in Eq. 5 punishes errors in pilot bit estimation as well as in the interference amplification due to rake combination. Solving for $\underline{w}$ we obtain:

$$\underline{w} = (R_S + \alpha R_F)^{-1} R_{SB} \tag{7}$$

where $R_{SB} \triangleq E s b_k^*$ and R_F was defined in Sec. III-A.1.

As one may notice, this solution is identical to the traditional pilot-based least-squares solution. The only difference is that the data covariance matrix is "regularized" with the term αR_F, which represents the interference plus noise covariance matrix. For that reason, the solution given in Eq. 7 can be easily put into an adaptive form: the matrices $P \triangleq (R_S + \alpha R_F)^{-1}$ and R_{SB} can be updated as follows:

$$\begin{aligned} \check{P} &= \mu^{-1}P - \frac{\mu^{-2}P\hat{z}\hat{z}^H P}{1+\mu^{-1}\hat{z}P\hat{z}} \\ \check{R}_{SB} &= \mu R_{SB} + \hat{s}b_k^* \end{aligned} \tag{8}$$

where the $\check{P}$ and $\check{R}_{SB}$ are the updated quantities and $\hat{z} \triangleq \hat{s} + \sqrt{\alpha}\hat{f}$.

4) Constrained Least-Squares Approach: Another possible approach for estimating the weight vector $\underline{w}$ is the following:

$$\underline{\hat{w}} = \arg\min_{\underline{w}} \ E|\underline{w}^H \hat{f}|^2 \quad \text{subject to} \quad \underline{w}^H\hat{b} = b_k \tag{9}$$

where b_k is the pilot bit sequence.

In this case, one wishes to minimize the rake receiver noise plus interference amplification subject to the (deterministic) constraint that there is no error in estimation the pilot bits b_k. The solutions to Eq. 9 can be obtained through the Lagrange multiplier method, by minimizing the cost function $J(w)$, defined as:

$$J(w) = \underline{w}^H R_F \underline{w} + Re\left\{\lambda^*(\underline{w}^H\hat{b} - b_k)\right\} \tag{10}$$

Taking the derivatives of both sides of Eq. 10, we get:

$$\frac{\partial J(\underline{w})}{\partial \underline{w}} = R_F\underline{w} + \lambda\hat{b} \ \Rightarrow \ \underline{\hat{w}} = R_F^{-1}\hat{b}\lambda \tag{11}$$

Imposing the constraints, we can now solve for λ:

$$\underline{w}^H\hat{b} = \lambda^*\hat{b}^H R_F^{-1}\hat{b} = p_k \quad \Rightarrow \quad \lambda = \frac{b_k^*}{\hat{b}^H R_F^{-1}\hat{b}} \tag{12}$$

Thus

$$\underline{\hat{w}} = \frac{R_F^{-1}\hat{b}b_k^*}{\hat{b}^H R_F^{-1}\hat{b}} \tag{13}$$

The estimate $\hat{w}$ depends on the instantaneous values of $\hat{b}$ and b_k, being thus very noisy. In a heuristic procedure, one may take expectations on both sides, obtaining:

$$\underline{\bar{w}} = \frac{R_F^{-1}R_{BB}}{R_{BF}} \tag{14}$$

where $R_{BB} \triangleq E\,\hat{b}b_k^*$ and $R_{BF} \triangleq E\,\hat{b}R_F^{-1}\hat{b}^H$.

These latter quantities can be easily estimated through an exponentially weighted approach:

$$\begin{aligned} \check{R}_F^{-1} &= \mu^{-1}R_F^{-1} - \frac{\mu^{-2}R_F^{-1}\hat{f}\hat{f}^H R_F^{-1}}{1+\mu^{-1}\hat{f}R_F^{-1}\hat{f}} \\ \check{R}_{BB} &= \mu R_{BB} + \hat{b}b_k^* \\ \check{R}_{BF} &= \mu R_{BF} + \hat{b}^H R_F^{-1}\hat{b} \end{aligned} \tag{15}$$

where the $\check{}$ sign indicates updated quantities and $\mu < 1$ is a positive constant.

