BLIND MULTIUSER ADAPTIVE COMBINING FOR ASYNCHRONOUS CDMA SYSTEMS*

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ABSTRACT

This paper presents a novel technique to globally estimate and track the direction of arrival (DOA) of different users in an asynchronous CDMA system.
The estimates are obtained exploiting the temporal structure of CDMA signals. No training signal nor a priori spatial information is required. The necessary information is extracted directly from the received signals. The proper combining of the overall information present at the receiver after the despreading, jointly with an Eigenvalue Decomposition (EVD), let us estimate the generalized steering vector for each user. Furthermore, a direct iteration method is introduced in our scheme in order to make the array robust to channel variations and to reduce the computational load of the EVD required for each user.

1 INTRODUCTION

In a CDMA system, the lack of orthogonality between the modulating pseudo-random sequences, worsen by the asynchronism between uses, makes the system specially vulnerable to the "near-far" effect: the higher power (near) sources overwhelm the lower power sources and so system capacity drops spectacularly [1]. If information of DOA is available, we can design specific beamformers with nulls at DOAs of signals with higher power [2], avoiding the requirement of perfect power control.

In [3] we proposed a robust method to carry out multiple DOA estimation in stationary environments. Nevertheless, when the goal is to track a time-varying scenario, as is the case of a mobile radio system, adaptive solutions are required. The aim of this paper is to present an adaptive algorithm able to globally estimate and track the DOAs of multiple users.

The system block diagram is shown in figure 1. The received signal vector is fed to a bank of filters, each one matched to one of the K active users. The outputs are sampled every T seconds, each synchronized to the corresponding source emission. For every user, a different array covariance matrix is computed after despreading the signal at all sensors. By means of a linear combination of these matrices a new set of matrices is obtained, one matrix for each user. Every matrix obtained through the linear operation has an only signal eigenvector which is exactly the steering vector of the corresponding user.

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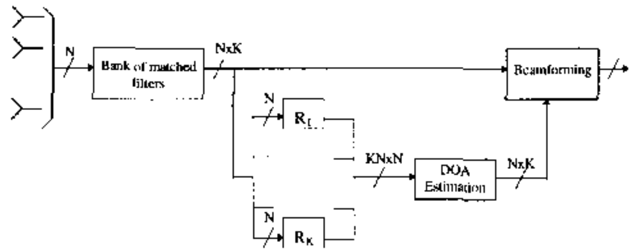

Figure 1: System Block Diagram

This is the basic idea of method proposed in [3], and the starting point of the work here presented. For this reason, it is briefly formulated in section 3. Then in section 4 a direct iteration method [4][5] is introduced in the scheme in order to make the algorithm able to track the channel. Finally, in section 5 simulation results and conclusions are presented.

2 SIGNAL MODEL

The system under consideration is a K-user asynchronous DS-CDMA system using BPSK modulation and operating over a frequency non-selective fading channel.

The baseband signal for the k-th user is given by

$$s_k(t) = \sum_m d_k[m]\, b_k(t - mT) \tag{1}$$

the data stream $d_k[m] \in \{+1, -1\}$ is pulse amplitude modulated by a period of the code waveform $b_k(t)$, with $b_k(t) = 0$ for $t \notin \{0, T\}$ and T the bit time.

The received baseband signal for the multichannel case is

$$\mathbf{x}(t) = \sum_{k=1}^{K} \sqrt{p_k} s_k(t - t_k)\mathbf{a}_k(t) + \mathbf{n}(t) \qquad (2)$$

p_k, τ_k and $\mathbf{a}_k$ are respectively the transmitted power, the propagation delay and the steering vector with dimension equal the number of sensors N. All for the k-th user. $\mathbf{n}(t)$ is the noise vector at the array input. We consider white Gaussian noise uncorrelated among different sensors and with equal variance σ^2 for all of them. As we are assuming frequency non-selective fading channels, $\mathbf{a}_k(t)$ may be considered as the sum of P coherent paths [6]. Then, we call $\mathbf{a}_k(t)$ the *generalized steering vector* (GSV) for the k-th user. This vector may be time-varying due to the combined effect of multipath and Doppler. Here, $\mathbf{a}_k$ is assumed to be slowly varying compared to the symbol time:

$$\mathbf{a}_k(t) \cong \mathbf{a}_k(t+T) \qquad (3)$$

The model [6] and the proposed method are easily generalizable to frequency selective channels.

