# Group-Based Space-Time Multiuser Detection with User Sharing 

Benoît Pelletier, Member, IEEE, and Benoît Champagne, Senior Member, IEEE


#### Abstract

To reduce the complexity of space-time multiuser detection, it has been proposed recently to exploit the spatial dimension by forming groups of users and apply the detection individually to each group. In this work we propose a new space-time receiver structure based on the group-optimal MMSE linear detector along with a new grouping algorithm that respects practical hardware limitations. Furthermore, an extension of the proposed structure which allows non-mutually exclusive grouping is presented. The simulation results show that the proposed reduced-complexity receiver structure provides a bit error rate (BER) performance close to the full linear MMSE multiuser detector.


Index Terms-Multiuser detection, space-time processing, signal detection, code-division multiple access (CDMA), group detection, least mean square methods.

## I. Introduction

MOST of the current and future cellular wireless systems based on direct-spread code-division multiple access (DS-CDMA) are interference-limited. Several techniques for interference reduction exist; in particular for DS-CDMA systems, where multiple access interference (MAI) is known to limit the system capacity, multiuser detection (MUD) and beamforming with antenna arrays have been widely studied [1,2]. Optimal MUD is very complex due the search space dimension which increases exponentially with the number of users and sequence length [3]. Several reduced complexity sub-optimal techniques for MUD have been studied, including linear filtering approaches such as minimum mean square error (MMSE) and zero forcing (ZF) [4, 5], and reduced-rank approaches such as $[6,7]$.

To further reduce complexity, it has been proposed in $[8,9]$ to exploit the spatial dimension with antenna arrays, by clustering users in mutually exclusive groups. The data symbols from each group are jointly detected using reduced dimension MUD while the inter-group interference (IGI), i.e. the interference caused by the users outside of the group of interest, is reduced by using beamforming. When implemented as a matrix inversion, the MUD for each group has complexity of order $K_{j}^{3}$, where $K_{j}$ is the size of group $j \in\{1, \ldots, G\}$, $G$ being the total number of groups. Thus the method in [8] can reduce the total complexity to an order of $\sum_{j} K_{j}^{3}$, compared to the full MUD complexity of order $K^{3}$, where $K=\sum_{j} K_{j}$. The complexity reduction therefore depends on

[^0]the number of groups and the size of each group. Other suboptimal techniques such as the block Fourier algorithm in [4] and the multistage Weiner filter in [6] can be used to further reduce the complexity.

The grouping concept for a single antenna DS-CDMA system has been studied in [10], where the maximum likelihood detector is derived. More recently, it is applied to a spacetime system in [8], where MUD is applied independently to each mutually exclusive group after beamforming and temporal filtering. Grouping is based on a thresholding of the normalized cross-correlation between user array signatures, as in $[9,11]$. Alternatively, the grouping can be based on the received signal direction-of-arrival or according to the received power (see [11] and [12], respectively). In [13], we derive and analyze the optimal group-based space-time multiuser linear detector with beamforming using the formalism of [4], and demonstrate the potential in complexity reduction of the proposed structure. A different kind of grouping is studied in [14], where the users with known and unknown spreading sequence are grouped separately for detection and interference suppression, respectively.

In this paper, we propose and study several improvements to the concept of grouping for MUD complexity reduction in base stations with antenna arrays. First, in contrast to the existing algorithms, the new group-based space-time multiuser detection (GRP-STMUD) receiver structure that we propose does not require a separate beamforming algorithm; the spatial filtering operation is implicit in the space-time matched filter (MF). Second, we present a new grouping algorithm that is based on the practical assumption that the number of groups and the number of users per group are limited by hardware constraints. Finally, the restriction on group mutual exclusivity is removed. This allows to fully exploit the available computing power and reduce even further the performance gap between the full space-time MUD (STMUD) and GRPSTMUD.

The paper is organized as follows. In Section II, the signal model is presented. In Section III, the proposed linear receiver is derived. Grouping algorithms are discussed in Section IV, and the simulation results are shown in Section V. Section VI contains a brief conclusion.