The algorithm defined in Eq. 14 and 15 has a computational complexity that is proportional to the square of the vector $\underline{w}$ dimension, which does not pose a serious problem in typical scenarios.

IV. Simulation Results

We evaluated the performance of the proposed space-time algorithms by Monte Carlo simulations in which we measured the uplink raw (without coding) bit error rate. The software we developed produces a W-CDMA compliant signal, as described in Sec. II. This signal passes through a multichannel discrete-time time-varying filter that simulates a multipath propagation environment based on the COST-259 spatial channel model.

The following scenarios [16] were adopted for performance evaluation:

- Reference Speech Scenario:
  In this scenario, the users (100 using speech services) are distributed uniformly across the cell sectors, moving at speeds that do not exceed 5 km/h. The propagation channels were obtained from the "Bad Urban" COST-259 scenario.
- Reference Data:
  Now, differently from the former scenario, 30% of the mobile units use low data rate services (LDR) and 20% high data rate services (HDR) (see Table I for service parameters).
- Rural:
  This scenario differs from the first only in that the mobile units speed can now achieve 50 km/h and the propagation channels are obtained from the "Rural" COST-259 scenario.

In all simulations we assumed perfect power control: the mean (taken over the array elements) power received from the $i-$th user is forced to equal $128/G_i$, where G_i is the $i-$th user processing gain. The intracell interference, in turn,

Service	Effective Data Rate (kbps)	Convolutional Code Rate	Raw Data Rate (kbps)	Processing Gain
Speech	12.2	1/2	30	128
LDR	32	1/3	120	32
HDR	144	1/3	480	8

TABLE I

PARAMETERS ADOPTED FOR EACH RADIO CONFIGURATION

is modeled as a spatially uniform white circular gaussian noise with variance $\sigma^2 = 10$. As a reference, we adopted that system capacity is achieved when the raw bit error rate of any user exceeds 5%.

In Fig. 6 we show the mean (over 30 independent realizations) raw bit error rate obtained for the algorithms described in Section III under the "reference speech" scenario, as a function of the number of interfering users in the cell. In each realization, 10 signal frames (100 ms) are transmitted and demodulated. The transmission channels are evaluated 10 times per frame (every 1 ms) and interpolated.

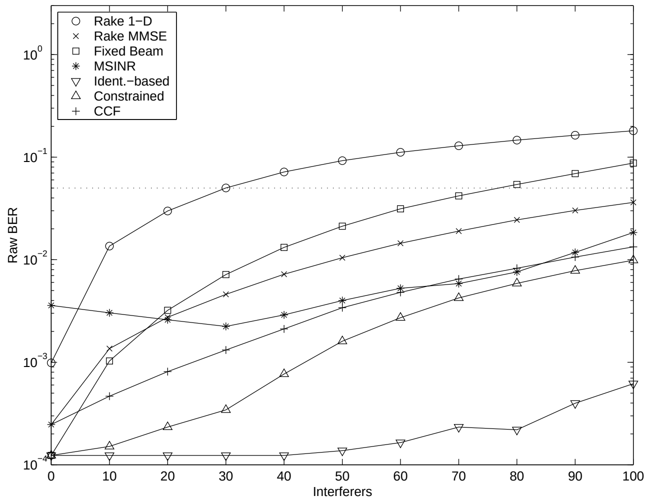

Fig. 6. Mean raw bit error rate obtained under the "reference speech" scenario, as a function of the number of interfering users in the cell, employing a Rake 1-D receiver (○) and the following 2-D Rake schemes: MMSE (×), Fixed Beam (□), MSINR (∗), Identification-based (▽), Constrained Least-Squares (△) and Combined Cost Function (+).

