SEMI-BLIND SPACE-TIME ESTIMATION OF CO-CHANNEL SIGNALS USING LEAST SQUARES PROJECTIONS

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Abstract - We propose a new method, Joint Space-Time DWILSF (Decoupled Weighted Iterative Least Squares with Subspace Fitting) Algorithm that maps array output signals to a known finite alphabet (FA) symbol constellation without preceding subspace estimation. We evaluate the performance of our approach by simulating space division multiple access (SDMA) and spatial filtering for interference reduction (SFIR) scenarios using the GSM radio interface. Two different semi-blind receivers act as performance references. We show that our linear approach requiring only matrix multiplications during iterations converges fast and provides promising performance with reasonable computational complexity.

I. INTRODUCTION

Utilisation of the spatial component of the radio channel for capacity increase of mobile radio systems has raised considerable interest during the last years. Traditionally adaptive antenna processing has been based on beamforming using spatial reference (DOA estimation) algorithms. An alternative technique is temporal reference adaptation minimising the error between known bit fields (training sequences) and array outputs after appropriate weighting. The most advanced case combines different antenna signals simultaneously with time domain equalisation (space-time processing)[1].

Recently, more attention has been paid to blind and semi-blind signal separation and detection using structural signal properties. We have previously introduced a semi-blind method for space-time equalisation, separation and detection of multiple co-channel signals [2]. This technique performs first *row space estimation* of the specially constructed data matrix [3], which means joint space-time equalisation of all incoming signals. Afterwards we make iterative projections to the finite alphabet structure of the symbols with the DWILSF (Decoupled Weighted Iterative Least Squares with Subspace Fitting) algorithm outputting detected symbol sequences. We initialise these iterations by the known bit fields included in the slot structure of the system. We have demonstrated a very promising performance of this algorithm but the decomposition of the data matrix leads to relatively high computational complexity.

In this paper we introduce a space-time technique combining received array signals in space and time domains using the DWILSF algorithm directly - *without* subspace estimation - for an appropriately structured received data matrix. The algorithm maps the different antenna signals and delay components to the finite alphabet (FA) constellation in a straightforward way. This approach is computationally very efficient requiring only matrix multiplications during the iterative projections and thus the complexity is essentially less than with subspace based techniques.

We employ two methods mainly known from the CDMA field to process multiple TDMA signals. We estimate all desired co-channel signals separately (decoupled detection) and then subtract the interference caused by the stronger user (serial interference cancellation, SIC) before starting the estimation of the next user signal.

As performance references we use two different receivers: a RAKE receiver and our previous semi-blind technique. The RAKE receiver combines first spatial components in each finger and afterwards sums different delay components with appropriate weighting. Before the combining of finger signals we discriminate the contributions carrying only interference by comparing finger outputs with the training sequence of the currently detected user.

For utilisation of adaptive antennas in TDMA networks two operational modes exist. In case of spatial division multiple access (SDMA) more than one co-cell users are served in one traffic channel. With spatial filtering for interference reduction (SFIR) only one user per traffic channel exists, but the reduced frequency re-use distance leads to presence of several interference sources. Additionally, the interference situation changes during a burst due to the asynchronous network. In this paper we show the performance of the proposed algorithm in both of these operational modes.

The paper is organised in the following way: Section 2 introduces the data model. In Sec. 3. we introduce all studied receiver structures: joint space-time DWILSF, DWILSF employing serial interference cancellation and modified RAKE receiver. Additionally we discuss the computational complexity of these receivers. Section 4. describes our simulation environment, used parameter selection and directional stochastic channel model. In Sec.5. we show simulation results and finally Sec.6 summarises and concludes this paper.

We use the following notation throughout the paper: For a matrix $\boldsymbol{A}$, $\boldsymbol{A}^{\#}$ and $\|\boldsymbol{A}\|$ are its Moore-Penrose pseudo-inverse and Frobenius norm, respectively. In general bold notations signify vectors and capitalised bold notations matrices.

II. DATA MODEL

In this paper we consider a scenario in which d co-channel signals impinge simultaneously at the receiving base station antenna array with M sensors. Assuming that the channel of each user is a FIR filter with a maximum length of L, the n:th sample of the sum signal $\boldsymbol{x}$ at the m:th antenna element can be written

$$\boldsymbol{x}_m(n) = \sum_{j=1}^{d}\sum_{l=0}^{L-1} h_{jml}\, \boldsymbol{s}_j(n-l) + \boldsymbol{v}(n)\,, \qquad (1)$$

where h_{jml} signifies a channel response of the j:th signal $\boldsymbol{s}_j$ to the m:th antenna element in the l:th channel tap, and $\boldsymbol{v}$ denotes additive Gaussian noise.