## II. BACKGROUND

Consider the uplink of a synchronous DS-CDMA communication system with $K$ users transmitting blocks of $N$ information symbols simultaneously through a chip-synchronous dispersive channel to a common multi-antenna base station receiver. At each antenna, the received signal is converted to baseband, matched filtered to the transmission pulse and sampled at the "chip" rate of $1 / T_{c}$, where $T_{c}$ denotes the
chip duration. The observed signal at the receiver therefore consists of a complex-valued vector of length $N Q+W-1$, where $Q=T_{s} / T_{c}$ is the spreading factor, $T_{s}$ is the symbol duration, and $W$ is the finite impulse response channel length.

Let $L$ be the number of antennas and $\mathbf{x}^{(l)} \in \mathbb{C}^{N Q+W-1}$ for $l=1, \ldots, L$, be the received signal vector for the $l^{\text {th }}$ antenna element. Following the linear model described in [4], it is convenient to represent the complete set of observations as vector $\mathbf{x}=\operatorname{vec}\left(\left[\mathbf{x}^{(1)} \ldots \mathbf{x}^{(L)}\right]^{T}\right) \in \mathbb{C}^{L(N Q+W-1)}$, where superscript $T$ denotes matrix transposition and $\operatorname{vec}(\cdot)$ is an operation that sequentially concatenates the columns of a matrix into a column vector of appropriate dimension.

Similarly, the vector of $N K$ information symbols transmitted by the $K$ users can be represented in vector form as $\mathbf{d}=\operatorname{vec}\left(\left[\mathbf{d}^{(1)} \ldots \mathbf{d}^{(K)}\right]^{T}\right) \in \mathcal{A}^{N K}$, where $\mathbf{d}^{(k)} \in \mathcal{A}^{N}$ is the vector of information symbols for user $k$ and $\mathcal{A}$ is the symbol alphabet of $N_{\mathcal{A}}$ elements (e.g.: for BPSK $\mathcal{A}=\{ \pm 1\}$ ). The information symbols are assumed to be independent, identically distributed (iid) and normalized such that $E\left[\mathbf{d d}^{H}\right]=$ $\mathbf{I}_{N K}$, where superscript $H$ represents Hermitian transposition, $\mathbf{I}_{N K}$ is the identity matrix of dimension $N K$ and $E$ denotes statistical expectation.

Let $\mathbf{v}_{k} \in \mathbb{C}^{L(Q+W-1)}$ be the $k^{\text {th }}$ user space-time effective signature vector, i.e. the space-time response to a unit pulse excitation sequence $\delta=[1,0, \ldots, 0]$ as observed by the multi-antenna receiver after demodulation, sampling and vector formatting as described above. The effective signature incorporates the multi-access and scrambling codes convolved with the channel impulse response, assumed fixed for the duration of a block. For short code DS-CDMA systems such as the TDD mode of 3GPP, both multi-access code and scrambling codes are fixed for the duration of a block, so that the MUD weights can be used for several consecutive symbols. Define $\mathbf{V}=\left[\begin{array}{lll}\mathbf{v}_{1} & \ldots & \mathbf{v}_{K}\end{array}\right] \in \mathbb{C}^{L(Q+W-1) \times K}$ to be the effective signature matrix for the set of $K$ users. Then the total received vector may be conveniently expressed as

$$
\begin{equation*}
\mathbf{x}=\mathbf{S d}+\mathbf{n} \tag{1}
\end{equation*}
$$

where $\mathbf{S} \in \mathbb{C}^{L(N Q+W-1) \times N K}$ is a block-Toeplitz matrix [4]. In this work the matrix $\mathbf{S}$ is assumed to be known with sufficient accuracy, as it is commonly presumed in linear MUD literature. The vector $\mathbf{n} \in \mathbb{C}^{L(N Q+W-1)}$ in (1) contains white circular complex Gaussian noise samples with covariance matrix $E\left[\mathbf{n n}^{H}\right]=\sigma^{2} \mathbf{I}_{L(N Q+W-1)}$, where $\sigma^{2}$ is the noise power.