As one may notice from Fig. 6, system capacity is limited to about 30 users if spatial diversity is not exploited. In this scenario, system capacity exceeded 100 users for all spatio-temporal algorithms, except the fixed-beam based. The bit error rates obtained, however, were much lower for the semi-blind algorithms.

In the next three figures, we show the results obtained under the "reference speech" scenario. In these simulations, the interfering users are added in groups comprising 10 mobile units: 2 high data rate, 3 low data rate and 5 speech users. In Fig. 7, we show the results regarding the high data rate users.

From Fig. 7, one may notice that the Rake 1-D receiver supports no more than a single high data rate user per cell under this scenario. One may also notice that the fixed beam algorithm performed reasonably, increasing the total

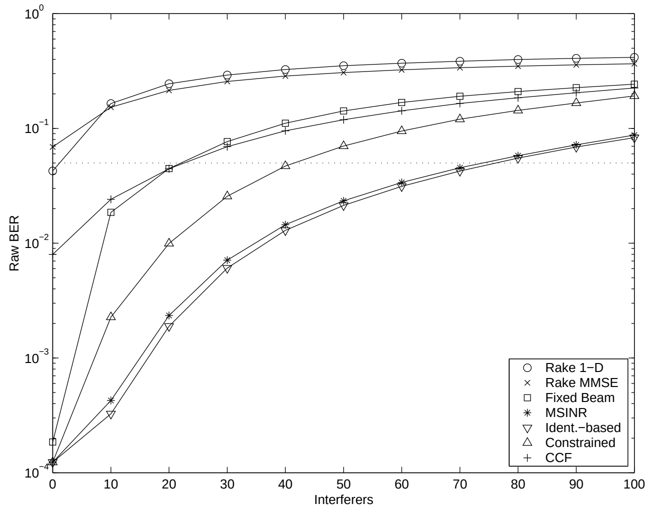

Fig. 7. Mean raw bit error rate obtained under the "reference data" scenario for the high data rate users, as a function of the number of interfering users in the cell, employing a Rake 1-D receiver (○) and the following 2-D Rake schemes: MMSE (×), Fixed Beam (□), MSINR (∗), Identification-based (▽), Constrained Least-Squares (△) and Combined Cost Function (+).

system capacity to about 20 users. Nevertheless, the semi-blind algorithms led to an even larger capacity increase: about 70 users are supported when the identification-based algorithm (Sec. III-A.2) is employed. In Figs. 8 and 9, we show the results of the same experiment, now measuring the error rates observed for the low data rate and speech users, respectively.

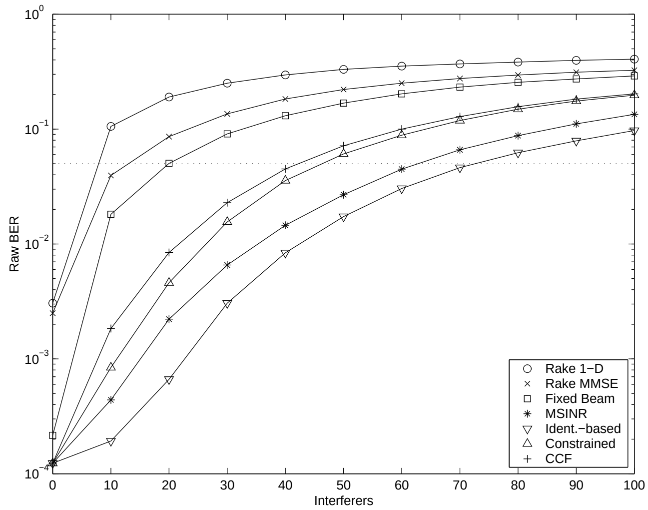

Fig. 8. Mean raw bit error rate obtained under the "reference data" scenario for the low data rate users, as a function of the number of interfering users in the cell, employing a Rake 1-D receiver (○) and the following 2-D Rake schemes: MMSE (×), Fixed Beam (□), MSINR (∗), Identification-based (▽), Constrained Least-Squares (△) and Combined Cost Function (+).

