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SEMI-BLIND SPACE-TIME EQUALIZATION FOR SINGLE-CARRIER MIMO SYSTEMS WITH BLOCK TRANSMISSION

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ABSTRACT

This paper proposes a novel semi-blind space-time equalization method for wireless Multiple-Input Multiple-Output (MIMO) spatial multiplexing systems using Single-Carrier Cyclic-Prefix (SC-CP) block transmissions. Independent Component Analysis (ICA) is employed to track the time-varying MIMO channel. It is shown that with a training overhead of only 0.05%, the proposed method can provide close performance to the case with perfect channel state information (CSI), even at relatively high Doppler frequency. The semi-blind SC-CP system also outperforms its OFDM counterpart with perfect CSI at high Signal to Noise Ratios (SNRs).

1. INTRODUCTION

Block transmissions are preferred over serial transmissions since FIR equalizers can be employed for symbol recovery instead of IIR equalizers required with serial processing [1]. A popular block transmission method is Orthogonal Frequency Division Multiplexing (OFDM), which is increasingly used to combat frequency-selective channels. Single-carrier (SC) block transmission methods, such as SC-Cyclic-Prefix (SC-CP), avoid the OFDM drawbacks of high peak-to-average power ratios and sensitivity to carrier frequency offsets [2] while retaining the advantages of block processing.

Employing semi-blind equalization has the benefit of increasing the bandwidth efficiency compared to training based systems, since only a small amount of training is required. However, most previous work on (semi-) blind equalization for Multiple-Input Multiple-Output (MIMO) block transmissions over frequency selective channels has focused on OFDM systems. Adaptive equalization methods based on training were proposed for SC-CP MIMO systems in [3] and [4] but they introduce a training overhead of 13% and 10%, respectively.

Approaches for (semi-) blind equalization include the Constant Modulus Algorithm (CMA) and Second Order Statistics (SOS) methods. The former employs HOS but may suffer from slow convergence and misconvergence in the presence of noise, while the use of SOS may result in sensitivity to Gaussian noise. The CMA was applied to SC MIMO serial transmission systems with non-frequency selective channels in [5] and SOS were applied to SC MIMO serial transmission systems with frequency selective channels in [6]. Independent Component Analysis (ICA) employs Higher Order Statistics (HOS) to estimate the transmitted streams from the received mixture. Blind estimation is achieved based on the assumption of mutual statistical independence of the source streams. The use of ICA promises reduced noise sensitivity over SOS methods, and by employing the FastICA algorithm [7] fast and robust convergence can be expected. To the best of our knowledge, ICA has not been applied to SC-CP systems to date.

In this paper, we propose a semi-blind space-time equalization method for SC-CP MIMO spatial multiplexing systems based on ICA. A small amount of training is used to initialise the equalizer in order to speed up convergence and to alleviate the order and scaling indeterminacies, from which blind methods such as ICA suffer [8]. In the proposed method the structure of the MIMO channel convolution matrix is exploited in order to reduce the number of parameters which have to be estimated. The method only requires an upper bound of the channel orders. Apart from employing ICA to SC-CP block transmissions, our work is different from [6] in that we provide simulation results over Rayleigh fading channels instead of fixed channels. It is also worth noting that the proposed method has the potential for blind equalization. Simulation results show that performance close to the case with perfect Channel State Information (CSI) can be obtained for a Signal to Noise Ratio (SNR) higher than 10 dB and at relatively high Doppler frequency, using a training overhead of 0.05%. Additionally, the proposed method outperforms OFDM with perfect CSI at high SNRs due to the diversity advantage of SC-CP over OFDM.

The remainder of this paper is organised as follows: First, the signal model is introduced in Section 2, followed by the proposed semi-blind space-time equalization in Section 3. Simulation results are presented in Section 4 and conclusions are drawn in Section 5.

Throughout the paper $(\cdot)^*$ denotes complex conjugation, $(\cdot)^H$ the Hermitian transpose, $(\cdot)^+$ the pseudo-inverse and $||\cdot||$ the Euclidean norm. All indices start from zero.

