

# Inter-Cell Interference Cancellation in CDMA Array Systems by Independent Component Analysis

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**Abstract**—The most important use of a spread spectrum communication system is that of interference mitigation. In fact, a spread spectrum communication system has an inherent temporal interference mitigation capability, usually called a processing gain. This gain enables the system to work properly in many cases. At times, however, the interference can be too strong, or the requirements for the link quality are more stringent, so that additional interference mitigation is needed.

In a cellular network the interference originating from the neighboring cells, called inter-cell interference, is one of the reasons for the need for additional interference mitigation capability in a receiver. In this paper we consider Independent Component Analysis (ICA) for the mitigation of inter-cell interference. Namely, we consider the use of ICA as an advanced pre-processing tool, which first mitigates the interference from the received array data and passes the residual signal for the conventional detection. Numerical experiments are given to evaluate the performance of two variants of the ICA-assisted receiver chains. They indicate clear performance gains in comparison to conventional detection without interference mitigation. In addition, the ICA-assisted receiver chains are robust against the fluctuations in the loads of the cells, which is an important feature in practice.

## I. INTRODUCTION

In wireless spread spectrum (SS) communication systems bandwidth expansion gives an inherent temporal interference suppression capability, usually called a processing gain. In many cases this gain is sufficient for the system to work properly. At times, however, additional interference capability is needed. First of all, bandwidth expansion results in bandwidth dependent suppression capability. It is quite understandable that due to the other existing wireless system, one cannot enlarge the bandwidth infinitely. Secondly, even though the system might work properly with no additional interference suppression, it usually works much better if such an additional capability is utilized. Thus, interference mitigation techniques can be used for either maintaining or improving the reliability of communications without the need for a wider spectrum.

Interference mitigation techniques in SS communications have been studied extensively in the past due to the inevitable gains in system performance and capacity [7]. In commercial cellular SS systems, like the systems based on direct sequence code division multiple access (DS-CDMA) [16], many types of interferences can appear, starting from multiuser interference inside each sector in a cell to inter-operator interference.

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Also unintentional jamming can be present due to co-existing systems at the same band, whereas intentional jamming arises mainly in military applications.

In DS-CDMA systems, the conventional RAKE receiver [8] is used widely in practice when multi-path scenario is present. This is because it is usually more robust against model imperfections and nonstationarities than more sophisticated receiver structures discussed for example in [6], [15]. However, RAKE is based only on the processing gain and frequency diversity, and hence it is vulnerable in the presence of higher interferences. Additional interference capability can be gained by the use of multiple antenna sensors utilizing spatial diversity. Multiple sensors enable the use of directional antennas, which can point their beam to a specific direction for reducing the interference level for a desired user. Direction-of-arrival (DOA) estimation thus becomes a prerequisite task for conventional array receivers.

Standard DOA estimation techniques require exact prior knowledge of the positions of the receiving antenna sensors. Blind techniques [3], [4], [5] relax this stringent requirement, making it possible to achieve performance gains when applied to uncalibrated arrays in which the positions of the sensors are known only roughly or not at all. Most blind techniques are based on the assumption that the original information (source) signals are statistically independent of each other. This assumption is quite realistic here, because the signals originating from different cells are typically independent.

Belouchrani and Amin [1] were the first to present the idea of applying blind source separation (BSS) techniques to aid conventional detection in array reception. They used BSS techniques to separate a set of independent information signals from their DOA dependent mixtures observed at the sensors. In [13], [11], [9], [14], [10] this framework was further developed. First of all, BSS based on independent component analysis was utilized to make the receiver chain applicable in separation of uncorrelated sources, which is usually the case due to data modulation. In addition, jamming or interfering signals can be temporally uncorrelated, too. Also, different types of switching strategies between ICA and conventional detection were developed and evaluated. The goal there was to activate ICA processing only when it is expected to improve the performance of the whole receiver chain.

In this paper we apply the ICA-assisted receiver chains in a more realistic setting. Namely, a piece of a cellular network is considered, where the mitigation of the interference originat-

ing from the neighboring cells are of primary interest. Numerical experiments are given to evaluate the achieved performance gains.