3 LINEAR COMBINING OF AUTOCORRELATION MATRICES

The sampled output of the l-th filter in fig. 1 is:

$$\mathbf{z}_l[n] = \frac{1}{T}\int_{nT+\tau_l}^{(n+1)T+\tau_l} \mathbf{x}(t) b_l(t - nT - \tau_l)dt \qquad (4)$$

and the spatial correlation matrix at the output of this filter is

$$\mathbf{R}_{zz,l}[n] = E\left\{\mathbf{z}_l[n]\,\mathbf{z}_l^H[n]\right\} \qquad (5)$$

In accord with [3], assuming different symbols are uncorrelated, it can be shown

$$\mathbf{R}_{zz,l} = p_l\mathbf{a}_l\mathbf{a}_l^H + \sum_{\substack{k=1\\k\neq l}}^{K} p_l\left(\beta_{kl}^2 + \gamma_{kl}^2\right)\mathbf{a}_k\mathbf{a}_k^H + \frac{\sigma^2}{T}\mathbf{I_N} \qquad (6)$$

$\mathbf{I_N}$ is the identity matrix with dimension NxN and

$$\beta_{kl} = \frac{1}{T}R_{b_kb_l}(\tau_l - \tau_k) \qquad (7)$$

$$\gamma_{kl} = \frac{1}{T}R_{b_kb_l}(\tau_l - \tau_k - (sgn(\tau_l - \tau_k))T) \qquad (8)$$

$sgn(\tau)$ denotes the sign function equal ± 1 depending on the sign of τ and equal 0 if τ=0. $R_{b_kb_l}(\tau)$ is the cross-correlation between the k-th and l-th signature signals:

$$R_{b_kb_l}(\tau) = \int_0^T b_k(t+\tau)\,b_l(t)dt \qquad (9)$$

It is easy to see that $\beta_{lk} = \beta_{kl}$ and $\gamma_{lk} = \gamma_{kl}$. For the k-th user $\beta_{kk} = 1$ and $\gamma_{kk} = 0$. Let's define now matrices $\mathbf{S}$ and $\mathbf{R}_{zz}$ as follows

$$\mathbf{S} = \begin{bmatrix} 1 & \beta_{12}^2+\gamma_{12}^2 & \cdots & \beta_{1K}^2+\gamma_{1K}^2 \\ \beta_{12}^2+\gamma_{12}^2 & 1 & \cdots & \beta_{2K}^2+\gamma_{2K}^2 \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{1K}^2+\gamma_{1K}^2 & \beta_{2K}^2+\gamma_{2K}^2 & \cdots & 1 \end{bmatrix} \qquad (10)$$

$$\mathbf{R}_{zz} = \begin{bmatrix} \mathbf{R}_{zz,1} \\ \vdots \\ \mathbf{R}_{zz,K} \end{bmatrix} \qquad (11)$$

Operating upon matrix $\mathbf{R}_{zz}$ a new matrix $\mathbf{M}$ is obtained [3] . This new matrix may be partitioned into K NxN blocks:

$$(\mathbf{S}^{-1}\otimes\mathbf{I_N})\mathbf{R}_{zz} = \mathbf{M} = \begin{bmatrix} \mathbf{M}_1^T & \ldots & \mathbf{M}_K^T \end{bmatrix}^T \qquad (12)$$

where $\otimes$ denotes Kronecker product.

The part of $\mathbf{M}$ corresponding to the k-th user is

$$\mathbf{M}_k = p_k\mathbf{a}_k\mathbf{a}_k^H + u_k\frac{\sigma^2}{T}\mathbf{I_N} \qquad (13)$$

u_k is the k-th element of vector $\mathbf{u} = \mathbf{S}^{-1}\mathbf{1}$ ($\mathbf{1}$ is an all ones column vector with K elements).