2. SIGNAL MODEL

We assume a MIMO spatial multiplexing system with N_t transmit and N_r receive antennas, where each transmit antenna emits one stream as length N vectors. Each vector is prepended by a Cyclic Prefix (CP) consisting of a copy of the last $L_{CP} \geq L$ symbols per vector, where L is the maximum channel order. By removing the CP at the receiver, the channel convolution matrix is circularised [1]. This provides simple equalization in frequency domain as the Discrete Fourier Transform (DFT) diagonalises the circular channel convolution matrix. However, we will exploit the structure of the

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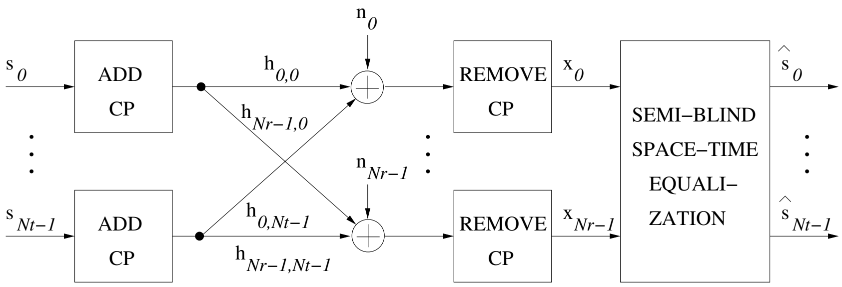

Figure 1: Overall SC-CP MIMO system with the proposed semi-blind space-time equalization, which is based on ICA.

channel convolution matrix in time domain, since ICA relies on non-Gaussian source signals. Equalization in frequency domain would involve the use of the DFT, which would gaussianise the signal distributions and thus prevent the use of HOS [8].

The stream emitted by transmit antenna t at time i is $\mathbf{s}_t(i) = [s_t(0+iN), s_t(1+iN), \cdots, s_t(N-1+iN)]^T$, with complex valued entries drawn from e.g. a QPSK constellation. The signal received by antenna r is $\mathbf{x}_r(i) = [x_r(0+iN), x_r(1+iN), \cdots, x_r(N-1+iN)]^T$ and $\mathbf{H}_{r,t}$ is the $(N \times N)$ circulant Toeplitz channel convolution matrix between transmit antenna t and receive antenna r given by [1]

$$\mathbf{H}_{r,t} = \begin{bmatrix} h_{r,t}(0) & 0 & \cdots & 0 & h_{r,t}(L) & \cdots & \cdots & h_{r,t}(1) \\ h_{r,t}(1) & h_{r,t}(0) & 0 & \cdots & 0 & h_{r,t}(L) & \cdots & h_{r,t}(2) \\ \vdots & & \ddots & & & & & \\ h_{r,t}(L) & & & & & & & \\ 0 & \ddots & & & & & & \\ \vdots & & & & & & & \\ \vdots & & & \ddots & & & \ddots & \\ 0 & \cdots & \cdots & 0 & h_{r,t}(L) & \cdots & \cdots & h_{r,t}(0) \end{bmatrix}, \tag{1}$$

which includes CP insertion and removal. The Channel Impulse Response (CIR) values $h_{r,t}(\cdot)$ are assumed to be i.i.d. complex random variables with Rayleigh distributed amplitude and uniformly distributed phase and remain constant for the duration of a block of N_s transmitted vectors. Each CIR is assumed to be of length $(L+1)$.

By stacking the signal vectors from all antennas we obtain

$$\mathbf{x}(i) = [\mathbf{x}_0^T(i), \mathbf{x}_1^T(i), \cdots, \mathbf{x}_{N_r-1}^T(i)]^T \tag{2}$$

$$\mathbf{s}(i) = [\mathbf{s}_0^T(i), \mathbf{s}_1^T(i), \cdots, \mathbf{s}_{N_t-1}^T(i)]^T \tag{3}$$

of size $(N_rN \times 1)$ and $(N_tN \times 1)$ respectively with the corresponding $(N_rN \times N_tN)$ MIMO channel convolution matrix

$$\mathbf{H} = \begin{bmatrix} \mathbf{H}_{0,0} & \cdots & \mathbf{H}_{0,N_t-1} \\ \vdots & & \vdots \\ \mathbf{H}_{N_r-1,0} & \cdots & \mathbf{H}_{N_r-1,N_t-1} \end{bmatrix}. \tag{4}$$

Fig. 1 shows the SC-CP MIMO spatial multiplexing system with the proposed semi-blind space-time equalization method.

