BLIND DECODING OF MISO-OSTBC SYSTEMS BASED ON PRINCIPAL COMPONENT ANALYSIS

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ABSTRACT

In this paper, a new second-order statistics (SOS) based method for blind decoding of orthogonal space time block coded (OSTBC) systems with only one receive antenna is proposed. To avoid the inherent ambiguities of this problem, the spatial correlation matrix of the source signals must be non-white and known at the receiver. In practice, this can be achieved by a number of simple linear precoding techniques at the transmitter side. More specifically, it is shown in the paper that if the source correlation matrix has different eigenvalues, then the decoding process can be formulated as the problem of maximizing the sum of a set of weighted variances of the signal estimates. Exploiting the special structure of OSTBCs, this problem can be reduced to a principal component analysis (PCA) problem, which allows us to derive computationally efficient batch and adaptive blind decoding algorithms. The algorithm works for any OSTBC (including the popular Alamouti code) with a single receive antenna. Some simulation results are presented to demonstrate the potential of the proposed procedure.

1. INTRODUCTION

Orthogonal space time block codes (OSTBC) [1, 2, 3] appear as an important class of space time block codes, which provides full diversity and low complexity maximum likelihood (ML) decoding. In recent years, blind decoding of STBCs [4] and OSTBCs has received increasing interest, for instance, in [5] the authors propose a PCA-based blind decoding method which is able to restore the channel and source signals for the most of the OSTBCs when more than one receive antenna is available.

In many real applications, the source signals exhibit autocorrelation properties, which can be exploited for developing blind equalization algorithms [6]. In this paper we present a new computationally efficient method for OSTBC decoding with only one receive antenna which exploits the correlation properties of the source signals. In particular, we prove that a sufficient condition for blind decoding is that one of the eigenvalues of the correlation matrix has multiplicity one. In this way, we can propose a blind decoding criterion which consists on the maximization of a weighted sum of the estimated signal variances. Furthermore, by exploiting the linear dependence between the multiple-input single-output (MISO) channel and the OSTBC equalizers, the criterion can be rewritten as a function of the estimated channel, which reduces the blind decoding problem to a single principal component analysis (PCA) [7] problem. Finally, the direct application of the Oja's rule [7], provide a fast and efficient adaptive blind decoding algorithm for OSTBCs.

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2. OVERVIEW OF MISO-OSTBC SYSTEMS

Let us consider a system with Q transmit antennas where the information symbols to be transmitted are taken M at a time to form a $P \times Q$ data block $\mathbf{S}[n]$. This block is transmitted in P channel uses, and hence, the average code rate is M/P symbols per channel use. For linear space time block codes the transmitted data block is generated as

$$\mathbf{S}[n] = \sum_{k=1}^{N} s_k[n]\mathbf{C}_k,$$

where $s_k[n]$ and $s_{M+k}[n]$ denote, respectively, the real and imaginary part of the k-th information symbol of the n-th data block, and the parameter N is $N = 2M$ for general complex constellations and $N = M$ for real constellations. In particular, for orthogonal space time block codes (OSTBC) the code matrices fulfil [3], for $k, l = 1, \ldots, N$

$$\mathbf{C}_k^H\mathbf{C}_l = \begin{cases} \mathbf{I} & k = l, \\ -\mathbf{C}_l^H\mathbf{C}_k & k \neq l. \end{cases} \tag{1}$$

Considering one receive antenna and a slow flat fading channel, i.e. a channel with coherence time substantially larger than the data block length P, the received signal can be written as

$$\mathbf{x}[n] = \mathbf{S}[n]\mathbf{h} + \mathbf{u}[n],$$

where $\mathbf{h}$ is the $Q \times 1$ complex channel response and $\mathbf{u}[n]$ is a $P \times 1$ noise vector. Defining the "tilde" operator $\tilde{\mathbf{A}} = [\Re(\mathbf{A})^T, \Im(\mathbf{A})^T]^T$, and applying it to the above equation yields

$$\tilde{\mathbf{x}}[n] = \tilde{\mathbf{W}}(\mathbf{h})\mathbf{s}[n] + \tilde{\mathbf{u}}[n],$$

where $\mathbf{W}(\mathbf{h}) = [\mathbf{w}_1(\mathbf{h}) \cdots \mathbf{w}_N(\mathbf{h})]$, $\mathbf{w}_k(\mathbf{h}) = \mathbf{C}_k\mathbf{h}$ and $\mathbf{s}[n] = [s_1[n], \ldots, s_N[n]]^T$.