Notice that the above model and ensuing results can be generalized to account for colored noise and to support the asynchronous case. For the latter, over-sampling may be required for robustness against timing offsets, in which case the structure of the system equations needs to be slightly modified. Also, by considering each symbol transmitted as originating from a different "virtual user", the model can support variable data rate scenarios.

Due to the large dimension of the observation vector, it is common to apply the linear MMSE filter at the output of the matched filter [3]. In this approach, the soft symbol estimate is given by $\mathbf{z}=\mathbf{M}_{\mathrm{o}}^{H} \mathbf{y}$, where $\mathbf{y} \triangleq \mathbf{S}^{H} \mathbf{x}$ is the MF output and $\mathbf{M}_{\mathrm{o}} \in \mathbb{C}^{N K \times N K}$ is the optimal filter matrix that minimizes the MMSE cost function $J(\mathbf{M})=E\left\|\mathbf{d}-\mathbf{M}^{H} \mathbf{y}\right\|^{2}$, where


Fig. 1. Block diagram for the proposed GRP-STMUD receiver.
$\|\cdot\|$ denotes the Euclidean vector norm. The optimal weights, taking both MAI and ISI into consideration, can be expressed as (see e.g. [3]):

$$
\begin{equation*}
\mathbf{M}_{\mathrm{o}}=\arg \min _{\mathbf{M}} J(\mathbf{M})=\left(\mathbf{S}^{H} \mathbf{S}+\sigma^{2} \mathbf{I}\right)^{-1} \tag{2}
\end{equation*}
$$

The soft symbol estimate vector z for this full STMUD receiver is quantized to provide the hard symbol estimates, i.e. $\hat{\mathbf{d}}=$ $\mathcal{Q}(\mathbf{z})$. For BPSK $\mathcal{Q}(\cdot)=\operatorname{sgn}(\operatorname{Re}(\cdot))$, where both the real part and sign functions operate element-wise on their respective vector argument.

## III. Linear ST-MUD with Grouping

The proposed group-based space-time MUD (GRPSTMUD) MMSE linear receiver is illustrated in block diagram form in Fig. 1. As pointed out in [13], the beamforming step for spatial filtering adds complexity and leads to a potential loss of information in a multipath channel. For this reason the proposed receiver does not use a separate and independent beamforming "unit". As shown in Fig. 1, the estimate for the information symbols of the users in group $j$ is given by $\hat{\mathbf{d}}_{j}=\mathcal{Q}\left(\mathbf{z}_{j}\right)$, where $\mathbf{z}_{j} \triangleq \mathbf{M}_{j}^{H} \mathbf{S}_{j}^{H} \mathbf{x}$ with $\mathbf{M}_{j}$ and $\mathbf{S}_{j}$ being the MMSE linear filter matrix and matched filter for users of group $j$, respectively.

The grouping block in Fig. 1 provides the user partitioning. We denote the system grouping as $\mathcal{G}=\left\{\mathcal{G}_{1}, \ldots, \mathcal{G}_{G}\right\}$, where $\mathcal{G}_{j} \subseteq\{1, \ldots, K\}$ is the subset of user indices belonging to group $j \in\{1, \ldots, G\}$. In general, the criterion for selecting the groups depends on the linear filter coefficients: grouping and filter design should ideally be performed jointly. Since grouping problems with $G>1$ are generally NP-hard [15], the optimization problem is carried out in two separate steps: grouping followed by filter design. As shown in Fig. 1, symbol detection is performed independently among groups; the choice of weights for a given group does not affect the other groups and can be carried out independently. Filter design is discussed next while practical approaches for grouping will be presented in Section IV.