Using the above definitions, the received signal of the MIMO system can be expressed as

$$\mathbf{x}(i) = \mathbf{H}\mathbf{s}(i) + \mathbf{n}(i). \tag{5}$$

The Additive White Gaussian Noise (AWGN) vector $\mathbf{n}(i)$ of size $(N_rN \times 1)$ is complex valued with zero mean and variance σ^2, with the variance of the real or imaginary part being $\sigma^2/2$. Further channel and source signal requirements are discussed in Section 3.3.

3. SEMI-BLIND SPACE-TIME EQUALIZATION

3.1 Independent Component Analysis (ICA)

In this section we introduce the proposed semi-blind space-time equalization method. Equation (5) describes a linear instantaneous mixture [8], to which we will first apply ICA directly. Later, the circulant structure of the sub-matrices $\mathbf{H}_{r,t}$ in $\mathbf{H}$ will be exploited to reduce the number of unknown parameters that have to be estimated in order to perform space-time equalization.

Some well-established ICA methods are: JADE [9], natural gradient algorithms [10] and FastICA [11]. We use the FastICA extension to complex valued signals (termed here CFastICA) in [7], since it can handle complex valued channels and signals. Also, estimates of the equalizer vectors can be used for initialisation.

Let us briefly review the CFastICA algorithm for the extraction of one transmitted stream when applied to (5) directly in the noiseless case. CFastICA finds the independent components by minimising the mutual information of the estimates. The received signal is first whitened $\mathbf{z}(i) = \mathbf{W}\mathbf{x}(i)$ such that

$$\underset{i}{\mathrm{E}}\{\mathbf{z}(i)\mathbf{z}^H(i)\} = \mathbf{I}_{N_t} \tag{6}$$

with the expectation with respect to i, $\mathbf{I}_{N_t}$ the $(N_t \times N_t)$ identity matrix and assuming unit variance streams. The $(N_tN \times N_rN)$ whitening matrix $\mathbf{W}$ can be found from the Eigenvalue Decomposition (EVD) of the covariance matrix of the received signal $\mathbf{R}_x = \mathrm{E}_i\{\mathbf{x}(i)\mathbf{x}^H(i)\}$ [12]. Next, an $(N_tN \times N_tN)$ unitary matrix $\mathbf{V}$ is sought, such that the overall equalizer is

$$\mathbf{G} = \mathbf{H}^+ = \mathbf{V}^H\mathbf{W} \tag{7}$$

with $\mathbf{H}^+ = (\mathbf{H}^H\mathbf{H})^{-1}\mathbf{H}^H$. The columns of $\mathbf{V}$ are estimated one by one. Define the $(N_tN \times 1)$ separating vector $\mathbf{v}_t(k)$, which is associated with stream t, as column $(k+tN)$ of $\mathbf{V}$. The soft estimate of the $k-th$ entry of $\mathbf{s}_t(i)$ then is

$$\bar{s}_t(k+iN) = \mathbf{v}_t^H(k)\mathbf{z}(i) = \mathbf{g}_t(k)\mathbf{x}(i). \tag{8}$$

The separating vector $\mathbf{v}_t(k)$ is obtained iteratively with Newton iterations by finding an extrema of the contrast function $J_P(\mathbf{v}) = \mathrm{E}_i\{P(|\mathbf{v}_t^H(k)\mathbf{z}(i)|^2)\}$ where $P(y) = \sqrt{0.1+y}$ is the non-linear learning function. The overall $(1 \times N_rN)$ equalizer vector is $\mathbf{g}_t(k) = \mathbf{v}_t^H(k)\mathbf{W}$. The estimated streams will not be affected by order or scaling indeterminacies if $\mathbf{v}_t(k)$ is initialised close enough to the true solution. Note that in the above approach, the structure of $\mathbf{H}$ is not used.