In this paper we use the principle of decoupled signal detection; we estimate one desired signal at a time and leave the other incoming signals to the interference term. By considering the k:th user to be a desired one, we can rewrite Eq.1 as

$$\boldsymbol{x}_m(n) = \sum_{l=0}^{L-1} h_{kml}\, \boldsymbol{s}_k(n-l) + \sum_{j=k}\sum_{l=0}^{L-1} h_{jml}\, \boldsymbol{s}_j(n-l) + \boldsymbol{v}(n)\,, \qquad (2)$$

$$\boldsymbol{x}_m(n) = \sum_{l=0}^{L-1} h_{kml}\, \boldsymbol{s}_k(n-l) + \boldsymbol{i}_m(n)\,, \qquad (3)$$

where vector $\boldsymbol{i}_m$ includes co-channel interference and thermal noise. In matrix form this can be written $\boldsymbol{X} = \boldsymbol{H}_k \cdot \boldsymbol{S}_k + \boldsymbol{I}$, where $\boldsymbol{S}_k$ is a block matrix with size $[L\times(N+L-1)]$. It is composed of shifted and stacked versions of the symbol vectors of the k:th user

$$\boldsymbol{S}_k = \begin{bmatrix} \boxed{\boldsymbol{s}_k} & 0\cdots 0 \\ 0 \; \boxed{\boldsymbol{s}_k} & 0 \\ & \ddots \\ 0\cdots 0 & \boxed{\boldsymbol{s}_k} \end{bmatrix} \updownarrow L \; . \qquad (4)$$

The term N denotes the number of collected snapshots. Matrix $\boldsymbol{H}_k$ means the $[M\times L]$ space-time channel matrix for the k:th user. $\boldsymbol{X}$ and $\boldsymbol{I}$ are $[M\times(N+L-1)]$ matrices including received data and interference terms, respectively.

III. RECEIVER ALGORITHMS

Joint Space-Time DWILSF Combiner

With our Joint Space-Time DWILSF Combiner the goal is to estimate the symbol matrix $\boldsymbol{S}_k$ consisting of elements belonging to a known finite alphabet (FA) constellation Ω by minimising the mean square error (MSE)

$$min_{S,T;S\in FA}\|\boldsymbol{S}_k - \mathsf{T}_k \cdot \mathsf{X}\|^2. \qquad (5)$$

The notation X denotes the extended data matrix with size $[p\cdot M\times(N+L_e+p-2)]$ including p stacked and left shifted original data blocks $\boldsymbol{X}$. Matrix T_k is the corresponding $[L_e\times(p\cdot M)]$ projection matrix mapping the received signal samples to the detected symbol matrix $\boldsymbol{S}_k$. The term L_e denotes the number of shifted rows of $\boldsymbol{S}_k$ (length of the time domain equaliser, which is not always the same than the instantaneous length of the channel). The influence of the stacking with factor p is better conditioning of the projection matrix and thus we can improve the numerical accuracy of the problem. This has a significant effect on the performance. Note, that in case $p>1$, we have to truncate matrix X to correspond to the number of the columns of matrix $\boldsymbol{S}_k$ before we can solve the minimisation problem of Eq.(5).

Finally considering the minimisation problem of Eq.5., we can now introduce the principle of the Joint Space-Time DWILSF Combining. The estimation steps of the algorithm are described shortly below and summarised in Table 1. The algorithm consists of an initialisation step and iterative projections updating either the estimate of the symbol matrix $\boldsymbol{S}_k$ or the corresponding projection matrix T_k. The structural basis for this kind of signal detection using alternating projections is the known finite alphabet constellation Ω of the modulation symbols.

The appropriate initialisation guarantees the convergence to the global minimum. In this step we create the initial signal matrix $\boldsymbol{S}_{k,mid}^{(0)}$ by stacking and shifting the midamble of the current user k. We calculate the initial estimate of the projection matrix $\mathsf{T}_k^{(0)}$ using a least-squares fit over the corresponding block of the X matrix; i.e. $\mathsf{T}_k^{(0)} = \boldsymbol{S}_{k,mid}^{(0)} \cdot \mathsf{X}^{\#}_{mid}$.

