Abstract— To improve the spectrum efficiency in wireless communication, two techniques are commonly used: adaptive digital signal processing and resource allocation. The aim of both techniques is to reduce the interference level. In this paper we study the performance improvement of using jointly these techniques for closed loop multiuser MIMO systems. We propose a closed loop spatial multiuser scheduling scheme that enables code-reuse without significantly degrading the performance of an Adaptive Blind Receiver (ABR).

Keywords— Blind, MIMO, Interference, Schedule.

I. INTRODUCTION

Closed loop transmit diversity (CL-TD) technique, applied on MIMO broadcasting channel, improves the system capacity in both, the single user scenario and the multiuser case (Caire and Shamai, 2003). However, in order to improve the spectrum efficiency of practical schemes while keeping small performance degradation, it is necessary a joint signal processing at both side of the radio link.

At the receiver, several algorithms have been proposed with the aim to reduce the interference level efficiently (Wurlich et al., 2008; Mehlfuhrer et al., 2008). On MIMO channels, the use of low complexity receivers that improve the performance of conventional scheme (that treats interference as white Gaussian noise), is of fundamental importance (Lupas and Verdu, 1990). In particular, blind adaptive receiver results attractive for high data rate packet communication because on such dynamic environment it is difficult for a mobile user to get precise information about the rest of active users. Closed loop multiuser MIMO is a promising technique for achieving high spectrum efficiency needed for the higher data rate of future wireless system. The standard WCDMA 3GPP (2006); Hottinen et al. (2003) allocates a limited feedback channel that can be used for sending back to the Base Station information about the channel back to the Base Station (BS). This information is used to support two closed loop transmit diversity modes, and can also enable spatial multiplexing techniques that increase the system’s capacity and potentially simplify the receiver architecture (Haikola et al., 2006).

Due to practical considerations, the most widely analyzed scenery for the down link broadcast channel considers a BS equipped with two antennas and single-antenna mobile users (Love et al., 2008). Schemes that schedule multiple users prefiltering them at the transmission by a matrix with channel information weights reported by these users, have been extensively studied in terms of capacity gain (Corral-Briones et al., 2005; Dowhuszko et al., 2007; Shenoy et al., 2009). Although achievable system capacity is important to study, the potential of those schemes does not give practical information about the type of transceiver that enable high spectrum efficiency with affordable complexity.

In this paper we analyze the performance in terms of Bit Error Rate (BER) of different user scheduling methods that use space signal processing at the BS (to reduce interference) and adaptive blind interference cancellation at the mobile stations. A new spatial Multiuser Scheduler (MS) is proposed based on the observation that a blind detector cancels the interference that belongs to a subspace orthogonal to the desired signal. The proposed scheme enables code-reuse doubling the number of users that can coexist without significant performance degradation. The results presented are for WCDMA closed loop transmit diversity mode 1 (Yoo et al., 2007).

The following notation is used in the paper. $\Re, \mathbb{C}$, $(\cdot)^s$, $(\cdot)^t$, $(\cdot)^d$, $\langle \cdot, \cdot \rangle$, $\| \cdot \|$ denote real part, complex number, complex conjugate, transpose, hermitian, correlation and norm, respectively. Scalars are written in lowercase, vectors in bold lowercase and matrices with bold uppercase letters. The system model is presented in Section II. Adaptive blind receiver is analyzed in Section III, followed by scheduling schemes presented in Section IV. Simulation results are presented in Section V, followed by paper conclusions.

II. SYSTEM MODEL

The system model for the downlink of a wireless communication system is illustrated in Fig. 1. The system consist of a single BS with 2 Tx antennas $j=1,2$ and $K \geq 2$ active user equipments (UEs) with single-elements antennas.