## II. DATA MODEL

A cellular spread spectrum network with direct sequence spreading is assumed. Without loss of generality, we consider here a downlink channel (for example base-to-mobile), and thus the data sent by one base station, describing the received block of  $M$  symbols is of the form [6], [15]

$$r(t) = \sum_{m=1}^M \sum_{k=1}^K a_m b_{km} s_k(t - mT - d) + n(t) \quad (1)$$

where the symbols  $b_{km}$  are sent to  $K$  users via a channel characterized by a complex path gain  $a_m$  and a path delay  $d$ . It is assumed that the delay  $d$  is discrete,  $d \in \{0, \dots, (C-1)/2\}$ , and remains constant for every block of  $M$  data symbols. Furthermore,  $s_k(\cdot)$  is  $k$ th user's binary chip sequence, supported by  $[0, T)$ , where  $T$  is the symbol duration, and  $n(t)$  is Gaussian noise.

Suppose the signal  $r(t)$  in (1) describes the cell of interest. The interference originating from the users of neighboring cell can be expressed as

$$j_\xi(t) = \sum_{\xi, m} a_\xi b_{\xi m} \left( \frac{r_{\xi_1}}{r_{\xi_2}} \right)^{\nu/2} 10^{\frac{\chi_{\xi_1} - \chi_{\xi_2}}{20}} s_\xi(t - mT - d_\xi) \quad (2)$$

Here the users are labeled with a symbol  $\xi$ , regardless of the cell where the user is. The complex path gain  $a_\xi$  includes the target signal strength.  $r_{\xi_1}$  and  $r_{\xi_2}$  tells the distance of a user  $\xi$  to its own base station and to the base station of interest, respectively. Parameter  $\nu$  indicates the power loss; here a fourth order law is assumed ( $\nu = 4$ ). The shadowing terms for the  $\xi$ th user, describing the attenuation due to buildings etc., are modeled as log-normally distributed random variables and constant over the observations interval, and therefore, the variables  $\chi_{n_1}$  and  $\chi_{n_2}$  are independent Gaussian random variables.

Assuming an antenna array, the received signal at the  $n$ th antenna element ( $n = 1, \dots, N$ ) before the down-conversion can be written as

$$u_n(t) = r(t)e^{j2\pi f_c t} e^{j(n-1)\theta_r} + \sum_{\xi} j_\xi(t) e^{j2\pi f_\xi t} e^{j(n-1)\theta_\xi} \quad (3)$$

where the baseband spread spectrum signals  $r(t)$  and  $j_\xi(t)$  are DSB modulated at the carrier frequencies  $f_c$  and  $f_\xi$ , respectively. Variables  $\theta_r$  and  $\theta_\xi$  are related to the directions of arrival of the information bearing signal  $r(t)$  and the out-of-cell interference signals  $j_\xi(t)$  respectively, and their form depends on the antenna configuration.

This signal is down-converted to the baseband, yielding

$$r_n(t) = u_n(t) e^{-j2\pi f_c t} = r(t) e^{j(n-1)\theta_r} + \sum_{\xi} j_\xi(t) e^{j2\pi(f_\xi - f_c)t} e^{j(n-1)\theta_\xi} \quad (4)$$

where, without loss of generality, the carriers have the same initial phase. In practice, the interfering signals  $j_\xi(t)$  arrive

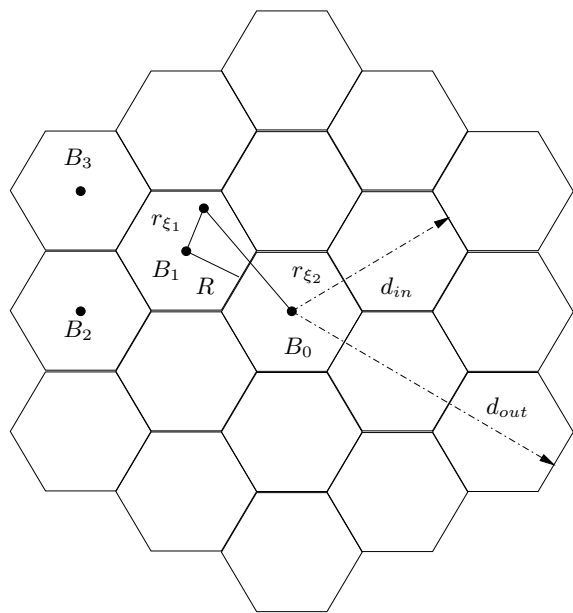


Fig. 1. Macro-cell geometry with a physical layout of the cell-of-interest and the first two layers of interfering cells. The inner layer of interfering cells is within a radius  $d_{in} = 2000$  m while the outer layer is within a distance of  $d_{out} = 3300$  m.