It can be derived in a straightforward manner that, under the conditions (1), the combined code-channel response vectors $\tilde{\mathbf{w}}_k(\mathbf{h})$ satisfy

$$\tilde{\mathbf{w}}_k^T(\mathbf{h})\tilde{\mathbf{w}}_l(\mathbf{h}) = \begin{cases} \|\mathbf{h}\|^2 & k = l, \\ 0 & k \neq l, \end{cases}$$

for $k, l = 1, \ldots, N$, which implies that assuming zero-mean, temporally and spatially white Gaussian noise uncorrelated with the data, the maximum likelihood (ML) estimator of $\mathbf{s}[n]$, given $\mathbf{h}$, is [3]

$$\hat{\mathbf{s}}_{\mathbf{h}}[n] = \frac{\tilde{\mathbf{W}}^T(\mathbf{h})\tilde{\mathbf{x}}[n]}{\|\mathbf{h}\|^2}, \tag{2}$$

where the subindex $\mathbf{h}$ has been included to denote the dependency on the true channel. Eq. (2) can be rewritten as

$$\hat{\mathbf{s}}_{\mathbf{h}}[n] = \begin{bmatrix} \tilde{\mathbf{x}}^T[n]\tilde{\mathbf{F}}_1 \\ \vdots \\ \tilde{\mathbf{x}}^T[n]\tilde{\mathbf{F}}_N \end{bmatrix} \frac{\tilde{\mathbf{h}}}{\|\mathbf{h}\|^2}, \tag{3}$$

where $\mathbf{F}_k = [\mathbf{C}_k \quad j\mathbf{C}_k]$, for $k = 1, \ldots, N$, $\tilde{\mathbf{h}} = [\Re(\mathbf{h})^T, \Im(\mathbf{h})^T]^T$, and the equalizers are given by $\tilde{\mathbf{w}}_k(\mathbf{h}) = \tilde{\mathbf{F}}_k\tilde{\mathbf{h}}$.

3. BLIND DECODING THROUGH PCA

Assuming zero mean white noise with variance η^2, and considering that the noise is uncorrelated with the data, the correlation matrix of the data vectors $\tilde{\mathbf{x}}[n]$ is given by

$$\mathbf{R}_{\tilde{\mathbf{x}}} = E[\tilde{\mathbf{x}}[n]\tilde{\mathbf{x}}^T[n]] = \tilde{\mathbf{W}}(\mathbf{h})E[\mathbf{s}[n]\mathbf{s}^T[n]]\tilde{\mathbf{W}}^T(\mathbf{h}) + \frac{\eta^2}{2}\mathbf{I},$$

and taking into account the eigenvalue decomposition of the correlation matrix $E[\mathbf{s}[n]\mathbf{s}^T[n]] = \mathbf{Q}\mathbf{\Sigma}^2\mathbf{Q}^T$, where $\mathbf{Q}$ and $\mathbf{\Sigma}$ are $N \times N$ unitary and diagonal matrices respectively, it is easy to realize that the eigenvectors associated to the N largest eigenvalues of $\mathbf{R}_{\tilde{\mathbf{x}}}$ are given by the columns of the matrix $\tilde{\mathbf{W}}(\mathbf{h})\mathbf{Q}$, and then we can propose the following criterion

$$J_1(\hat{\mathbf{h}}) = \text{Tr}\left(\tilde{\mathbf{W}}^T(\hat{\mathbf{h}})\mathbf{R}_{\tilde{\mathbf{x}}}\tilde{\mathbf{W}}(\hat{\mathbf{h}})\right), \tag{4}$$

which is maximized for any estimated channel $\hat{\mathbf{h}}$ such that the corresponding code-channel matrix $\tilde{\mathbf{W}}(\hat{\mathbf{h}})$ satisfies [5]

$$\text{range}(\tilde{\mathbf{W}}(\hat{\mathbf{h}})) = \text{range}(\tilde{\mathbf{W}}(\mathbf{h})). \tag{5}$$

Finally, by combining equations (2), (3) and (4), the function to be maximized can be rewritten as

$$J_1(\hat{\mathbf{h}}) = \|\mathbf{h}\|^2\|\hat{\mathbf{h}}\|^2 E[\hat{\mathbf{s}}_{\hat{\mathbf{h}}}^T[n]\hat{\mathbf{s}}_{\hat{\mathbf{h}}}[n]] = \hat{\tilde{\mathbf{h}}}^T\left(\sum_{k=1}^{N}\tilde{\mathbf{F}}_k^T\mathbf{R}_{\tilde{\mathbf{x}}}\tilde{\mathbf{F}}_k\right)\hat{\tilde{\mathbf{h}}},$$

which reduces the problem of estimating the channel to a principal component analysis (PCA) [7] problem, i.e. the true channel can be obtained, with a sign and scale indeterminacy, as the channel providing an estimated output signal $\hat{\mathbf{s}}_{\hat{\mathbf{h}}}[n]$ with maximum variance.