3.2 Using the Channel Convolution Matrix Structure

Improved performance can be expected by exploiting the structure of the channel convolution matrix $\mathbf{H}$. We note that $\mathbf{H}$ contains only $N_t N_r(L+1)$ unknown parameters. In the following we will thus only estimate this minimum number of parameters. We begin by expanding the received signal to allow estimation of all N entries of one stream vector $\mathbf{s}_t(i)$ with the same overall equalizer vector $\mathbf{g}_t$. Define

$$\widetilde{\mathbf{X}}(i) = \begin{bmatrix} \mathbf{x}_0^{(0)}(i) & \mathbf{x}_0^{(1)}(i) & \cdots & \mathbf{x}_0^{(N-1)}(i) \\ \mathbf{x}_1^{(0)}(i) & \mathbf{x}_1^{(1)}(i) & \cdots & \mathbf{x}_1^{(N-1)}(i) \\ \vdots & \vdots & & \vdots \\ \mathbf{x}_{N_r-1}^{(0)}(i) & \mathbf{x}_{N_r-1}^{(1)}(i) & \cdots & \mathbf{x}_{N_r-1}^{(N-1)}(i) \end{bmatrix} \quad (9)$$

of size $(N_r N \times N)$ and

$$\widetilde{\mathbf{S}}(i) = \begin{bmatrix} \mathbf{s}_0^{(0)}(i) & \mathbf{s}_0^{(1)}(i) & \cdots & \mathbf{s}_0^{(N-1)}(i) \\ \mathbf{s}_1^{(0)}(i) & \mathbf{s}_1^{(1)}(i) & \cdots & \mathbf{s}_1^{(N-1)}(i) \\ \vdots & \vdots & & \vdots \\ \mathbf{s}_{N_t-1}^{(0)}(i) & \mathbf{s}_{N_t-1}^{(1)}(i) & \cdots & \mathbf{s}_{N_t-1}^{(N-1)}(i) \end{bmatrix} \quad (10)$$

of size $(N_t N \times N)$ with $\mathbf{x}^{(n)}$ the cyclically shifted version of $\mathbf{x}$ where each element is shifted up by n positions and wrapped around the top, $\mathbf{s}^{(n)}$ is constructed accordingly. Due to the circulant sub-matrices $\mathbf{H}_{r,t}$ in $\mathbf{H}$, it follows from (5) and (7) in the noiseless case

$$\widetilde{\mathbf{S}}(i) = \mathbf{G}\widetilde{\mathbf{X}}(i). \quad (11)$$

Since stream t is contained in row (tN) of $\widetilde{\mathbf{S}}(i)$ we can write

$$\bar{s}_t(k+iN) = \mathbf{g}_t \widetilde{\mathbf{X}}^{(:,k)}(i) = \mathbf{v}_t^H \widetilde{\mathbf{Z}}^{(:,k)}(i) \quad (12)$$

where $\mathbf{g}_t$ is row (tN) of $\mathbf{G}$ while $\widetilde{\mathbf{X}}^{(:,k)}$ and $\widetilde{\mathbf{Z}}^{(:,k)}$ are column k of $\widetilde{\mathbf{X}}$ and $\widetilde{\mathbf{Z}} = \mathbf{W}\widetilde{\mathbf{X}}$, respectively. Hence, only one equalizer vector $\mathbf{g}_t$ per stream t is required to recover all entries of $\mathbf{s}_t(i)$. In the context of ICA, this translates to the use of one separating vector $\mathbf{v}_t$ to recover $\mathbf{s}_t(i)$, where $\mathbf{v}_t$ is column (tN) of $\mathbf{V}$.

To further exploit the structure of $\mathbf{H}$, we relate the size $(N_t N \times 1)$ separating vector $\mathbf{v}_t$ to a CIR vector $\widetilde{\mathbf{h}}_t$ of reduced size $(N_r(L+1) \times 1)$. The CIR vector $\mathbf{h}_t = [\mathbf{H}_{0,t}^{(:,0)T}, \mathbf{H}_{1,t}^{(:,0)T}, \cdots, \mathbf{H}_{N_r-1,t}^{(:,0)T}]^T$, which is column (tN) of $\mathbf{H}$, contains only $N_r(L+1)$ non-zero entries. From (7) we have $\mathbf{v}_t = \mathbf{W}\mathbf{h}_t$. By defining $\widetilde{\mathbf{h}}_t$ as the modified $\mathbf{h}_t$ with the zero entries removed, we obtain