As for the full STMUD case in (2), the optimal MMSE GRP-STMUD weights are applied to the MF output. Given a set of mutually exclusive groups, the received vector is first expressed as the sum of the signal from the users within the group of interest, the so-called inter-group interference which comes from the users outside of the group of interest
(considered as a random unknown contribution for the purpose of filter design), and the additive Gaussian noise, i.e.:

$$
\begin{equation*}
\mathbf{y}_{j}=\mathbf{S}_{j}^{H}\left(\mathbf{S}_{j} \mathbf{d}_{j}+\overline{\mathbf{S}}_{j} \overline{\mathbf{d}}_{j}+\mathbf{n}\right) \tag{3}
\end{equation*}
$$

where $\mathbf{y}_{j}$ is the group matched filter output, $\overline{\mathbf{d}}_{j}$ is the vector of symbols for the users outside of group $j, \mathbf{S}_{j}$ and $\overline{\mathbf{S}}_{j}$ are the matrices containing the columns related to the users of group $j$ and its complement, respectively. The optimal MMSE filter output for group $j$ can be expressed as $\mathbf{z}_{j}=\mathbf{M}_{j, \mathrm{o}}^{H} \mathbf{y}_{j}$, where $\mathbf{M}_{j, o}$ is the optimal group MMSE, which can be shown to take the form

$$
\begin{equation*}
\mathbf{M}_{j, \mathrm{o}}=\left(\mathbf{R}_{j} \mathbf{R}_{j}^{H}+\mathbf{C}_{j} \mathbf{C}_{j}^{H}+\sigma^{2} \mathbf{R}_{j}\right)^{-1} \mathbf{R}_{j}^{H} \tag{4}
\end{equation*}
$$

where $\mathbf{R}_{j} \triangleq \mathbf{S}_{j}^{H} \mathbf{S}_{j}$ and $\mathbf{C}_{j} \triangleq \mathbf{S}_{j}^{H} \overline{\mathbf{S}}_{j}$. It may be advantageous for two or more groups to share a user to improve symbol detection. In non-mutually exclusive grouping the output of the different groups MMSE filters sharing a common user must be combined to form a single symbol estimate. In the following, we suggest two approaches for combining the estimates.

## A. MMSE combining

In this approach, the outputs from the groups sharing a given user are linearly weighted to provide an optimal MMSE output. Assume, without loss of generality, that the groups with indices 1 to $N_{k}$ share user $k$, and let $\tilde{\mathbf{z}}_{k}$ denote the concatenated linear filter output for user $k$ such that $\tilde{\mathbf{z}}_{k} \triangleq$ $\left[\mathbf{z}_{1, k}^{T}, \ldots, \mathbf{z}_{N_{k}, k}^{T}\right]^{T}$, where $\mathbf{z}_{j, k} \in \mathbb{C}^{N}$ is the vector of soft estimates for the $k^{\text {th }}$ user from group $j$. Let $\mathbf{d}^{(k)} \triangleq\left(\mathbf{I}_{N} \otimes\right.$ $\left.\mathbf{e}_{k}^{T}\right) \mathbf{d}$ be the information symbol vector for user $k$, where $\mathbf{e}_{k}$ is an elementary vector of dimension $K$ with all zero entries except at position $k$, where it contains the value one ${ }^{1}$. Similarly, let the elementary vector $\mathbf{e}_{j, k} \in \mathbb{R}^{K_{j}}$ have a one at the index position of user $k$ in group $j$. Then it can be shown that $\mathbf{z}^{(k)}=\mathbf{W}_{k, \mathrm{o}} \tilde{\mathbf{z}}_{k}$ is the optimal MMSE combined symbol estimate for user $k$, where

$$
\begin{equation*}
\mathbf{W}_{k, \mathrm{o}}=\left[\mathbf{M}_{\mathrm{o}}^{(k) H}\left(\mathbf{S S}^{H}+\sigma^{2} \mathbf{I}\right) \mathbf{M}_{\mathrm{o}}^{(k)}\right]^{-1} \mathbf{M}_{\mathrm{o}}^{(k) H} \mathbf{S}^{(k)}, \tag{5}
\end{equation*}
$$

$$
\mathbf{M}_{\mathrm{o}}^{(k) H} \triangleq\left[\begin{array}{c}
\left(\mathbf{I}_{N} \otimes \mathbf{e}_{1, k}^{T}\right) \mathbf{M}_{1, \mathrm{o}}^{H} \mathbf{S}_{1}^{H}  \tag{6}\\
\vdots \\
\left(\mathbf{I}_{N} \otimes \mathbf{e}_{N_{k}, k}^{T}\right) \mathbf{M}_{N_{k}, \mathrm{o}}^{H} \mathbf{S}_{N_{k}}^{H}
\end{array}\right],
$$