In case of flat fading and rich scattering, the channel gain from a $j^{\text{th}}$ Tx antenna to a $k^{\text{th}}$ User (UE) is described by a zero-mean circularly symmetric complex Gaussian Random Variable (RV) $g_{jk}$, for $j=1,2$ and $k=1,\ldots,K$. For simplicity we assume that all UE’s are homogeneous and experience independent fading. We also assume that each UE has a low-rate, reliable, and delay-free feedback channel to the BS.
For convenience, we will assume that the user of interest is $k=1$. The signal received by user 1, in a single symbol interval $[0,T]$, can be written as

$$r_1(t) = \sum_{i=1}^{K} (g_{1}^T \cdot w_i) b_i(t) + \sigma n_1(t),$$

where $g_{1} = [g_{11}, g_{12}]^T$ is the channel gain vector from the BS to the desired user with unit variance entries. $w_i = [w_{i1}, w_{i2}]^T$ is the Tx weight vector that maximizes the received energy for the desired user. $b_i \in \{+1,-1\}$ represents the identical and independent distributed (iid) users data stream with zero mean and unit variance. $s(t)$ is the unit-energy signature waveform of the $k^{th}$ user. $n(t)$ is Additive White Gaussian Noise (AWGN) component with unit variance and $\sigma$ is a scalar factor that affects the variance level of the AWGN component.

Let $\{\psi(t), \ldots, \psi_L(t)\}$ be a set of $L$ orthonormal signals defined on $t$ in $[T,T+T]$ time interval. The received signal vector $r_1 \in \mathbb{C}^{L \times 1}$ of the desired user is the $L$-dimensional representation of $r_1(t)$ on the basis $\{\psi(t), \ldots, \psi_L(t)\}$, that is, the $l$ component of the column vector $r_1$ is

$$r_1(l) = \int_{T}^{T+T} r_1(t) \psi(l)^T dt, \quad l = 1, \ldots, L.$$

Furthermore, we define the components of the signature vector $s_i \in \mathbb{C}^{L \times 1}$ as

$$s_i(l) = \int_{T}^{T+T} s_i(t) \psi(l)^T dt, \quad l = 1, \ldots, L,$$

and the component of the $L$-dimensional Gaussian vector $n_i \in \mathbb{C}^{L \times 1}$ as

$$n_i(l) = \int_{T}^{T+T} n_i(t) \psi(l)^T dt, \quad l = 1, \ldots, L.$$

For convenience, the received signal (2) is expressed in vector form:

$$r_1[l] = h_{1} b_{1} + \ldots + h_{K} b_{K} + \sigma n_1[l],$$

where

$$r_1[l] = \mathbf{S} \mathbf{b}_l[l] + \sigma n_1[l],$$

and $\mathbf{S} \in \mathbb{C}^{K \times L}$ is the channel gain matrix from the BS to the desired user with unit variance entries. $\mathbf{b}_l \in \mathbb{C}^{L \times 1}$ represents the channel coefficient that the impulse response can be decomposed as a sum of two orthogonal components. One of those components is equal to the signature waveform of the desired user which is assumed known and fixed throughout this section. That is, $\mathbf{c}_l = s_1 + \mathbf{x}_l[l]$, where $\mathbf{x}_l[l] = 0$. The cost function is the variance of the filter output, known as the Output Energy (OE), and minimized over the adaptive component $\mathbf{x}_l[l]$ subject to the constraint $<\mathbf{c}_l[l], \mathbf{s}_l[l]> = 1$ (Honig et al., 1995).

The OE is given by

$$R_{oe} = E[|r_1[l] r_1[l]^*|] = (\mathbf{S} \mathbf{H})^H + \sigma^2 \mathbf{I},$$

where $\mathbf{B} = \mathbf{H}^H$ is the Toeplitz matrix $H$. The MMSE detector to within a scaling factor (Verdu, 1998). Figure 3 shows the implementation structure.

A key property of every linear multiuser receiver is that the impulse response can be decomposed as a sum of two orthogonal components. One of those components is equal to the signature waveform of the desired user which is assumed known and fixed throughout this section. That is, $\mathbf{c}_l = s_1 + \mathbf{x}_l[l]$, where $\mathbf{x}_l[l] = 0$. The cost function is the variance of the filter output, known as the Output Energy (OE), and minimized over the adaptive component $\mathbf{x}_l[l]$ subject to the constraint $<\mathbf{c}_l[l], \mathbf{s}_l[l]> = 1$ (Honig et al., 1995).