Having an initial estimate of the projection matrix $\mathsf{T}_k^{(0)}$, we update first the signal matrix $\check{\boldsymbol{S}}_k$ (in which elements are soft estimates of the transmitted symbols) solving the least squares equation $\check{\boldsymbol{S}}_k^{(r)} = T_k^{(r-1)} \cdot X$, where r indexes the current iteration round. Projections using the symbol matrix including stacked and left shifted versions of the symbol vectors lead to the joint combining and equalisation in space and delay domains in a straightforward way. Rows of the $\check{\boldsymbol{S}}_k$ matrix correspond the shifted contributions of the different time-domain equaliser taps. Before projecting $\check{\boldsymbol{S}}_k$ to the finite alphabet constellation Ω, we utilise its Toeplitz property by summing the row elements with appropriate shifting and rounding this sum to the nearest discrete modulation symbol. Table 1 denotes this rounding with operator "*proj*". This provides the symbol vector $\boldsymbol{s}_k$ consisting of the hard symbol estimates (see step *ii)* of Table 1, where we denote row of $\check{\boldsymbol{S}}_k^{(r)}$ with l and time samples with n). Before updating the projection matrix $T_k^{(r)}$ we extend the hard decision vector again to the form of the stacked and shifted symbol matrix $\boldsymbol{S}_k^{(r)}$. By employing this matrix we update the projection matrix using a least-squares solution $T_k^{(r)} = \boldsymbol{S}_k^{(r)} \cdot X^{\#}$.

We repeat these iterations until convergence is achieved, i.e. until two consecutive estimates do not differ any more. Afterwards we perform the same procedure for the next desired user. Note that only *desired* incoming signals must be detected, e.g. in an SFIR application, iterations have to be performed only once for the user situated in the served cell. In SDMA case we have to repeat the iterations for all co-cell users within the same traffic channel. These co-cell users can also be synchronised, which allows joint channel estimation for the initialisation of the iterations [4].

TABLE 1:

SOLVE $\min_{S,T;S\in FA} \|\boldsymbol{S}_k - T_k \cdot X\|^2$ FOR EACH DESIRED USER k

for $k = 1{:}d$

initialise T_k using midamble $T_k^{(0)} = \boldsymbol{S}_{k,mid} \cdot X_{mid}^{\#}$

for r = 1,2, ... (iterative projections)

i) $\check{\boldsymbol{S}}_k^{(r)} = [\, T_k^{(r-1)} \cdot X \,]$

ii) $\boldsymbol{s}_k^{(r)}(n) = proj_\Omega \left[\sum_{l=1}^{L_e} \check{\boldsymbol{S}}_k^{(r)}(l, n+l) \right]$

iii)

$$\boldsymbol{S}_k^{(r)} = \begin{bmatrix} \boldsymbol{s}_k^{(r)} & 0 \cdots 0 \\ 0 \;\; \boldsymbol{s}_k^{(r)} & 0 \\ \ddots & \\ 0 \cdots 0 & \boldsymbol{s}_k^{(r)} \end{bmatrix}$$

iv) $T_k^{(r)} = \boldsymbol{S}_k^{(r)} \cdot X^{\#}$

repeat until $(T_k^{(r)}, \boldsymbol{S}_k^{(r)}) = (T_k^{(r-1)}, \boldsymbol{S}_k^{(r-1)})$

The DWILSP (Decoupled Weighted Iterative Least Squares with Projections) algorithm [5], proposed for separate space and time combining using the RAKE approach, is quite similar, but our approach is computationally more efficient requiring only pseudo-inverse of the input data matrix. This means that the expensive pseudo-inverse must be calculated only once before starting the iterative projections, not during each iteration round. This enables extension to joint space-time combining with a reasonable computational load.

DWILSF Algorithm with Serial Interference Cancellation

Due to the decoupled estimation principle of our algorithm it is straightforward to include serial interference cancellation [6] in the DWILSF algorithm when several desired signals are present in the same traffic channel (SDMA scenario). Employing interference cancellation requires some additional steps in the algorithm. First, we perform channel estimation utilising modulated training sequences. This step also provides information about the signal with the strongest power which has to be detected first. After detection of the first desired bit sequence with the ordinary DWILSF algorithm, we generate the corresponding modulated signal sequence. After multiplication with the channel estimate of the stronger user, this estimated interference is subtracted from the original data matrix before starting the detection of the next desired signal.