$\mathbf{M}_{\mathrm{o}}^{(k) H} \in \mathbb{C}^{N N_{k} \times L(N Q+W-1)}$ and $\mathbf{S}^{(k)} \triangleq \mathbf{S}\left(\mathbf{I}_{N} \otimes \mathbf{e}_{k}\right) \in$ $\mathbb{C}^{L(N Q+W-1) \times N}$ contains the columns of $\mathbf{S}$ belonging to user $k$ only.

## B. Selective combining

In this approach, a single group output among the multiple groups sharing the given user is selected for detection. In this work the selection is based on the grouping algorithm cost criterion presented in the next Section.

[^1]
## IV. Practical grouping approach

For a grouping algorithm to be applicable to real-time systems, an efficient cost function must be used: we propose to base this function on the MSE at the output of the group optimal filter in (4), which can be shown to be $J_{j} \triangleq \operatorname{tr}\left[\mathbf{I}-\mathbf{R}_{j}\left(\mathbf{R}_{j} \mathbf{R}_{j}^{H}+\mathbf{C}_{j} \mathbf{C}_{j}^{H}+\sigma^{2} \mathbf{R}_{j}\right)^{-1} \mathbf{R}_{j}^{H}\right]$. To simplify the development of the grouping algorithm, we assume that $N=1$ so that the grouping is essentially based on the columns of $\mathbf{V}$, effectively ignoring ISI.

Intuitively, it is preferable to have users with strong crosscorrelation in the same group because they benefit the most from joint detection. To demonstrate the validity of this supposition, let $\mathbf{C}_{j} \mathbf{C}_{j}^{H}=\boldsymbol{\Gamma} \boldsymbol{\Lambda} \boldsymbol{\Gamma}^{H}$, where $\boldsymbol{\Gamma}$ is a unitary transformation, $\boldsymbol{\Lambda}=\operatorname{diag}\left(\lambda_{1}, \ldots, \lambda_{K_{j}}\right)$ with $\lambda_{k} \geq 0, \forall k$. The group MSE may thus be expressed as $J_{j}=K_{j}-$ $\operatorname{tr}\left[\left[\mathbf{I}+\mathbf{S}_{R R}^{-1}\left(\boldsymbol{\Lambda}+\sigma^{2} \mathbf{S}_{R}\right)\right]^{-1}\right]$, where $\mathbf{S}_{R R}=\boldsymbol{\Gamma}^{H} \mathbf{R}_{j} \mathbf{R}_{j}^{H} \boldsymbol{\Gamma}$ and $\mathbf{S}_{R}=\boldsymbol{\Gamma}^{H} \mathbf{R}_{j} \boldsymbol{\Gamma}$. For large signal to interference plus noise ratio (SINR), with $\sigma^{2}$ and $\operatorname{tr}(\boldsymbol{\Lambda})$ small enough so that $\left\|\mathbf{S}_{R R}^{-1}\left(\boldsymbol{\Lambda}+\sigma^{2} \mathbf{S}_{R}\right)\right\|_{2}<1$ where $\|\cdot\|_{2}$ denotes the matrix 2norm, the term $\left[\mathbf{I}+\mathbf{S}_{R R}^{-1}\left(\boldsymbol{\Lambda}+\sigma^{2} \mathbf{S}_{R}\right)\right]^{-1}$ in $J_{j}$ above may be expanded in a series [16]. Neglecting the higher order terms and taking the limit as $\sigma^{2} \rightarrow 0$, the MSE becomes $J_{j} \simeq \operatorname{tr}\left(\boldsymbol{\Lambda} \mathbf{S}_{R R}^{-1}\right)=\sum_{k=1}^{K_{j}} \lambda_{k}\left[\mathbf{S}_{R R}^{-1}\right]_{k k}$, where $[\cdot]_{k l}$ is the $(k, l)$ element of the matrix argument. Since matrix $\mathbf{S}_{R R}$ is similar to $\mathbf{R}_{j} \mathbf{R}_{j}^{H}$, and since both $\mathbf{C}_{j} \mathbf{C}_{j}^{H}$ and $\mathbf{R}_{j} \mathbf{R}_{j}^{H}$ are normal [16], it can be shown using the Cauchy-Schwartz inequality on $J_{j}$ that