By means of a linear operation over the "global" spatial-covariance matrix $\mathbf{R}_{zz}$ a new set of matrices $\mathbf{M}_k$ has been obtained. These matrices have $N-1$ eigenvalues equal to $u_k\frac{\sigma^2}{T}$ and one different eigenvalue equal to $p_k + u_k\frac{\sigma^2}{T} >> u_k\frac{\sigma^2}{T}$. The eigenvector associated with this eigenvalue is exactly the GSV of the k-th user. Once we have the estimation $\widehat{\mathbf{a}}_k$ of GSV for every active user, we can design an specific beamformer for each one as the k-th column of matrix $\mathbf{W}$:

$$\mathbf{W} = \widehat{\mathbf{A}}(\widehat{\mathbf{A}}^H\widehat{\mathbf{A}})^{-1}\mathbf{I_K} \qquad (14)$$

with $\widehat{\mathbf{A}} = [\widehat{\mathbf{a}}_1 \ldots \widehat{\mathbf{a}}_k \ldots \widehat{\mathbf{a}}_K]$ and $\mathbf{I_K}$ the identity matrix with dimension KxK.

4 ADAPTIVE IMPLEMENTATION

Estimating the GSV of active users in the way described in section 3 requires knowledge of the spatial correlation matrix $\mathbf{R}_{zz}$, at the output of the matched filters. In practice, it is impossible to dispose of the exact $\mathbf{R}_{zz}$, because it is defined as the expected vale over the realizations. However, assuming ergodicity of the involved signals, $\mathbf{R}_{zz}$ may be estimated by temporal averaging of the despreaded snapshots. To do so, the channel must be stationary for the block size in which $\mathbf{R}_{zz}$ is estimated. Another possibility, that allows to take into account only the most recent samples, is to take an iterative estimator of the form:

$$\mathbf{R}_{zz,l}\big|_{n+1} = \beta\, \mathbf{R}_{zz,l}\big|_n + (1-\beta)\mathbf{z}_l\,[n]\,\mathbf{z}_l^H\,[n] \tag{15}$$

From eq. 12 and 15, matrix $\mathbf{M}$ may be estimated as:

$$\begin{aligned} \mathbf{M}\big|_{n+1} &= \beta\,\mathbf{M}\big|_n + (1-\beta)(\mathbf{S}^{-1}\otimes\mathbf{I}_N)\begin{bmatrix} \mathbf{z}_1\,[n]\,\mathbf{z}_1^H\,[n] \\ \vdots \\ \mathbf{z}_K\,[n]\,\mathbf{z}_K^H\,[n] \end{bmatrix} \\ &= \beta\,\mathbf{M}\big|_n + (1-\beta)\,\widetilde{\mathbf{M}}\Big|_n \end{aligned} \tag{16}$$

An easy way of obtaining the GSVs from $\mathbf{M}$ is given by the direct iteration method [4]. No direct EVD is required using this method. In order to reduce the computational load of the algorithm, we use here a similar solution to that proposed in [5], which is based on the direct iteration method. Using this solution we work directly with the despreaded snapshots:

a) Assume that the k-th part of $\mathbf{M}$ may be decomposed in the following form:

$$\mathbf{M}_k\big|_n \simeq \widehat{\mathbf{a}}_k\widehat{\mathbf{a}}_k^H\lambda_k\big|_n \tag{17}$$

and $\widehat{\mathbf{a}}_k\big|_n$ is normalized in some way (i.e. $\mathbf{v}_k\mathbf{v}_k^H\big|_n = 1$)

b) Computing matrix $\mathbf{M}_k\big|_{n+1}$ and projecting $\widehat{\mathbf{a}}_k\big|_n$ onto this matrix yields a vector we call $\mathbf{u}_k\big|_{n+1}$

$$\mathbf{u}_k\big|_{n+1} = \beta\,\lambda_k\widehat{\mathbf{a}}_k\big|_n + (1-\beta)\,\widetilde{\mathbf{M}_k}\widehat{\mathbf{a}}_k\Big|_n \tag{18}$$

$\widetilde{\mathbf{M}_k}\Big|_n$ is the k-th part (dimension NxN)of matrix $\widetilde{\mathbf{M}}\Big|_n$

c) Normalizing $\mathbf{u}_k\big|_{n+1}$ yields the estimated GSV $\widehat{\mathbf{a}}_k$ at iteration $n+1$ and the associated eigenvalue λ_k:

$$\lambda_k\big|_{n+1} = \mathbf{u}_k\mathbf{u}_k^H\big|_{n+1} \tag{19}$$

$$\widehat{\mathbf{a}}_k\big|_{n+1} = \frac{\mathbf{u}_k}{\lambda_k}\bigg|_{n+1} \tag{20}$$