Reference RAKE Receivers

As a reference, we study a RAKE receiver performing space and time domain combining separately. Each finger combines signals from different antenna elements in the space domain. Standard space-only version of DWILSF updating $\boldsymbol{s}_k$ and $\boldsymbol{t}_k$ vectors is used in each finger. Temporal combining is performed when the outputs of the different fingers, separated by the multiples of the symbol period T_S, are summed.

In ordinary RAKE receivers used to detect DS-CDMA signals, matched filtering provides information about the instantaneous channel impulse response. This allows to allocate fingers with the delays of the strongest multipath components. This is unfortunately not the case with narrowband TDMA signals. Therefore we have to allocate a certain number of fingers without knowing if the signal energy is received with the corresponding delays or not. As a consequence, we propose a pre-selection step to pick only the fingers carrying useful information for temporal combining. This pre-selection is essential because the linear mapping of each finger converges to arbitrary soft output vector in case that the desired signal does not exist with the corresponding delay. To prevent such fingers to cause additional interference, they are switched off before the combining process. In practice we perform this by comparing the hard decisions of the midamble part of the finger outputs with the known training bits. All fingers providing more errors than the selected threshold value are rejected. The effect on the performance is essential, without hard finger pre-selection the BER saturates just below the 10^{-2} level. Figure 1 shows the structure of the reference RAKE receiver, where we draw the reader's attention to the finger pre-selection.

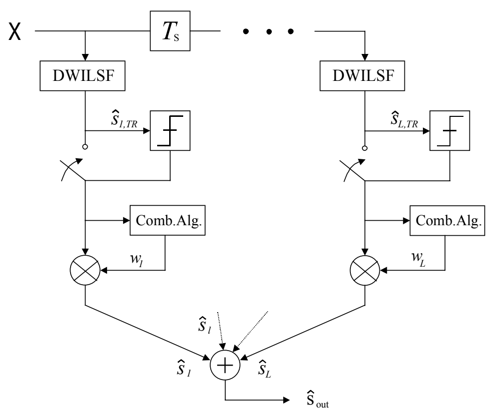

Fig. 1. Principle of the DWILSF-RAKE Receiver

For temporal combining of the finger outputs we used modified maximum ratio combining (MRC) [5]. In this case the output of the RAKE receiver for the k:th user is

$$\boldsymbol{S}_k = proj\left[\sum_{l=0}^{L_a} \frac{1}{\sigma_{lk}^{\ \alpha}} \breve{\boldsymbol{S}}_{lk}\right] , \qquad (6)$$

where

$$\sigma_{lk}^{\ 2} = var\,[\boldsymbol{s}_{lk} - \check{\boldsymbol{s}}_{lk}] \ . \qquad (7)$$

L_a is the total number of active fingers after pre-selection, $\boldsymbol{s}_{lk}$ and $\check{\boldsymbol{s}}_{lk}$ are hard and soft estimate vectors of the l:th finger. We tested also DWILSF algorithm for temporal combining of the fingers. This approach is more complex and did not show improvement in performance.

Complexity Aspects

In all of the studied receiver structures the Moore-Penrose pseudo-inverse of the stacked input data matrix X with size $[p{\cdot}M{\times}(N{+}p{-}1)]$ must be calculated before starting the iterations. After that the joint space-time combiner requires $L_e{\cdot}M{\cdot}p{\cdot}N$ multiplications and additions for updating either $\boldsymbol{S}_k$ or T_k matrices during each iteration. Assuming Γ_{joint} iterations before convergence this leads to total number of $\Gamma_{joint}{\cdot}2{\cdot}L_e{\cdot}M{\cdot}p{\cdot}N$ multiplications and additions per each desired user. In case of the RAKE receiver each finger requires $M{\cdot}p{\cdot}N$ iterations for updating $\boldsymbol{s}_k$ or $\boldsymbol{t}_k$ vectors.

This leads to the total complexity of

$$\sum_{l=1}^{L_e} \Gamma_l \cdot 2 \cdot M \cdot p \cdot N \ ,$$

where Γ_l corresponds to the number of the required iteration rounds in finger l. Assuming the same mean number of iterations with RAKE fingers than with joint approach, the number of required operations is exactly the same. However, in practice the convergence of the fingers not carrying the desired signal components is slower and this makes the RAKE receiver more complex. Additionally we need some operations for the combining step.

Finally we give an example about the required absolute number of operations. With the parameters of Fig.3 and two required iterations (see CDF in Fig. 2, SNR 15 dB, ~90% level) this leads to $14{\cdot}10^3$ complex multiplications and additions per desired user. Note that this value includes separation, equalisation and detection of the desired user.