from somewhat different directions  $\theta_\xi$ , which may be closer or farther away from each other depending on the situation. The interferences are often fairly weak, and their sum constitutes a kind of additive noise term which disturbs reception of the information signal  $r(t)$ . In this paper, we make the simplifying assumption that the interfering signals  $\theta_\xi$  all come from the same ‘‘average’’ direction  $\theta_q$ . Then the last term in Eq. (4) can be expressed in simpler form as

$$q(t) e^{j(n-1)\theta_q} \quad (5)$$

where  $q(t)$  is the combined interfering signal:

$$q(t) = \sum_{\xi} j_\xi(t) e^{j2\pi(f_\xi - f_c)t} \quad (6)$$

Using these definitions the received antenna data  $r(t)$  can be represented more concisely in vector form as

$$\mathbf{r}(t) = \Theta \mathbf{z}(t) + \mathbf{n}(t) \quad (7)$$

where the vector

$$\mathbf{r}(t) = [r_1(t) r_2(t) \dots r_N(t)]^T \quad (8)$$

contains the signals received at the  $N$  array elements at time  $t$ ,

$$\mathbf{z}(t) = [r(t) q(t)]^T \quad (9)$$

is a vector having as its elements the information signal  $r(t)$  and down-converted combined interfering signal  $q(t)$  at time  $t$ , and the array steering matrix

$$\Theta = \begin{bmatrix} 1 & 1 \\ e^{j\theta_r} & e^{j\theta_q} \\ \vdots & \vdots \\ e^{j(N-1)\theta_r} & e^{j(N-1)\theta_q} \end{bmatrix} \quad (10)$$

The  $N$ -vector  $\mathbf{n}(t)$  is similar in form to (8), containing additive white Gaussian noise (AWGN) terms  $n_i(t)$  at each antenna element  $i$ .

### III. INDEPENDENT COMPONENT ANALYSIS

Independent Component Analysis (ICA) [5] is a fairly new statistical technique which has recently drawn a lot of attention. The goal of ICA is to express a set of observed signals or random variables as linear combinations of statistically independent components, which are often called sources or source signals. In standard linear ICA, the  $m$  observed signals  $x_1(t), \dots, x_m(t)$  at the time instant  $t$  are assumed to be linear combinations of  $n$  unknown but statistically independent source signals  $s_1(t), \dots, s_n(t)$  at the time  $t$ . The ICA problem is blind, because not only the source signals but also the mixing coefficients are unknown.

We introduce the data vector  $\mathbf{x}(t) = [x_1(t), \dots, x_m(t)]^T$  for the observed signals  $x_i(t)$  at time  $t$ , and the source vector  $\mathbf{s}(t) = [s_1(t), \dots, s_n(t)]^T$  for the source signals  $s_j(t)$ . Then the instantaneous noisy linear ICA mixture model is given by

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{n}(t) \quad (11)$$

Here the  $m \times n$  unknown but constant mixing matrix  $\mathbf{A}$  contains the mixing coefficients, and  $\mathbf{n}(t)$  denotes the additive noise vector at time  $t$ . We make the standard assumptions that  $\mathbf{A}$  has full rank, and that  $n \leq m$ , meaning that there are at most as many source signals  $s_j(t)$  as mixtures  $x_i(t)$ .

The source signals  $\mathbf{s}(t)$  are estimated using only the observations  $\mathbf{x}(t)$  by finding an  $n \times m$  unmixing matrix  $\mathbf{W}$ . This matrix should be such that the  $n$ -vector  $\mathbf{W}\mathbf{x}(t)$  recovers the set of original sources as well as possible. Because of the blindness of the problem, only the waveforms of the sources can be estimated. For estimating the unmixing (separating) matrix  $\mathbf{W}$ , many different methods have been proposed [5]. Most of these are ICA methods exploiting the statistical independence of the sources, but there exist other approaches which utilize temporal correlations or nonstationarity of the sources. The mutual performance of these methods depends largely on the validity of the assumptions made on them in the problem at hand.

A comparison of the array signal model (7) with the mixing model (11) shows immediately that (7) is actually a noisy mixing model with a mixing matrix  $\Theta$  and source vector  $\mathbf{z}(t)$ . Hence ICA or other BSS techniques can be applied to separation of the information signal  $r(t)$  and inter-cell interference signal  $q(t)$ . Estimates of these signals are obtained as the components of the two-dimensional vector  $\mathbf{W}\mathbf{r}(t)$ , but their order and scaling is arbitrary.

In our experiments, we applied the so-called FastICA algorithm for complex mixtures [2], [5], [12]. FastICA is a fast method for performing linear ICA, and its basic form relies on the sample fourth-order statistics kurtosis [5]. However, other forms of the algorithm employing more robust lower-order statistics have been developed [5]. Instead of FastICA, other ICA algorithms developed for complex-valued mixtures could be used.