$$
\begin{equation*}
J_{j}^{2} \leq\left(\sum_{k=1}^{K_{j}}\left(\left\|\mathbf{c}_{j k}\right\|^{2}\right)^{2}\right)\left(\sum_{k=1}^{K_{j}}\left[\left(\mathbf{R}_{j} \mathbf{R}_{j}^{H}\right)^{-1}\right]_{k k}^{2}\right) \tag{7}
\end{equation*}
$$

where $\mathbf{c}_{j k}^{T}$ is the $k^{\text {th }}$ row of $\mathbf{C}_{j}$. Notice that $\mathbf{R}_{j} \mathbf{R}_{j}^{H}$ in (7) is positive definite, diagonally dominant under power control and thus for a constant group size and for relatively low cross-correlation power, the second product term in (7) remains approximately constant regardless of the actual group membership. We can thus argue that the MSE upper bound can be reduced by choosing $\mathcal{G}$ such that $J_{c c}^{(j)} \triangleq \sum_{\forall k \in \mathcal{G}_{j}}\left\|\mathbf{c}_{j k}\right\|^{2}$ is minimized $\forall j$, and thus this sum represents an appropriate choice of cost criterion for grouping.

The cost $J_{c c}^{(j)}$ has a computational advantage over the MSE because it only requires the correlation matrix $\mathbf{S}^{H} \mathbf{S}$, which is already available from computing the optimal MMSE filter in (4). We therefore define the cost criterion for a set of groups $\mathcal{G}=\left\{\mathcal{G}_{1}, \ldots, \mathcal{G}_{G}\right\}$ as:

$$
\begin{equation*}
J_{\mathrm{cc}}(\mathcal{G}) \triangleq \sum_{j=1}^{G} J_{c c}^{(j)}=\sum_{j=1}^{G} \sum_{\forall k \in \mathcal{G}_{j}} \sum_{l \notin \mathcal{G}_{j}}\left|\mathbf{v}_{\mathcal{G}_{j}(k)}^{H} \mathbf{v}_{l}\right|^{2} \tag{8}
\end{equation*}
$$

where $\mathbf{v}_{\mathcal{G}_{j}(k)}$ is the effective signature waveform of the $k^{\text {th }}$ user of group $j$. The optimal grouping with respect to this cost criteria is then given by $\mathcal{G}_{c c}^{\circ}=\arg \min _{\mathcal{G}} J_{\mathrm{cc}}(\mathcal{G})$. Even with the reduced complexity cost function in (8), finding $\mathcal{G}_{\mathrm{cc}}^{\circ}$ represents a significant challenge because of the large search space dimension. Furthermore, in practice the grouping will have to be recomputed at regular intervals because of user mobility.

We now propose a new practical and sub-optimal grouping algorithm based on the assumption that the receiver can
accommodate a maximum of $G_{\text {max }}$ groups and $K_{g \text {,max }}$ users per group, where $G_{\max }$ and $K_{g, \text { max }}$ depend on the hardware implementation. The basic grouping principle is to combine pairs of users or groups with large cross-correlation or "proximity".