The implementation of serial interference cancellation requires channel estimation by modulated training sequences and re-modulation of the first detected bit sequence at the receiver. Additionally the pseudo-inverse of the new data matrix after interference subtraction must be calculated.

IV. SIMULATIONS AND PROPAGATION MODELLING

Our simulations refer to the GSM radio interface, but the estimation principle is not restricted to the GSM case. We show performance for both operational modes of adaptive antenna systems (SDMA and SFIR). In SDMA mode we had two co-channel users in the same cell. Both of them had equal average powers at the base station, leading to a mean carrier to interference ratio (C/I) of 0 dB. In this case other interfering sources from neighbouring cells were omitted. In the SFIR case we considered 3 simultaneously active interferers and their average power was varied to provide different C/I values. Due to the non-synchronous operation of the GSM network we additionally changed the DOAs and channel situations of each interferer randomly during each burst. As a result we show raw bit error rates without any error correction. In the SDMA case the BER values are averaged over both desired users.

As a propagation model we used the directional stochastic channel model [7]. In this model we first prescribe the shape of the azimuthal delay power spectrum (ADPS). We used exponential shape for the power delay profile (PDP) and Laplacian shape for the azimuthal power spectrum (APS), which were the shapes obtained in recent spatial channel measurements [8]. For delay and angular spread we used values 2 μs and 7°, respectively. For each instantaneous channel realisation we selected a large number of taps randomly positioned in the delay-angular domain and weighted their power by means of predefined ADPS shape. Instantaneous tap powers were taken from Rayleigh distribution.

V. SIMULATION RESULTS

Figure 2 shows the cumulative distribution function (CDF) for the number of the required iterations of the DWILSF algorithm in SDMA operation mode. After appropriate initialisation with known system specific bit fields (e.g. midambles in GSM) we need only some iteration rounds for convergence. For example in 90% of the cases only four iterations were enough with SNR = 10 dB and C/I = 0 dB.

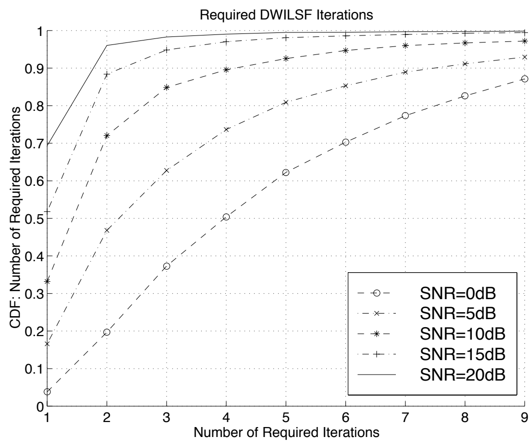

Fig. 2. Number of required iterations of DWILSF

Figure 3 compares the performance of the different receiver structures in the SDMA scenario with two users. In this simulation we used an array with M=4 antennas with inter-element spacing of 7 λ. The length of the time domain equalisation process (stacking factor, L_e) was set to 3 symbol periods, which was also the number of the fingers of the RAKE receiver. With both combining schemes all fingers carrying three or less errors in the midamble were included in the combining process after the finger pre-selection. We used the weighting exponent α=4 for the modified MRC in this simulation, but other higher values had no significant effect on the BER. In all cases the input data matrix collected from the array was stacked with a factor p=2. As a performance reference we use our subspace based semi-blind algorithm [2]. The price to be paid for its excellent performance is additional complexity compared to the methods proposed in this paper. This figure demonstrates the significant performance improvement of the joint space-time combining compared to the RAKE receiver. This is due to the fact that inter-symbol interference disturbs the performance of the individual fingers, because each of them is performing space-only processing. The performance gain of the joint approach can be obtained even with reduced computational complexity. Different combining algorithms did not lead to a significant difference in BER with the RAKE receiver. In 99% of the cases more than one RAKE finger was active.