The iterative equation for the weights is:

$$\mathbf{W}_k\big|_{n+1} = \alpha\,\mathbf{W}_k\big|_n + (1-\alpha)\,\widehat{\mathbf{A}}(\widehat{\mathbf{A}}^H\widehat{\mathbf{A}})^{-1}\Big|_{n+1}\mathbf{I}_\mathbf{K} \tag{21}$$

5 SIMULATIONS AND CONCLUSIONS

An asynchronous CDMA system was simulated in order to investigate the performance, convergence and tracking capabilities of the multiuser detection algorithm presented in this paper. The modulating signals in this system are Gold sequences with length L=31.

The proposed detector permits capacity increase exploiting the different spatial signature of users impinging from different angles. As an example we illustrate the separation of three users (K=3) that are received by an array of six $\lambda/2$ linearly spaced sensors (N=6). Their angle of arrival are 38°, 70° and 45° from broadside whereas the signal to noise ratio (SNR) at each of the sensors is 3, 0 and 10dB respectively. The relative propagation delays are τ_1=0, τ_2=1.86T_c, and τ_3=1.14T_c, with T_c the chip time of the modulating sequence, i.e. $T/31$. The parameters of the adaptive algorithm are β=0.98 and α=0.9. The algorithm was initialized with $\mathbf{w}_k$=[1 0...0]^T, $\mathbf{v}_k$=[0 0...0]^T and $\lambda_k = 0$ for k=1, 2, 3. The beamformer designed for each user after 250 iterations in this scenario is shown in fig. 2. Fig. 3 depicts the evolution of λ_k/N during 250 symbols (solid line). As can be observed this parameter converges to the power of the k-th user (dotted line).

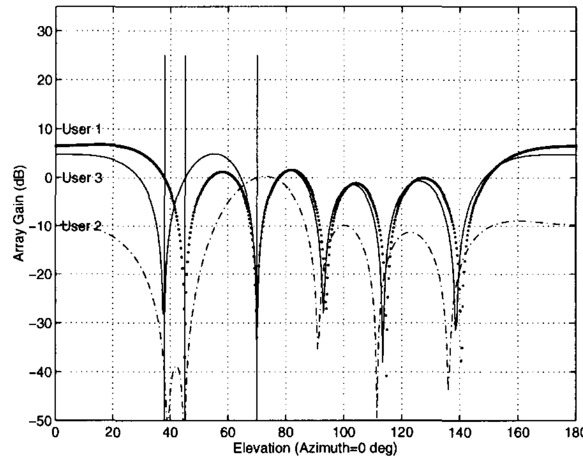

Figure 2: Radiation pattern after 250 symbols

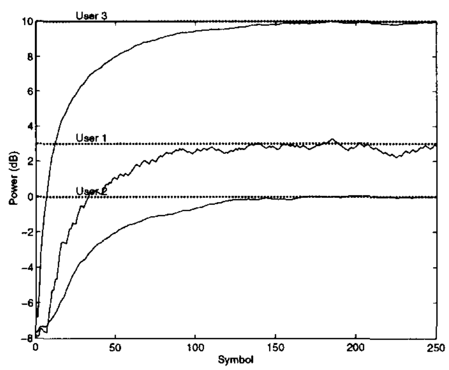

Figure 3: Estimated power

Fig. 4 shows the evolution of the signal to noise plus interference ratio ($SNIR$) at the array output (solid line). The $SINR$ of each user at the output of the classical receiver (a single matched filter) is also illustrated with dotted line. As can be observed, this $SINR$ is clearly reduced with respect to that achieved in a synchronous system. In synchronous systems, the diagonal elements of matrix $\mathbf{S}$ are much greater than the elements out of the diagonal, but this is not true for the time delays considered. As can be deduced from fig. 2 to 4, in such a situation the use of an antenna array may be very useful. The full rejection of the interference yields a substantial improvement of the $SINR$ with respect to the classical receiver. This improvement is specially important for the weakest signals.