The OE is given by

$$\mathbf{z}_l[l] = \mathbb{E}[|r_1[l] r_1[l]^*|]^2.$$
along the subspace orthogonal to \( s_i \). The unconstrained gradient of (14) is
\[
V \xi'[i] = 2(\mathbf{c}'[i] \mathbf{r}_i[i])^T \mathbf{r}_i[i],
\]
where the component orthogonal to \( s_i \) results in a scaled version of the component of \( \mathbf{r}_i \) orthogonal to \( s_i \), that is
\[
\mathbf{r}_i[i] - <s_i, \mathbf{r}_i[i]> s_i = \mathbf{r}_i[i] - (\mathbf{s}_{ii'}^T \mathbf{r}_i[i]) s_i.
\]
Therefore, the projected gradient (in the subspace orthogonal to \( s_i \)) is
\[
V_{\xi_{ii}}'[i] = 2(\mathbf{c}'[i] \mathbf{r}_i[i])^T [I - \mathbf{s}_{ii'}^T] \mathbf{r}_i[i]
\]
where \( z[i] = e[i] \mathbf{s}_{ii'} \) is the filter output. According to (19) the stochastic gradient adaptation rule is
\[
\mathbf{x}_i[i+1] = \mathbf{x}_i[i] - \mu \left( V_{\xi_{ii}}'[i] \right) \mathbf{r}_i[i].
\]
From (30), \( x_{i_{opt}} \) could not be calculated because, as will show later, \( R_{w_{opt}} \) is singular, but could be calculated from \( c_{opt} \), that is
\[
x_{i_{opt}} = \frac{\mathbf{R}_{s_{ii}}^T \mathbf{s}_{ii} - \mathbf{R}_{s_{ii}}^T \mathbf{s}_{ii}^T}{\mathbf{s}_{ii}^T \mathbf{s}_{ii}}.
\]
Therefore the expression for the trajectory of the tap as a function of the adaptive component is given by
\[
E[\mathbf{e}[i+1]] = (I - \mu \mathbf{R}_{w_{opt}}) E[\mathbf{e}[i]],
\]
where \( \mathbf{e}_{i_{opt}} = \mathbf{P}_{s_{ii}} \mathbf{r}_{s_{ii}} \). From (28) the matrix \( \mathbf{R}_{w_{opt}} = \mathbf{P}_{s_{ii}} \mathbf{R}_{s_{ii}} \mathbf{P}_{s_{ii}}^T \) may be seen as the equivalent correlation matrix for the adaptive part in (24) in performance analysis, since is similar to \( \mathbf{R}_{w} \) but Hermitian, Gong et al. (2001). Deeping in the eigen-analysis of both matrix \( \mathbf{R}_{w} \) and \( \mathbf{R}_{w_{opt}} \), can be verified that an eigenvector of \( \mathbf{R}_{w_{opt}} \) with zero eigenvalue \( \lambda_{i_{max}} \) plays no role in the convergence of the blind detector because the tap-weight vector is never adapted in the direction of \( s_i \). To gain more insight into the convergence of the mean tap vector, it is necessary to study the eigenvalues of \( \mathbf{R}_{w_{opt}} \). It can be done by applying the Minimax theorem (Simon, 1996) which state
\[
\lambda_{i_{max}} = \max_{\mathbf{p}_{s_{ii}} \neq 0} \lambda_{i_{opt}} = I_{\mathbf{P}_s} \left( \mathbf{R}_{s_{ii}} \mathbf{P}_{s_{ii}} \right) \mathbf{p}_{s_{ii}} = \left( \mathbf{R}_{s_{ii}} \mathbf{P}_{s_{ii}} \right) \mathbf{p}_{s_{ii}} = \frac{\mathbf{R}_{s_{ii}}}{\mathbf{P}_{s_{ii}}}
\]
where \( \mathbf{P}_s = \mathbf{R}_{s_{ii}}^T \mathbf{R}_{s_{ii}} \mathbf{P}_{s_{ii}} \). Upon convergence, we can consider
\[
E[\mathbf{x}[i+1]] = E[\mathbf{x}[i]],
\]
and
\[
\Rightarrow \mathbf{R}_{w_{opt}} \mathbf{x}_{i_{opt}} = -\mathbf{s}_{ii}^T \mathbf{r}_{s_{ii}} \mathbf{P}_{s_{ii}} = -\mathbf{p}_{s_{ii}},
\]
which determines the transient behavior of \( \mathbf{t} \).