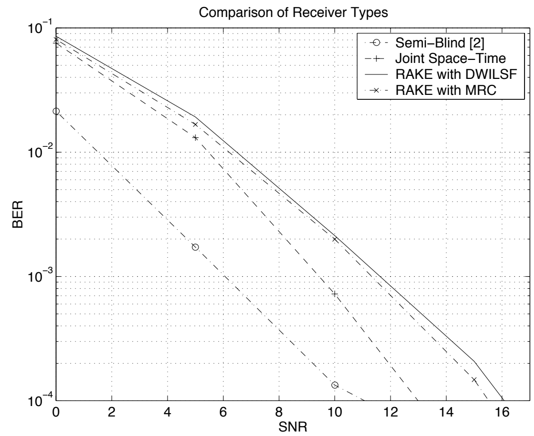

Fig. 3. Comparison of studied receiver types, SDMA scenario

Figure 4 shows the performance of the joint combining approach in a non-synchronous SFIR scenario as a function of the input SNR. The C/I ratio was varied between -20 dB and 0 dB. In this simulation we used a λ/2 spaced array of M=8 antenna elements. Otherwise the same parameters as with the SDMA scenario were used. This scenario demonstrates that our algorithm is robust against changes of the interference situation during the considered burst.

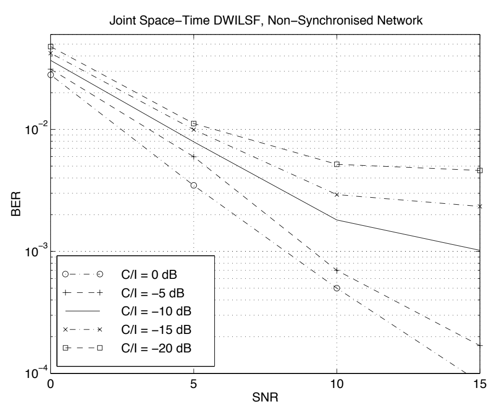

Fig. 4. Performance of Joint Space-Time DWILSF, non-synchronised SFIR scenario

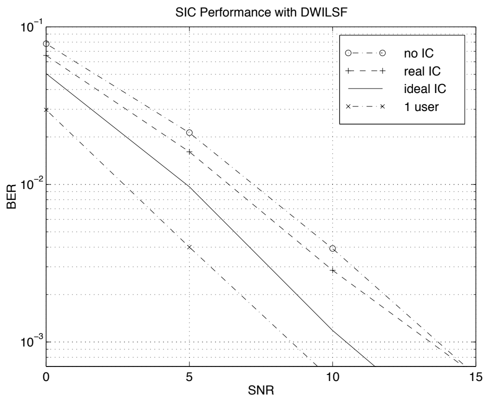

Fig. 5. Performance of DWILSF with serial interference cancellation (SIC)

Figure 5 shows the performance improvement if serial interference cancellation (SIC) is employed in a flat fading SDMA situation. As a reference we show the curve for one user without interfering sources. We also show an upper bound for the performance gain of more than 2 dB with an ideal SIC. In this case we first detected the user with the strongest instantaneous power normally and after that we assumed perfect cancellation of this signal contribution. Because of the non-ideal channel estimation we do not reach the ideal performance gain in a real situation. However, we obtain an improvement in the order of 1 dB. This gain can be obtained without increasing the number of required operations significantly. Employing more advanced methods for channel estimation can also allow approaching the upper bound.

VI. SUMMARY AND CONCLUSIONS

In this paper we introduced the Joint Space-Time DWILSF Algorithm. It is based on straightforward linear mapping of the array output signals to the known finite alphabet (FA) constellation, using simultaneous combining in space and time domains. During the iterations of the algorithm we perform alternating projections updating either the symbol matrix to be detected or the corresponding projection matrix. In addition to the finite alphabet property of the modulation symbols, we utilise also the Toeplitz structure of the symbol matrix. Our iterations require only matrix multiplications, which allows this kind of joint space-time approach with reasonable computational complexity.

We demonstrated the performance using realistic SDMA and SFIR simulation scenarios including also the effect of a non-synchronised network. For modelling of the radiowave propagation we used a directional stochastic channel model with realistic delay and angular spreads. As a reference we used a RAKE receiver based on separate spatial and temporal combining. Before combining the individual RAKE fingers we proposed a hard finger pre-selection procedure fully switching off the contributions carrying only interference. As a second reference receiver we used the subspace-based semi-blind algorithm [2].

Our simulations showed a significant performance gain compared to the RAKE approach. The main reason is that inter-symbol interference limits the performance of the individual fingers performing space-only processing. Compared to the subspace estimation based semi-blind processing the BER performance of the proposed algorithm is slightly worse, but savings in computational complexity are significant. Our results showed that this kind of simple and straightforward linear space-time combining without subspace estimation can provide appropriate performance with reasonable complexity.

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