$$\mathbf{v}_t = \widetilde{\mathbf{W}}\widetilde{\mathbf{h}}_t \quad (13)$$

where $\widetilde{\mathbf{W}}$ is the modified whitening matrix with the columns that correspond to the zero entries in $\mathbf{h}_t$ removed. Instead of estimating $\mathbf{v}_t$, we can now estimate $\widetilde{\mathbf{h}}_t$ for every stream $t \in \{0, 1, \cdots, N_t - 1\}$, which results in $N_t N_r(L+1)$ parameters

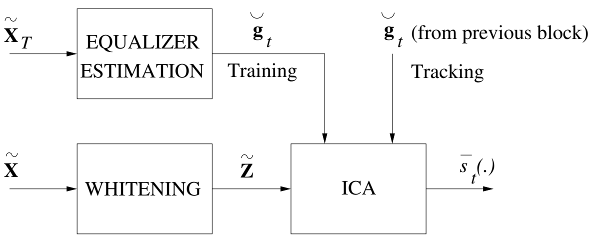

Figure 2: Proposed semi-blind space-time equalizer for the estimation of one stream t. ICA is employed for tracking the channel variations.

to be estimated for the whole MIMO system. If the channel order is unknown, $L = L_{CP}$ can be used as an upper bound.

To speed up convergence and to alleviate the order and scaling indeterminacies inherent in ICA methods, a small amount of training is employed. Every T blocks T_n training vectors are added to each stream for initialisation of the equalizer. The Least Squares (LS) estimate of the equalizer vector for stream t is

$$\breve{\mathbf{g}}_t = \mathbf{s}_{T,t}\widetilde{\mathbf{X}}_T^+ \quad (14)$$

where the training data for stream t is given by $\mathbf{s}_{T,t} = [\mathbf{s}_t^T(0), \mathbf{s}_t^T(1), \cdots, \mathbf{s}_t^T(T_n-1)]$, the received signal during training is $\widetilde{\mathbf{X}}_T = [\widetilde{\mathbf{X}}(0), \widetilde{\mathbf{X}}(1), \cdots, \widetilde{\mathbf{X}}(T_n-1)]$ and $\widetilde{\mathbf{X}}_T^+ = \widetilde{\mathbf{X}}_T^H(\widetilde{\mathbf{X}}_T\widetilde{\mathbf{X}}_T^H)^{-1}$.

3.3 Semi-Blind Space-Time Equalization Method

Using the above reductions of the number of unknown parameters and training for initialisation, we finally obtain the proposed semi-blind space-time equalization algorithm depicted in Fig. 2. It operates on a block of N_s transmitted vectors $(i = 0, 1, \cdots, N_s - 1)$ to estimate stream t from the noisy received signal $\widetilde{\mathbf{X}}(i)$. Here $(\cdot)^j$ denotes the CFastICA iteration number j.

1. Use training every T blocks: $\breve{\mathbf{g}}_t = \mathbf{s}_{T,t}\widetilde{\mathbf{X}}_T^+$
2. Whiten the expanded received signal: $\widetilde{\mathbf{Z}}(i), \mathbf{W} \Leftarrow \widetilde{\mathbf{X}}(i)$
3. Initialise the CFastICA iteration number: $j = 0$
4. Initialise the separating vector: $\mathbf{v}_t^j = (\breve{\mathbf{g}}_t \mathbf{W}^+)^H$
5. Normalise the separating vector: $\mathbf{v}_t^j = \mathbf{v}_t^j / ||\mathbf{v}_t^j||$
6. Estimate stream t: $\bar{s}_t(k+iN) = (\mathbf{v}_t^j)^H \widetilde{\mathbf{Z}}^{(:,k)}(i)$
7. Update the CIR vector: $\widetilde{\mathbf{h}}_t^{j+1} = \widetilde{\mathbf{W}}^+ \widetilde{\mathbf{v}}_t^{j+1}$, see (15)
8. Corresponding separating vector: $\mathbf{v}_t^{j+1} = \widetilde{\mathbf{W}}\widetilde{\mathbf{h}}_t^{j+1}$
9. Repeat CFastICA iteration (steps 5 to 8) until convergence or maximum number of iterations $(j = j_{\max})$
10. If converged, keep last equalizer vector for initialisation of next block: $\breve{\mathbf{g}}_t = (\mathbf{v}_t^{j+1})^H \mathbf{W}$