A. Trajectory of the Tap-Weight Vector

The trajectory of the vector coefficients is analyzed in a similar way to that given in Honig et al. (1995) but is re-stated here for convenience. Adding \( \mathbf{c}_{opt} \) to both sides of (20) gives
\[
\mathbf{c}_i[i+1] = (I - \mu \mathbf{u}[i] \mathbf{r}_i[i]) \mathbf{c}_i[i] = (I - \mu \mathbf{c}_{opt}[i] \mathbf{r}_i[i]) \mathbf{c}_i[i],
\]
where \( \mathbf{c}_{opt} = \mathbf{c}_{min} = \mathbf{s}_{ii}^T \mathbf{R}_{s_{ii}} \mathbf{P}_{s_{ii}} \). From (23) the equivalent correlation matrix which determines the transient behavior of \( \mathbf{t} \) is \( \mathbf{R}_{w_{opt}} \). Since \( \mathbf{R}_{w_{opt}} \) can not be symmetric, eigenvalues can be complex and the analysis becomes quite difficult to carry out. However, if we consider the fact that
\[
\mathbf{x}_i[i+1] = \mathbf{x}_i[i] - \mu \mathbf{r}_i[i],
\]
then taking expectation at both sides of (27) and assuming that \( \mathbf{x}_i[i] \) and \( \mathbf{r}_i[i] \) are independent, we have
\[
E[\mathbf{x}_i[i+1]] = [I - \mu \mathbf{R}_{w_{opt}}] E[\mathbf{x}_i[i]] = [I - \mu \mathbf{R}_{w_{opt}}] \mathbf{p}_{s_{ii}}^T \mathbf{r}_{s_{ii}},
\]
where \( \mathbf{R}_{w_{opt}} = E[\mathbf{u}[i] \mathbf{u}^H[i]] = \mathbf{P}_{s_{ii}} \mathbf{R}_{s_{ii}} \mathbf{P}_{s_{ii}}^T \) and
\[
\mathbf{p}_{s_{ii}} = \mathbf{s}_{ii}^T \mathbf{r}_{s_{ii}} \mathbf{P}_{s_{ii}}. \]

then, using $R_m$ in place of $R_n$, we have

$$p_n^T R_m p_n = (p_n^T)^T R_m p_n = \sum_{k=1}^{L+1} g_{nk} \left( p_n^+ s_k \right) + \sigma^2 \left\| p_n^+ \right\|^2$$

(37)

with

$$\left\| p_n^+ s_k \right\| = \begin{cases} 1 & n = k \\ 0 & n \neq k \end{cases}$$

Maximizing (33) with respect to $p_n$ requires to make $p_n$ as large as possible, while keeping $p_n^+ = 1$. Consequently $p_n$ must be set to 0, that is

$$\left\| p_n^+ \right\|^2 = 1 - \left\| p_n \right\|^2 = 1 \Rightarrow \left\| p_n^+ \right\| = 0.$$  

(39)

Takin into account (39) and (13), we arrive at the following result:

$$\lambda_n^{(\text{MOE})} = \begin{cases} h_{\text{opt}}^2 + \sigma^2 & n = 1, \ldots, K \\ 0 & n = 1, \ldots, L-1 \\ \text{max} & n = 0 \end{cases}$$

(40)

We therefore conclude that $x_n[i]$ converges to $x_{\text{opt}}$ along $L-1$ modes, each of which decays exponentially with parameter $(1-\mu_{\lambda_n^{(\text{MOE})}})$, where $\lambda_n^{(\text{MOE})}$ is the $n$th eigenvalue of $R_m$.