The results presented in Figs. 8 and 9 are qualitatively equivalent to the results shown in Fig. 7. However, comparing them, we can notice that the overall system capacity under the "reference data" scenario is limited by the error rates observed by the speech (lowest rate) users, a "non-intuitive" result that deserves further investigation. In Fig. 10, we finally present

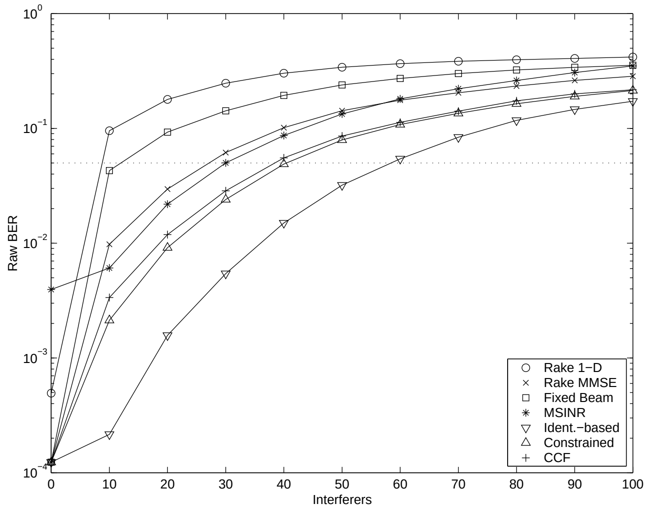

Fig. 9. Mean raw bit error rate obtained under the "reference data" scenario for the speech users, as a function of the number of interfering users in the cell, employing a Rake 1-D receiver (○) and the following 2-D Rake schemes: MMSE (×), Fixed Beam (□), MSINR (∗), Identification-based (▽), Constrained Least-Squares (△) and Combined Cost Function (+).

the performances obtained under the "rural" scenario. Under this scenario, the mobiles move at most at 50 km/h, and only speech services are used. Now, the COST-259 propagation scenario is set to "rural".

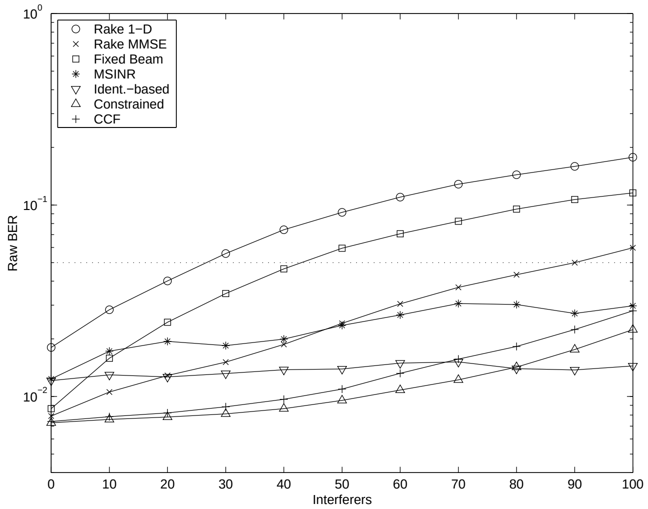

Fig. 10. Mean raw bit error rate obtained under the "rural" scenario, as a function of the number of interfering users in the cell, employing a Rake 1-D receiver (○) and the following 2-D Rake schemes: MMSE (×), Fixed Beam (□), MSINR (∗), Identification-based (▽), Constrained Least-Squares (△) and Combined Cost Function (+).

Under this scenario, mobile unit high speeds induces fast propagation channel variations, impacting the error rates observed for all algorithms. Interestingly, under this scenario the proposed adaptive algorithms perform better than the identification-based and the MSINR batch algorithms over a wide range of interference intensities. It is important to notice, however, that the employment of semi-blind algorithms did not enhance the overall system capacity as in the other scenarios.