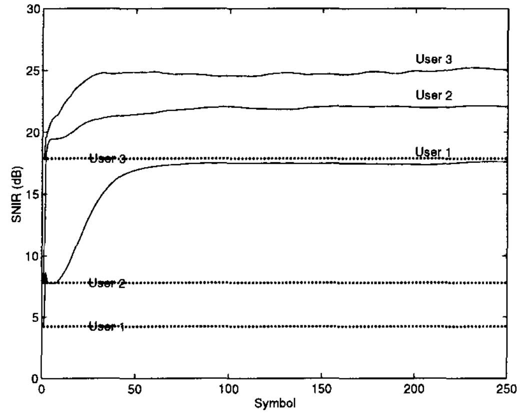

Figure 4: Output SNIR

Nevertheless, CDMA systems are currently being envisioned for use in wireless communications. In such systems, the time-varying fading of the radio link is an important problem jointly with the interference from other users. Array processing can be efficiently used to suppress multiple access interference and increase the robustness of the signal detection in the presence of fading. Now, we present a second set of simulations to illustrate the tracking capabilities of our multiuser detector in time-varying channels.

We consider two users propagated through independent Rayleigh channels and received by a four sensor array ($\lambda/2$ spaced). The 2nd user arrives with a delay of $1.86T_c$ with respect to the 1st one. For this delay, the processing gain of the code for both users is reduced from L^2=29.8dB (synchronous system) to 13.2dB. The received $SNRs$ are 15 and 5dB respectively. The mobiles' speed is 90km/h and the carrier frequency 900MHz generating a Doppler frequency of 75Hz. The bit time is 3.6 μs. The adaptive algorithm of section 4 with β=0.95 and α=0.5 was applied to the received signal. The estimated channel amplitude (module of each component of $\widehat{\mathbf{a}}_k$) is depicted in fig. 5 and 6. The real channel amplitude is also shown with dotted line. As can be observed, convergence is attained within very few symbols and channel variations are accurately tracked after convergence.

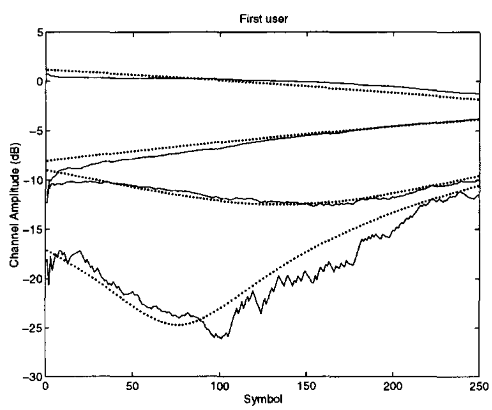

Figure 5: Channel amplitude (1st user)

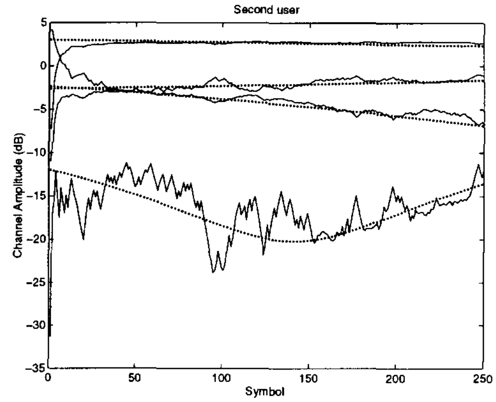

Figure 6: Channel amplitude (2nd user)

Finally, fig. 7 shows the $SNIR$ at the array output for both users (solid line). A substantial improvement with respect to the classical receiver (dotted line) is achieved, despite of we have considered for the classical receiver a Gaussian channel with constant unitary amplitude.

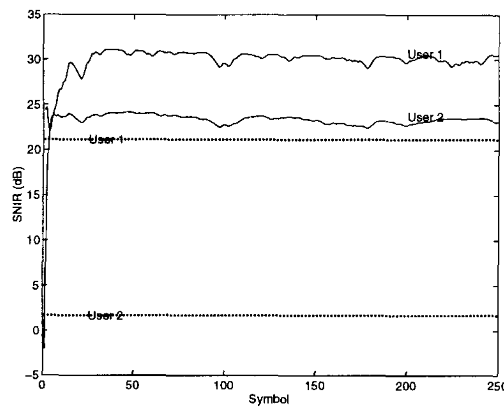

Figure 7: Output SNIR

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