The pseudo-inverses are $\mathbf{W}^+ = \mathbf{W}^H(\mathbf{W}\mathbf{W}^H)^{-1}$ and $\widetilde{\mathbf{W}}^+ = (\widetilde{\mathbf{W}}^H\widetilde{\mathbf{W}})^{-1}\widetilde{\mathbf{W}}^H$. Using the CFastICA update equation in [7], $\widetilde{\mathbf{v}}_t^{j+1}$ in step 7 is

$$\widetilde{\mathbf{v}}_t^{j+1} = \mathop{\mathrm{E}}_{i,k}\left\{\widetilde{\mathbf{Z}}^{(:,k)}(i)\bar{s}_t^*(k+iN)p(|\bar{s}_t(k+iN)|^2)\right\} - \quad (15)$$
$$\mathop{\mathrm{E}}_{i,k}\left\{p(|\bar{s}_t(k+iN)|^2) + |\bar{s}_t(k+iN)|^2 p'(|\bar{s}_t(k+iN)|^2)\right\}\mathbf{v}_t^j$$

where $p(\cdot)$ and $p'(\cdot)$ denote the first and second derivative of the non-linear learning function $P(\cdot)$, respectively.

Convergence is obtained when $\mathbf{v}_t^{j+1}$ and $\mathbf{v}_t^j$ are approximately linearly dependent, which can be expressed as $1-|(\mathbf{v}_t^{j+1})^H\mathbf{v}_t^j| \approx 0$ [12]. Although the use of training avoids order indeterminacies, phase shift errors of $\bar{s}_t(\cdot)$ may accumulate over several blocks. Thus, the proposed method recovers the original streams up to an overall phase shift per block. After hard estimation of $\bar{s}_t(\cdot)$, the stream estimates $\hat{s}_t(\cdot)$ are obtained.

From the above and the ICA requirements in [7, 8], it follows that the subsequent assumptions must be met for the proposed semi-blind space-time equalization method:

A1. The streams $\mathbf{s}_t(\cdot)$ are mutually statistically independent.
A2. Up to one stream $\mathbf{s}_t(\cdot)$ may have a Gaussian distribution.
A3. The MIMO channel convolution matrix $\mathbf{H}$ is of full column rank.
A4. The modified whitening matrix $\widetilde{\mathbf{W}}$ is of full column rank.
A5. The received training signal $\widetilde{\mathbf{X}}_T$ is of full row rank.

A necessary condition imposed by A3. is $N_r \geq N_t$ while A4. imposes $N_r \leq (N_t N)/(L+1)$. By combining the two, we obtain the following requirement for the number of transmit and receive antennas: $N_t \leq N_r \leq (N_t N)/(L+1)$. Furthermore, from A5. we obtain the necessary requirement for the number of training vectors $T_n \geq N_r$.

4. SIMULATION RESULTS

The performance of the proposed semi-blind space-time equalization method was tested in a MIMO system with $N_t = N_r = 2$ and $N_t = N_r = 4$ antennas. The data vector length was $N = 32$, the CP length $L_{CP} = 8$ and the block length $N_s = 200$ vectors. The results were averaged over 1000 runs, with $T_n = 5$ training vectors added every $T = 50$ blocks. This results in 0.05% training overhead. The individual channel paths were assumed uncorrelated in time with Rayleigh block fading obtained from Clarke's model, with a block duration of N_s transmitted vectors. The symbol rate was 16 Mbit/s using QPSK data. Exponential power delay profiles were used with a normalised RMS delay spread of $\sigma_n = 1.1$, unless otherwise noted. The Signal to Noise Ratio (SNR) was defined as the spatial average across all receive antennas. A raised-cosine pulse shaping filter with roll-off factor $\alpha = 0.5$ was employed. The upper bound of the channel order was set to $L = L_{CP}$ and the performance measures were averaged over all N_t streams.