V. Conclusions

In this work, we examined the problem of multichannel equalization/identification for W-CDMA systems employing long codes. We developed four semi-blind algorithms and compared their performance with that exhibited by the most common approaches. We verified through numerical simulations, employing the COST-259 channel propagation model, that classical pilot-based approaches do not allow W-CDMA systems to achieve satisfactory capacity, specially in the presence of high data rate users, and that the proposed semi-blind approaches performed robustly, leading in general to much smaller error rates.

Acknowledgments

We would like to thank Prof. Luiz C. Trintinalia for his helpful suggestions in the implementation of the simulation programs.

References

[1] X. Wang and H. V. Poor, "Blind multiuser detection: a subspace approach," *IEEE Journal on Selected Areas in Communications*, vol. 44, no. 2, Mar. 1998.

[2] U. Mitra, "Comparison of maximum likelihood-based detection for two multi-rate access schemes for cdma signals," *IEEE Transactions on Communications*, vol. 86, no. 1, pp. 64–77, Jan. 1999.

[3] S. Parkvall, "Variability of user performance in cellular ds-cdma - long versus short spreading sequences," *IEEE Transactions on Communications*, vol. 48, no. 7, July 2000.

[4] H. Liu and M. D. Zoltowski, "Blind equalization in antenna array cdma systems," *IEEE Transactions on Signal Processing*, vol. 45, no. 1, Jan. 1997.

[5] Z. Xu and M. K. Tsatsanis, "Blind channel estimation for multiuser cdma systems with long spreading codes," in *IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP 99)*, vol. 5, 1999, pp. 2531–2534.

[6] Z. Yang and X. Wang, "Blind turbo multiuser detection for long-code multipath cdma," *IEEE Transactions on Communications*, vol. 50, no. 1, Jan. 2002.

[7] ——, "Blind multiuser detection for long-code multipath cdma," in *Conf. Rec. of the Thirty-Fourth Asilomar Conference on Signals, Systems and Computers*, vol. 2, 2000, pp. 1148–1152.

[8] M. Torlak, B. L. Evans, and G. Xu, "Blind estimation of fir channels in cdma systems with aperiodic spreading sequences," in *Conf. Record of the 31st Asilomar Conf. on Signals, Systems and Computers*, Pacific Grove, CA, 1997, pp. 495–499.

[9] A. J. Weiss and B. Friedlander, "Channel estimation for ds-cdma downlink with aperiodic spreading codes," *IEEE Transactions on Communications*, vol. 47, no. 10, pp. 1561–1569, Oct. 1999.

[10] S. Choi and D. Shim, "A novel adaptive beamforming algorithm for a smart antenna system in a cdma mobile communication environment," *IEEE Transactions on Vehicular Technology*, vol. 48, no. 5, Sept. 2000.

[11] *Technical Specification Group Radio Access Network - Physical channels and mapping of transport channels onto physical channels (FDD) - Release 5*, 3^{rd} Generation Partnership Project Std. 3GPP TS 25.211 V5.0.0 (2002-03), 2002.

[12] *Technical Specification Group Radio Access Network - Multiplexing and channel coding (FDD) - Release 5*, 3^{rd} Generation Partnership Project Std. 3GPP TS 25.212 V5.0.0 (2002-03), 2002.

[13] *Technical Specification Group Radio Access Network - Multiplexing Spreading and modulation (FDD) - Release 5*, 3^{rd} Generation Partnership Project Std. 3GPP TS 25.213 V5.0.0 (2002-03), 2002.

[14] J. G. Proakis, *Digital Communications*. New York, NY: McGraw-Hill, 1995.

[15] A. H. Sayed, T. Kailath, and B. Hassibi, *Linear Estimation*. Upper Saddle River, N.J: Prentice Hall, 2000.

[16] B. Göransson, B. Hagerman, and J. Barta, "Adaptive antennas in wcdma systems - link level simulation results based on typical user scenarios," in *Proceedings of the IEEE Vehicular Technology Conference*, 2000, pp. 157–164.