In most ICA methods, the data are first pre-whitened spatially. This makes the subsequent separation task easier, because the separating matrix is then constrained to be orthogonal [5]. In whitening, the observed mixtures  $\mathbf{r}(t)$  are transformed linearly so that their components become uncorrelated and have unit variance:

$$\mathbf{y}(t) = \mathbf{T}\mathbf{r}(t), \quad \mathbf{E}\{\mathbf{y}(t)\mathbf{y}(t)^H\} = \mathbf{I} \quad (12)$$

Here  $\mathbf{y}(t)$  is the whitened data vector,  $\mathbf{T}$  a whitening transformation matrix,  $\mathbf{I}$  the unit matrix, and  $H$  denotes complex conjugation and transposition. Whitening is often carried out via principal component analysis (PCA), which yields for complex-valued data the transformation matrix

$$\mathbf{T} = \mathbf{\Lambda}_s^{-\frac{1}{2}}\mathbf{U}_s^H \quad (13)$$

There the matrices  $\mathbf{\Lambda}_s$  and  $\mathbf{U}_s$  respectively contain the eigenvalues and eigenvectors of the autocorrelation matrix  $\mathbf{E}\{\mathbf{r}(t)\mathbf{r}(t)^H\}$  of the received data vectors  $\mathbf{r}(t)$ . When PCA is used for whitening, it is easy to reduce the dimensionality of the data vectors simultaneously if desired by using only the principal eigenvectors in  $\mathbf{\Lambda}_s$  and  $\mathbf{U}_s$ ; see [5] for details.

The FastICA algorithm is then used to separate the sources, given their whitened mixtures  $\mathbf{y}(t)$ . The core of this algorithm is updating of the  $i$ th column  $\mathbf{w}_i$  of the orthogonal separating matrix  $\mathbf{W}$  according to [2], [5]

$$\mathbf{w}_i^+ = \mathbf{E}\{\mathbf{y}(t)[\mathbf{w}_i^H\mathbf{y}(t)]^*|\mathbf{w}_i^H\mathbf{y}(t)|^2\} - \gamma\mathbf{w}_i \quad (14)$$

where  $\mathbf{w}_i^+$  is the updated value of  $\mathbf{w}_i$ , and  $*$  denotes complex conjugation. The constant  $\gamma$  is 2 for complex-valued signals, and 3 for real ones. In practice, the expectation  $\mathbf{E}$  in (14) is replaced by computing the respective average over the available set of whitened data vectors  $\mathbf{y}(t)$ . The update rule (14) uses the standard cubic nonlinearity arising from the maximization of the kurtosis, but other versions of the complex FastICA algorithm exist, too [2]. These typically apply slower growing nonlinearities which are more robust against outliers and impulsive noise in the data. In addition to (14), the columns of  $\mathbf{w}_i^+$  must be orthonormalized after each step. This can be carried out for example via Gram-Schmidt orthogonalization. FastICA and its different variants are discussed thoroughly in [5].

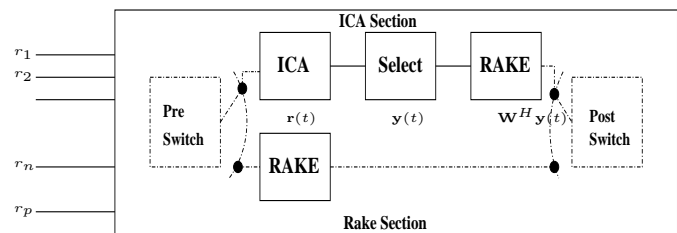


Fig. 2. Semi-blind pre- and post-switching interference cancellation schemes combining ICA and RAKE.  $r_1 \dots r_n$  is the received data,  $r_p$  is the preamble sequence used for switching between the two sections,  $\mathbf{W}$  is the orthogonal separating matrix. The dashed blocks are the pre-switching portion and the post-switching portion of the receiver.