## A. Mutually exclusive grouping

Let $\mathcal{F}_{l} \subseteq\{1, \ldots, K\}$ be the subset of user indices defining group $l \in\{1, \ldots, G\}$, and let $\mathcal{F}=\left\{\mathcal{F}_{1}, \ldots, \mathcal{F}_{G}\right\}$, where $\mathcal{F}_{k} \bigcap \mathcal{F}_{l}=\emptyset, \forall k \neq l$. We define the proximity metric between subsets $\mathcal{F}_{k}, \mathcal{F}_{l} \in \mathcal{F}$ as the largest pairwise proximity between all possible pairs of corresponding users:

$$
\begin{equation*}
\delta_{\mathcal{F}_{k}, \mathcal{F}_{l}}=\arg \max _{\substack{\forall p \in \mathcal{F}_{k} \\ \forall q \in \mathcal{F}_{l}}}\left|\mathbf{v}_{p}^{H} \mathbf{v}_{q}\right|^{2}, \tag{9}
\end{equation*}
$$

where $\left|\mathbf{v}_{p}^{H} \mathbf{v}_{q}\right|^{2}$ is the proximity between user $p$ and $q$.
The flow diagram for the proposed grouping algorithm is illustrated in Fig. 2. The algorithm starts with $\mathcal{F}=$ $\{\{1\}, \ldots,\{K\}\}$ and $G=K$. The subsets composing $\mathcal{F}$ are "refined" at each iteration until no more grouping can be done, at which point $\mathcal{G}=\mathcal{F}$. At each iteration, the proximity metric is computed for all $N_{p}=\binom{G}{2}$ possible pairs of subsets in $\mathcal{F}$, where $G$ is the number of subsets in $\mathcal{F}$. Grouping is then attempted in decreasing order of proximity metric (close pairs first) by trying to merge $\mathcal{F}_{k}$ and $\mathcal{F}_{l}$ to either form a new group (both $\mathcal{F}_{k}$ and $\mathcal{F}_{l}$ contain a single element), combine two existing groups (both $\mathcal{F}_{k}$ and $\mathcal{F}_{l}$ contain two or more elements), or add a new elements to an existing group. If the elements cannot be merged because of the hardware constraint, the algorithm tries with the next pair. The algorithm stops when attempts for grouping have failed for all of the $N_{p}$ pairs, at which point $\mathcal{G}=\mathcal{F}$. The total number of resources is $K_{\text {max }} \triangleq G_{\text {max }} K_{g, \text { max }}$ and if $K \leq K_{\text {max }}$, the algorithm will allocate all the users successfully.

## B. Grouping with user sharing

Based on the hardware limitations assumptions discussed above, a practical receiver for GRP-STMUD would provide a total of $K_{\max }$ "detections units". If $K<K_{\max }$ there are $K_{\text {extra }}=K_{\max }-K$ extra resources available for sharing, that are essentially free of extra computational cost. The proposed algorithm for grouping with user sharing starts with the mutually exclusive grouping $\mathcal{G}$ obtained using the algorithm of Fig. 2. Since adding users to an existing group does not deteriorate the performance [10], the new algorithm "fills" the unused resources in each group with shared users, and provides a new "shared" grouping, $\mathcal{G}^{(s)}=\left\{\mathcal{G}_{1}^{(s)}, \ldots, \mathcal{G}_{G}^{(s)}\right\}$.

The flow diagram in Fig. 3, illustrates the grouping procedure for user sharing. The algorithm proceeds group by group; for the $j^{\text {th }}$ group, the $K_{g \text {,max }}-K_{j}$ empty resources, if any, are filled with a user $k \notin \mathcal{G}_{j}$. The users are selected in order of decreasing proximity with the group of interest. Note that the algorithm does not create new groups.

## V. Results

We consider the received signal model of (1) for the uplink of a DS-CDMA system. The users have orthogonal spreading


Fig. 2. Flow diagram for the grouping algorithm without sharing.


Fig. 3. Flow diagram for the grouping algorithm extension for user sharing.


Fig. 4. BER versus SNR average performance.


Fig. 5. BER versus SNR performance for user \# 8 .
codes of length $Q=16$ and transmit BPSK data symbols in blocks of $N=50$. The signals are received by $L=6$ antennas in a standard linear array configuration. The channel consists of $W=6$ equal power multipaths, which destroy code orthogonality and cause MAI; similar results can also be obtained under this scenario with non-orthogonal codes such as m-sequences. The main path has DOA $\theta_{0}$ uniformly distributed within the sector width of $120^{\circ}$, and all other paths are uniformly distributed within $\left[\theta_{0}-\Delta \theta, \theta_{0}+\Delta \theta\right]$, with $\Delta \theta=$ $30^{\circ}$. The GRP-STMUD structure has $G_{\max }=4$ groups of a maximum of $K_{g \text {, max }}=4$ users each. The active users share the $K_{\max }=16$ detection units.