**B. Learning Curve of MOE**

The OE at the filter output is given by

$$\xi[i] = \sum_{k=1}^{K} \left( p_n^+ r_k[i] s_k^T \right)^2 + \sum_{k=1}^{K} p_n^+ x_k[i] + x_n[i] R_m x_n[i],$$

where the expectation value is taken over the received signal. The MOE is

$$\bar{\xi} = \mathbb{E}\left[ \left( p_n^+ r_k[i] s_k^T \right)^2 + \sum_{k=1}^{K} p_n^+ x_k[i] + x_n[i] R_m x_n[i] \right]$$

(42)

where we use (28). Substracting (42) from (41), we have

$$\bar{\xi} = \xi_{\text{max}} + \sum_{k=1}^{K} \lambda_n^{(\text{MOE})} e_k^T s_k R_m e_k.$$  

(43)

Making a similar derivation with (43) as described in Farhang-Boroujeny (1999), the expression (43) can be written as

$$\bar{\xi} = \xi_{\text{max}} + \sum_{k=1}^{K} \lambda_n^{(\text{MOE})} e_k^T s_k R_m e_k.$$  

(44)

where $q_k$ is the normalize eigenvector of $R_m$ with corresponding eigenvalue $\lambda_n^{(\text{MOE})}$. Since $s_k$ is an eigenvector of $R_m$, we can assign $q_1, q_2, \ldots, q_{K+1}, q_{K+1} = s_k$ to the eigenvectors associated with the $K$-1 largest eigenvalues; and $q_{K+2}, q_{K+3}, \ldots, q_{K}$ to the eigenvectors spanning the noise subspace. It can be shown that $q_{K+1}, n = 1, \ldots, K$ span the same subspace as $p_n^+ s_k, k = 2, \ldots, K$. And all these subspaces are orthogonal to $s_1$. Parallel to this, $c_{\text{opt}}$ is known to belongs to the subspace generated by $s_1, k = 1, \ldots, K$. It is clear to see that $x_{\text{opt}} = c_{\text{opt}} s_1$, also lies in the same subspace, but it is orthogonal to $s_1$. Then, $x_{\text{opt}}$ must lie in span $p_n^+ s_k, k = 2, \ldots, K$. Consequently this implies that $x_{\text{opt}} \in \{ q_1, q_2, \ldots, q_{K+1} \}$. From this property of $x_{\text{opt}}$, it may be seen that when $x_1[0] = 0$, (44) can be simplified to

$$\xi[i] = \xi_{\text{min}} + \sum_{k=1}^{K} \lambda_k \left( q_k^T x_{\text{opt}} \right)^2 \left( 1 - \mu \lambda_k^{(\text{MOE})} \right).$$  

(45)

where is clear that only the $K$-1 largest eigenvalues of $R_m$ affect the transient behavior of the algorithm when the adaptive component is initialized in $x_1[0] = 0$.

**C. Probability of Error**

To analyze the bit error-rate of the blind adaptive receiver $P_b(\sigma)$, we can consider $K$-users case. In first place we treat the channel coefficient as a constant value (block fading) to derive a first expression. Then, the result is averaged over the pdf of the adjusted channel gain.

The probability of error is

$$P_b(\sigma) = \sum_{b \in \{-1,1\}} P[\hat{b} \neq b] P[|\hat{b}|]$$

(46)

$$P[\hat{b} \neq b] | b = 1 = \frac{1}{2} \sum_{k=1}^{K} \sum_{j=1}^{K} P[\hat{b} \neq b].$$

(47)

Proceeding in similar way with the other terms of (47) and replacing in (50), we have $P_b(\sigma)$ in (50). Then we must take expectation value over the pdf of $h_{11}$ and $h_{1k}$ in order to get $P_b(\sigma)$.