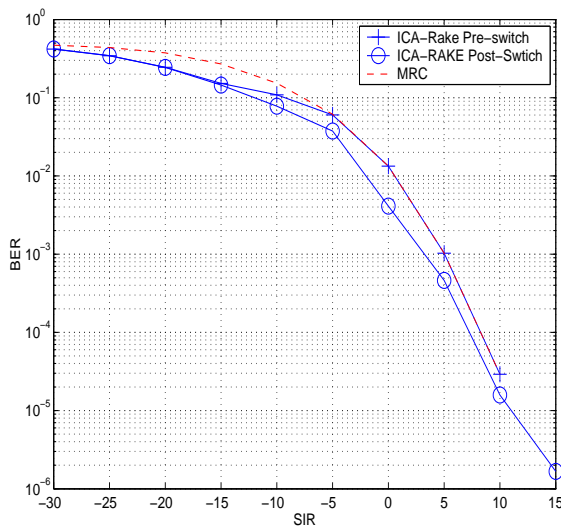


Fig. 3. Bit-error-rate as a function of SIR at an average SNR = 10 dB for  $K = 16$  users (half load) of equal strength in an AWGN channel with 6 interfering cells. Each cell has 16 users, who interfere with the user-of-interest in the cell-of-interest. Semi-blind solutions include ICA-RAKE with pre-switching and post-switching. MRC is with  $N_a = 3$  antennas, while ICA always includes dimensionality reduction during the whitening stage.

#### IV. SIMULATION RESULTS

The simulated macro-cell model is a two layered cell structure as shown in Fig. 1. The cell-of-interest is surrounded by two layers of interfering cells. Each cell is assumed to have a radius of  $d_c = 666$  m. The inner layer of interfering cells are at a distance of  $d_{in} = 2000$  m while the second layer of cells was included when the interfering sources were within the radius of  $d_{out} = 3300$  m.

A simulated DS-CDMA downlink model with Additive White Gaussian Noise (AWGN) channel is assumed. The path delay of the channel is assumed to be known. The system uses short Gold Codes of length  $C = 31$ . The load in each cell is assumed to be with respect to the spreading factor  $C$ . A quarter load implies  $K = 8$  users per cell in both the cell-of-interest and the interfering cells, while a full load implied  $K = 31$  users. In addition to determining the interference cancellation capabilities of ICA, we wanted also to examine the loss of performance due to increasing loads. The length of the data block for each user was  $M = 200$  symbols, modulated by QPSK modulation. The user-of-interest is chosen randomly, and the receiver has a  $N_a = 3$  element antenna array. The results are based on 3000 independent runs, and they are compared with two ICA structures and with standard RAKE receiver which uses Maximum Ratio Combination (MRC) over the antenna elements [8]. The compared ICA structures, pre- and post-switching [14], [10], are depicted in the schematic diagram of Fig. 2.

First, the effect of inner layer interferences due to adjacent cells was studied. Different loads were used to generate the interferences. It was initially assumed that the number of interfering sources in each cell was identical (meaning that if the cell-of-interest was half loaded, so were all the cells). This is

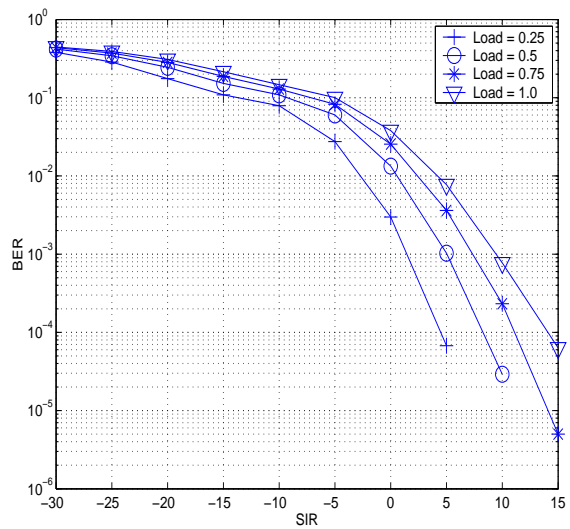


Fig. 4. Bit-error-rate as a function of SIR at an average SNR = 10 dB for different load factors. With  $C = 31$  codes, full load is  $K = 31$  users, while quarter load is  $K = 8$  users. Solutions here are for ICA-RAKE pre-switching.

not a necessity, but the results given in this paper are for this situation. Fig. 3 shows the performance of ICA pre- and post-switches with respect to MRC for a half-loaded cell with a constant SNR ratio of 10dB.

For the signal-to-interference ratios (SIR) of  $-20$ dB to  $-5$ dB, ICA with post-switching offers a gain of about 7 to 2 dB. Pre-switched version of ICA starts to deteriorate after  $-10$ dB and beyond 0 dB offers no gain when compared to MRC. This is because pre-switching starts to favor MRC when the contribution of the interfering signal deteriorates and finally ICA is not applied to the multiuser signal beyond SIR of 0 dB.