The first experiment proceeds in three steps: first, the optimal grouping with respect to the MSE is found through exhaustive search of all possible mutually exclusive grouping and the optimum MSE $J^{\circ}$ is found. Second, the optimal grouping with respect to the cost criterion is also found using exhaustive search with corresponding MSE $J_{c c}^{0}$. Finally the grouping based on the proposed algorithm is determined along with its MSE $J_{\text {grp }}$. This procedure is repeated over 250 different


Fig. 6. Numerical complexity comparison between the full STMUD with resources for $K=16$ users and GRP-STMUD with selective combining for $G_{\max }=4$, and $K_{\mathrm{g}, \max }=4$.
scenarios. We define the normalized MSE difference for the optimum cost and grouping algorithm $\Delta_{\mathrm{cc}} \triangleq\left(J_{\mathrm{cc}}^{\mathrm{o}}-J^{\mathrm{o}}\right) / J^{\mathrm{o}}$ and $\Delta_{\text {grp }} \triangleq\left(J_{\text {grp }}-J^{\circ}\right) / J^{\circ}$, respectively.

Gathering the statistics, we observe that for a deviation of $t=2.5 \%$ from the optimal MSE, a very large proportion of the grouping obtained using the sub-optimal algorithms provided MSE very close to the optimal one, specifically $P\left(\Delta_{\mathrm{cc}} \leq t\right)=0.95$ and $P\left(\Delta_{\mathrm{gpr}} \leq t\right)=0.91$. These results show that the proposed grouping algorithm performs well and also demonstrate that the use of (8) is justified since a very large proportion of the grouping obtained using the cost criterion lead to a MSE very close to the optimal MSE $J^{\circ}$.

In the second experiment, the BER is measured using numerical simulations with $K=12$ users. The channel coefficients are fixed for the simulation; similar results have been obtained with other channel realizations. Figure 4 shows the BER averaged over all users. The different grouping approaches in the GRP-STMUD structure perform similarly well; there is a measurable difference of more than 2 dB at BER of $10^{-3}$ between the group-based approaches and the MF.

In general, sharing involves a few users and only some might benefit from it significantly, a fact concealed by the averaging of Fig. 4. The performance of user \#8, which benefits from having a strong user shared in its group, is shown in Fig. 5. The gain obtained from sharing with either MMSE or selective combining is significant in this case; it can be measured to be approximately 1.5 dB at $10^{-3} \mathrm{BER}$ when compared to the GRP-STMUD approach without sharing. Our experiments show that this situation is common. Cases where MMSE combining performs significantly better than selective combining are however much less frequent.

To compare the complexity between the full STMUD and GRP-STMUD approaches, the number of complex floating point operations (CFLOPS) is counted for the different parts of equations (2) and (4) by taking advantage of the symmetries as in [13]. The total complexity is divided in two distinct parts: overhead $(\mathrm{OH})$ and linear system solution (Sol.). Figure 6 shows the numerical complexity in terms of CFLOPS. The results show that the total complexity associated to the full STMUD is more than three times that of the proposed GRPSTMUD system.

## VI. Conclusion

In this work we have proposed a new group-based spacetime receiver structure for DS-CDMA derived from the groupoptimal MMSE linear detector, and a grouping algorithm based on the group MSE. An extension of the proposed structure that frees from group-mutual exclusivity is also presented along with the corresponding grouping algorithm. The new structure provides a means for combining group multiuser detector outputs for shared users.

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    The authors are with the Department of Electrical and Computer Engineering, McGill University, Montréal, QC, H3A 2A7, Canada (e-mail: benoit.pelletier@mail.mcgill.ca, benoit.champagne@mcgill.ca).

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[^1]:    ${ }^{1}$ The $\otimes$ operator denotes the Kronecker matrix product [16].