Fig. 3 shows the Bit Error Rate (BER) vs SNR performance for an $N_t = N_r = 2$ MIMO system. It can be observed that for the maximum Doppler shifts of $f_m = 50$ Hz and 100 Hz the BER approaches the case with perfect CSI at the receiver for SNR > 10 dB. The simulation demonstrates that the proposed method is able to track the time varying channel for all investigated f_m. Note that the BER curves for the perfect CSI case are slightly different for each f_m, but only the case with $f_m = 50$ Hz is shown. Also, the performance of OFDM, using the same system parameters and perfect CSI, is included. Clearly, SC-CP has superiority over OFDM at moderate and high SNRs. Even in the semi-blind case, SC-CP outperforms OFDM with perfect CSI in that SNR range.

The next simulation in Fig. 4 was carried out with an $N_t = N_r = 4$ MIMO system. It is evident that in this case the BER performances are not as close to the perfect CSI case as

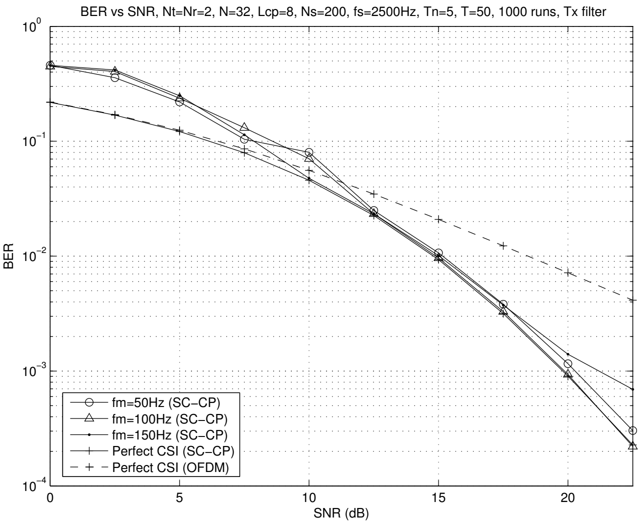

Figure 3: BER performance with 2 transmit and 2 receive antennas.

with $N_t = N_r = 2$ in Fig. 3, since a larger number of parameters has to be estimated now to perform space-time equalization. Nonetheless, the BER curves are relatively close to the ideal case with perfect CSI at the receiver for SNR > 10 dB. Again, semi-blind SC-CP outperforms OFDM with perfect CSI for moderate to high SNRs.

Next, the influence of the block size N_s on the Mean Squared Error (MSE) between the soft estimated streams $\bar{\mathbf{s}}_t(\cdot)$ and the true streams $\mathbf{s}_t(\cdot)$ was studied for an $N_t = N_r = 2$ MIMO system. Fig. 5 shows the MSE vs N_s performance at SNR $= 10, 15,$ and 20 dB and for a maximum Doppler shift of $f_m = 50$ Hz. The MSE was averaged over all N_t streams, defined as

$$MSE = \frac{1}{N N_s N_t} \sum_{t=0}^{N_t-1} \sum_{i=0}^{N_s-1} ||\bar{\mathbf{s}}_t(i) - \mathbf{s}_t(i)||^2. \qquad (16)$$

The results show that for all investigated SNRs, a block length of $N_s \approx 200$ is sufficient to obtain an MSE close to the case with perfect CSI. Results for $N_t = N_r = 4$ are not included, but the required block length was found to be $N_s \approx 300$ for performance close to the perfect CSI case.

Fig. 6 shows the influence of the normalised RMS delay spread σ_n on BER performance for the $N_t = N_r = 2$ case. It can be observed that SC-CP benefits from the increased diversity which longer CIR lengths provide, while the performance of OFDM does not improve when σ_n is increased.

From the MSE vs N_s simulations it follows that the proposed semi-blind space-time equalization method is suitable for a high bit rate system, where the MIMO channel can be assumed to remain constant for the duration of several hundred data vectors. Also, from the BER vs SNR simulations it can be concluded that the proposed semi-blind method is a viable alternative to a training based method, since it can obtain good BER performance and requires only a small training overhead.