In the next series of simulations, the effect of increasing load on ICA was studied. The adjacent cells and the cell-of-interest had loads of  $K = 8, 16, 24, 31$  users which correspond to quarter, half, three quarters, and full loads, respectively. As expected, all the three methods showed a degradation in performance as the load increases. Consider first Fig. 6, which shows the loss of performance of MRC receivers. As the load increases from  $K = 8$  users to  $K = 31$  users, the performance drops by 2.5 dB initially, and further by 2 dB at every subsequent addition.

In Figs. 4 and 5, a similar trend is observed. A closer examination of the figures reveals an interesting feature of ICA-assisted receiver structures. Since the final stage of all ICA-assisted receivers is RAKE (or MRC) based, and ICA is only applied to cancel interferences from adjacent cells, this loss of performance is mainly due to RAKE (or MRC). Furthermore, these interferences are mainly due to intra-cell interferences or multi-user interferences, which exists even after ICA has been used to separate the interferences due to other cells. These intra-cell interferences cause a degradation of performance in RAKE (and MRC) which affects ICA-assisted receivers. Subtracting the degradation of performance due to MRC, one can see that ICA is insensitive to the increase in the load. ICA considers all these interferences as a single interference which has to be

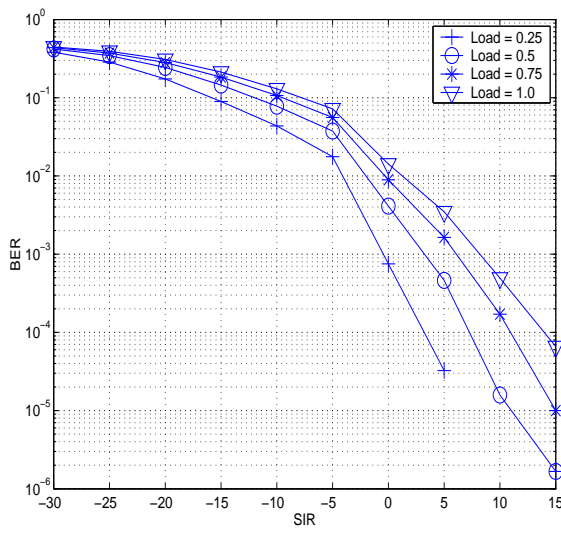


Fig. 5. Bit-error-rate as a function of SIR at an average SNR = 10 dB for different load factors. With  $C = 31$  codes, full load is  $K = 31$  users, while quarter load is  $K = 8$  users. Results here are for ICA-RAKE post-switches.

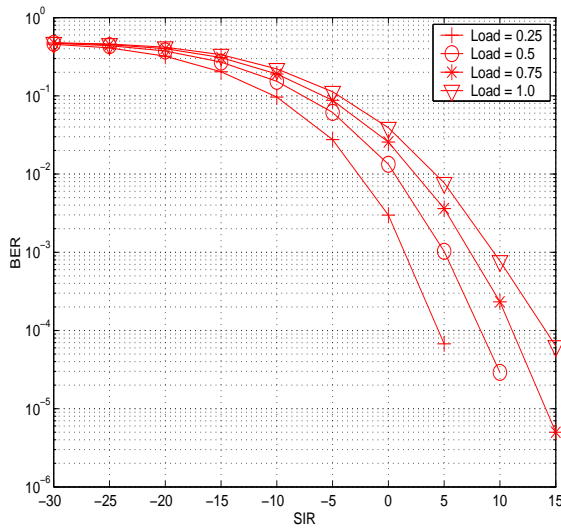


Fig. 6. Bit-error-rate as a function of SIR at an average SNR = 10 dB for different load factors. With  $C = 31$  codes, full load is  $K = 31$  users, while quarter load is  $K = 8$  users. Results here are the MRC solutions without interference cancellation.

removed, and hence separates a summed signal of interferences rather than every interfering source. Such a feature is important in receivers, because it makes the receiver robust against load fluctuations.

Finally, the errors in blocks (Block-error-rates) were also calculated. They follow a similar trend than the bit-error-rate curves, and are shown in Figs. 7, 8, 9, and 10. Simulations with outer-layer interferences provided about 7 to 5dB performance gains using ICA-assisted receiver structures, too, confirming that ICA is robust against load fluctuations.