In (50) the phase term $h_{11} / |h_{11}|$ just affect the phase distribution of the random variable $h_{11}$ inside of the $Q(.)$ function, which statistic is uniform over $[0, 2\pi]$, so can be dropped. The expression of $P_b(\sigma)$ can be re-written as in (51) where the expectation value is taken over each $h_{1k}$.
From (51) we can observe that error probability depends of the blind adaptive algorithm and the other one depends directly of the beam weights. In order to minimize the interference level experienced by the receiver, the first idea is to schedule users with orthogonal beam weights. From (50) we can observe that error probability depends of the number of users, receiver side of each user. In the case of an even number of transmit antennas defines the number of orthogonal space orthogonal to the desired data by selecting users that the blind adaptive algorithm decodes the desired sequences. Three scenarios are considered: one with two users with different signature codes, other with twelve users with six signature sequence (code-reuse), and the other one similar to the previous scenario except that a pair of them, the ones whose performance is analyzed, does not share the same signature code. A Gold sequence of length 7 and quantized weights for HSDPA mode 1 are used for all the cases 3GPP (2006).

Figure 4 shows that signature code-reuse lead to a full performance degradation for both detection schemes when scheduling (52) is used. This behavior can be explained taking into account that both interference and desired signals are collinear with this scheduling strategy. In this case, the use of different signature sequences is essential to recover performance degradation. For comparison, the two user scenario are plotted in the figure in order to evaluate the performance degradation with higher multiuser interference.

Figure 5 shows the performance of the adaptive blind receiver in the same three scenarios, mentioned earlier, but now the scheduling scheme uses π/2 rotation. In the 10 interference users scenario, a performance improvement of about 3 dB in the high SNR zone can be achieved with Scheduler B. This scheduler enable the code-reuse. It is easy to note that in the case of 12 users the BER of the blind adaptive schemes is almost the same as that of the blind scheme with Scheduler A and different signature codes. On the other hand, the matched filter does not show any performances change due to the particular interference treatment given by Scheduler B.

The different behavior of the ABR is due to fact that Scheduler A force data user 1 and user 2 to travel collinear and with opposite phase, so the ABR algorithm cannot separate efficiently the users because they are collinear. On the other hand, Scheduler B adjusts the data of the scheduled users to arrive with π/2 rotation, so the ABR algorithm can work properly.

with \( w_{2k}^H w_{2k-1} = 0 \). The condition imposed by (53) minimizes the interference caused by user 2 because its real component is almost cancelled.

V. SIMULATION RESULT

In this section we investigate the system performance under scheduling schemes (52) and (53), using two type of detection: matched filtering and adaptive blind interference cancelation. Three scenarios are considered: one with two users with different signature codes, other with twelve users with six signature sequence (code-reuse), and the other one similar to the previous scenario except that a pair of them, the ones whose performance is analyzed, does not share the same signature code. A Gold sequence of length 7 and quantized weights for HSDPA mode 1 are used for all the cases 3GPP (2006).

IV. SCHEDULING SCHEMES

From (51) we can observe that error probability depends of the two term of MAI. One of them is function of the blind adaptive algorithm and the other one depends directly of the beam weights.
Figure 4: Blind Adaptive Receiver performance with Scheduler A. Cross-correlation of the Gold spreading code is -0.1429.

Figure 5: Blind Adaptive Receiver performance with Scheduler B.

VI. CONCLUSIONS

We have studied the performance of the adaptive blind MOE receiver in a 2x1 MIMO scenario with practical MS schemes for taking advantage of multiuser diversity in a multiple antenna broadcasting channel with limited feedback.

A new scheduling scheme that tried to reduce interference while keeping the not cancelled interference in a subspace orthogonal to the desired signal at the receiver is proposed in this paper for closed loop MIMO system. The combination of the proposed scheduler with an adaptive blind receiver enables code reuse making possible to achieve higher spectrum efficiency with low complexity receivers. The proposed scheduler is analyzed for the practical case when the amount of feedback channel is compatible with mode 1 of the HSDPA technology.

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