5. CONCLUSIONS

We have proposed a semi-blind equalizer based on ICA for SC-CP MIMO systems. By making use of the channel convolution matrix structure, only a reduced number of parameters have to be estimated. The simulations show that the proposed method can obtain performance close to the ideal

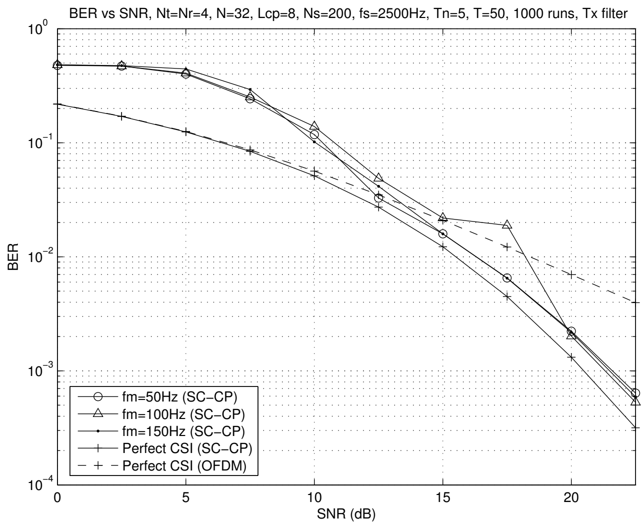

Figure 4: BER performance with 4 transmit and 4 receive antennas.

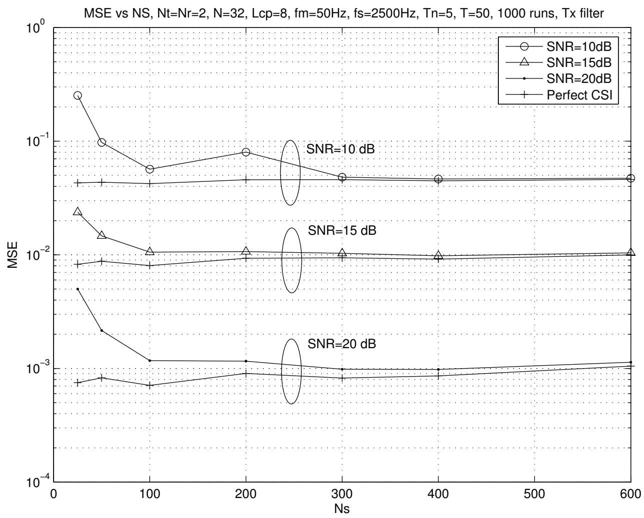

Figure 5: Influence of the block length N_s with 2 transmit and 2 receive antennas.

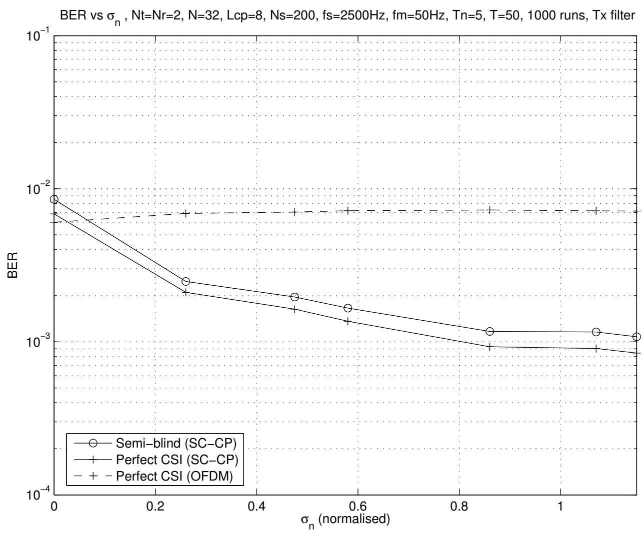

Figure 6: Influence of the normalised RMS delay spread σ_n with 2 transmit and 2 receive antennas, SNR $=20$ dB, $f_m=$ 50 Hz.

case with perfect CSI at the receiver for SNR higher than 10 dB. Compared to training based methods, the proposed semi-blind method increases the bandwidth efficiency of the system, since only a small amount of training is required. This makes it a suitable alternative to a system with training based equalization. Besides, the semi-blind SC-CP method outperforms OFDM with perfect CSI at moderate to high SNRs.

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