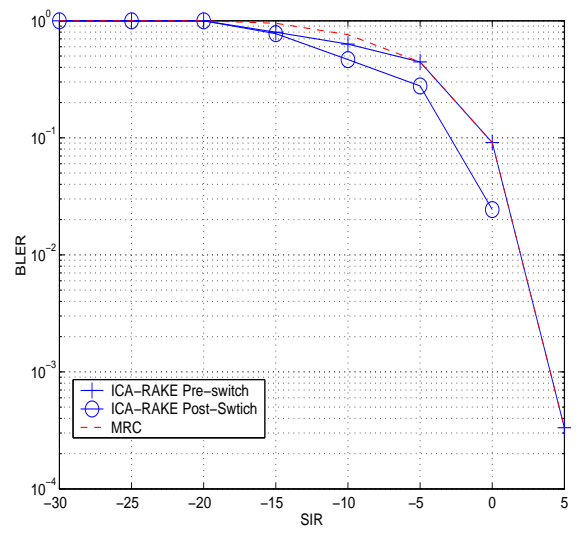


Fig. 7. Block-error-rate as a function of SIR at an average SNR = 10 dB for  $K = 16$  users (half load) of equal strength in an AWGN channel with 6 interfering cells. Each cell has 16 users, who interfere with the user-of-interest in the cell-of-interest. Semi-blind solutions include ICA-RAKE with pre-switching and post-switching. MRC is with  $N_a = 3$  antennas, while ICA always includes dimensionality reduction during the whitening stage.

## V. CONCLUSIONS

Interference cancellation forms an important part of wireless communication. The quality of communications degrades severely when the interfering signal is not canceled effectively. Furthermore, robust schemes should be able to work even when the number of interfering sources increases. This paper considers the use of a blind procedure in combination with a popular practical receiver structure - RAKE - to help in interference cancellation. RAKE utilizes prior information on the problem, but neglects the strong and realistic independence assumption of the desired information signal and disturbing interfering signal. The resulting ICA-RAKE methods are thus semi-blind in nature, combining efficiently the available information on the cancellation problem. ICA treats interferences originating from several sources as a single interference, and hence its performance does not severely degrade when the number of sources increases. Furthermore, ICA-assisted receiver structures provide around 7 to 2 dB gain in the regions of strong interference. This work can be extended into several directions by combining in various ways out-of-cell and multi-user interference cancellation schemes.

## REFERENCES

- [1] A. Belouchrani and M. Amin. Jammer mitigation in spread spectrum communications using blind source separation. *Signal Processing*, 80:723–729, 2000.
- [2] E. Bingham and A. Hyvärinen. A fast fixed-point algorithm for independent component analysis of complex-valued signals. *Int. J. of Neural Systems*, 10:1–8, 2000.
- [3] G. Giannakis, Y. Hua, P. Stoica, and L. Tong, editors. *Signal Processing Advances in Wireless and Mobile Communications, Vol. 2: Trends in Single- and Multi-User Systems*. Prentice-Hall, 2001.
- [4] S. Haykin, editor. *Unsupervised Adaptive Filtering, Vol. 1: Blind Source Separation*. John Wiley & Sons Inc., 2000.

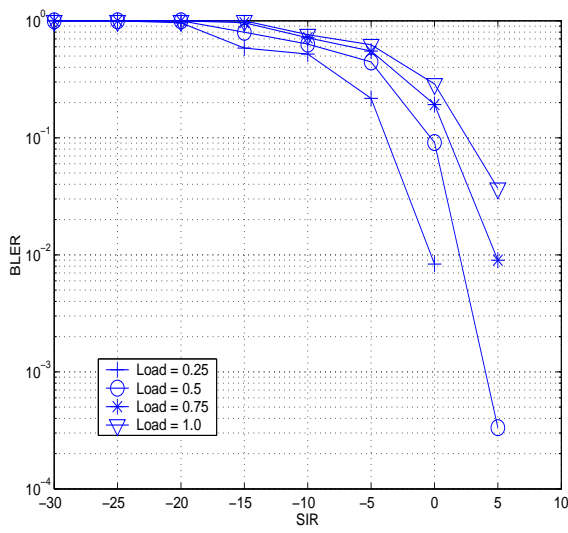


Fig. 8. Block-error-rate as a function of SIR at an average SNR = 10 dB for different load factors. With  $C = 31$  codes, full load is  $K = 31$  users, while quarter load is  $K = 8$  users. Solutions here are for ICA-RAKE pre-switching.

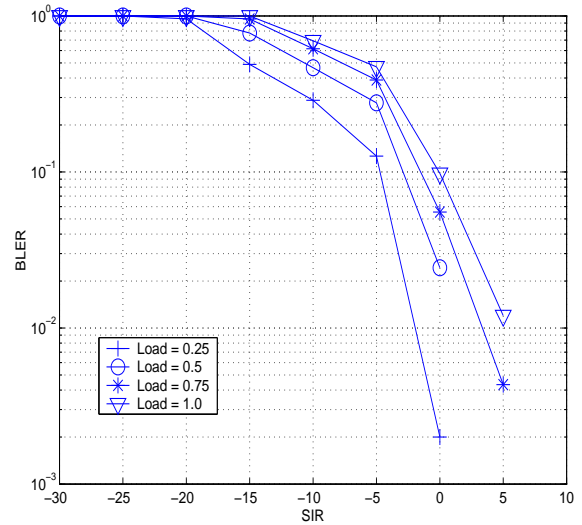


Fig. 9. Block-error-rate as a function of SIR at an average SNR = 10 dB for different load factors. With  $C = 31$  codes, full load is  $K = 31$  users, while quarter load is  $K = 8$  users. Results here are for ICA-RAKE post-switches.

[5] A. Hyvärinen, J. Karhunen, and E. Oja. *Independent Component Analysis*. John Wiley & Sons Inc., 2001.

[6] U. Madhow. Blind adaptive interference suppression for direct-sequence CDMA. *Proc. of the IEEE*, 86:2049–2069, October 1998.

[7] L. Milstein. Interference rejection techniques in spread spectrum communications. *Proc. of the IEEE*, 66:657–671, June 1988.

[8] J. G. Proakis. *Digital Communications 3rd ed.* McGraw-Hill, 1995.

[9] K. Raju and T. Ristaniemi. ICA-RAKE-switch for jammer cancellation in DS-CDMA array systems. In *Proc. of the 2002 IEEE Int. Symposium on Spread Spectrum Techniques and Applications (ISSSTA 2002)*, pages 638 – 642, Prague, Czech Republic, September 02 - 05, 2002, 2002.

[10] K. Raju, T. Ristaniemi, J. Karhunen, and E. Oja. Jammer cancellation in DS-CDMA array systems using independent component analysis. *IEEE Transaction on Wireless Communication*, 2002. submitted.

[11] K. Raju, T. Ristaniemi, J. Karhunen, and E. Oja. Suppression of bit-pulsed jammer signals in a DS-CDMA array system using independent component analysis. In *Proc. of the 2002 IEEE Int. Symposium on Circuits and Systems (ISCAS 2002)*, pages I–189/I–192, Phoenix, USA, May 26 - 29, 2002, 2002.

[12] T. Ristaniemi and J. Joutsensalo. Advanced ica-based receivers for block fading ds-cdma channels. *Signal Processing*, 82:417–431, 2002.

[13] T. Ristaniemi, K. Raju, and J. Karhunen. Jammer mitigation in DS-CDMA array system using independent component analysis. In *Proc. of the 2002 IEEE Int. Conference on Communications (ICC 2002)*, New York, USA, April 28 - May 02, 2002, 2002.

[14] T. Ristaniemi, K. Raju, J. Karhunen, and E. Oja. Jammer cancellation in DS-CDMA array systems: Pre and post switching of ICA and RAKE. In *Proc. of the 2002 IEEE Int. Symposium on Neural Networks for Signal Processing (NNSP 2002)*, pages 495–504, Martigny, Switzerland, September 04 - 06, 2002, 2002.

[15] S. Verdú. *Multuser Detection*. Cambridge University Press, 1998.

[16] A. Viterbi. *CDMA: Principles of Spread Spectrum Communications*. Addison-Wesley, 1995.

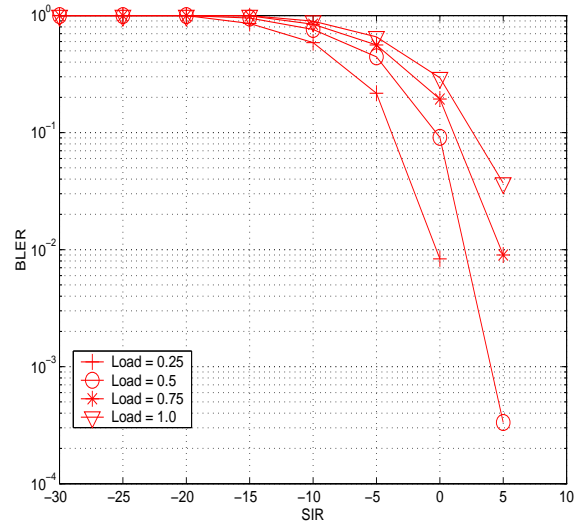


Fig. 10. Block-error-rate as a function of SIR at an average SNR = 10 dB for different load factors. With  $C = 31$  codes, full load is  $K = 31$  users, while quarter load is  $K = 8$  users. Results here are the MRC solutions with out interference cancellation.