Unfortunately, in the case of a single receive antenna, most of the practical OSTBCs provide a non-null subspace of possible estimates $\hat{\mathbf{h}} \neq c\mathbf{h}$ satisfying (5), which implies that the largest eigenvalue of the new correlation matrix

$$\sum_{k=1}^{N}\tilde{\mathbf{F}}_k^T\mathbf{R}_{\tilde{\mathbf{x}}}\tilde{\mathbf{F}}_k,$$

has a multiplicity larger than one and introduces an additional ambiguity among the eigenvectors associated to the largest eigenvalue and their linear combinations. To overcome this problem, in [5] the authors extend the idea to the case of several receive antennas, which reduces drastically the number of OSTBCs provoking this ambiguity. Another possibility consists on selecting the estimate $\hat{\mathbf{h}}$ which maximizes $J_1(\hat{\mathbf{h}})$ and simultaneously optimizes some additional criterion. For instance, we could use a criterion based on the higher order statistics (HOS) of the source signal or its finite alphabet property in order to eliminate this ambiguity. As an alternative, in the next section we propose a technique based solely on the exploitation of the second order statistics (SOS) of the source signal.

4. AVOIDING THE AMBIGUITY WITH CORRELATED SOURCES

In many real situations, the source signal to be transmitted exhibits a non-white spectrum, which can be use to blindly equalize the channel [6]. The autocorrelation properties of the source sequences can be due to a previous precoding step, such as a convolutional code or a partial response system (PRS) [8, 9, 10]. In this section we propose a modified cost function which exploits the correlation properties of the source signal to blindly estimate the channel response with only one receive antenna.

4.1. Uncorrelated source signals with different variances

Let us start by considering that the source signals are uncorrelated, which implies that $E[\mathbf{s}[n]\mathbf{s}^T[n]] = \mathbf{\Sigma}^2$ is a diagonal matrix with elements $\sigma_1^2, \ldots, \sigma_N^2$. Assuming, without loss of generality, that $\sigma_1^2 \geq \sigma_2^2 \geq \ldots \geq \sigma_N^2$, we propose the following modified function

$$J_2(\hat{\mathbf{h}}) = \text{Tr}\left(\mathbf{\Lambda}\tilde{\mathbf{W}}^T(\hat{\mathbf{h}})\mathbf{R}_{\tilde{\mathbf{x}}}\tilde{\mathbf{W}}(\hat{\mathbf{h}})\mathbf{\Lambda}\right), \tag{6}$$

where $\mathbf{\Lambda}$ is a weighting matrix with elements $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_N$ in its diagonal and zeros elsewhere. Then, combining equations (2) and (6), the criterion to be maximized now is

$$J_2(\hat{\mathbf{h}}) = \|\mathbf{h}\|^2\|\hat{\mathbf{h}}\|^2 E[\hat{\mathbf{s}}_{\hat{\mathbf{h}}}^T[n]\mathbf{\Lambda}^2\hat{\mathbf{s}}_{\hat{\mathbf{h}}}[n]], \tag{7}$$

and taking into account that

$$\tilde{\mathbf{W}}^T(\hat{\mathbf{h}})\tilde{\mathbf{W}}(\hat{\mathbf{h}})/\|\hat{\mathbf{h}}\|^2 = \tilde{\mathbf{W}}^T(\mathbf{h})\tilde{\mathbf{W}}(\mathbf{h})/\|\mathbf{h}\|^2 = \mathbf{I},$$

it is easy to realize that

$$\|E[\hat{\mathbf{s}}_{\hat{\mathbf{h}}}[n]\hat{\mathbf{s}}_{\hat{\mathbf{h}}}^T[n]]\|_F^2 \leq \sum_{k=1}^{N}\left(\sigma_k^2 + \frac{\eta^2}{2\|\mathbf{h}\|^2}\right),$$

where the equality is satisfied iff (5) holds. Furthermore, we can find that

$$E[\hat{\mathbf{s}}_{\hat{\mathbf{h}}}^T[n]\mathbf{\Lambda}^2\hat{\mathbf{s}}_{\hat{\mathbf{h}}}[n]] \leq \sum_{k=1}^{N}\lambda_k^2\left(\sigma_k^2 + \frac{\eta^2}{2\|\mathbf{h}\|^2}\right),$$

and the above equality is satisfied iff

$$\text{range}(\tilde{\mathbf{W}}_k(\hat{\mathbf{h}})) = \text{range}(\tilde{\mathbf{W}}_k(\mathbf{h})), \qquad k = 1, \ldots, N,$$

where $\tilde{\mathbf{W}}_k(\mathbf{h})$ is defined as the matrix containing the equalization vectors $\tilde{\mathbf{w}}_l(\mathbf{h})$, for $\sigma_l^2 = \sigma_k^2$ or $\lambda_l^2 = \lambda_k^2$. In this way, a sufficient (but not necessary) condition to avoid the ambiguity is that the variance and the corresponding weight of one of the source signals $s_k[n]$ be different from the remaining ones.

Finally, combining equations (3) and (7), the function to be maximized is

$$J_2(\hat{\mathbf{h}}) = \hat{\tilde{\mathbf{h}}}^T\left(\sum_{k=1}^{N}\lambda_k^2\tilde{\mathbf{F}}_k^T\mathbf{R}_{\tilde{\mathbf{x}}}\tilde{\mathbf{F}}_k\right)\hat{\tilde{\mathbf{h}}},$$

which reduces the estimation problem to a PCA problem where the true channel is obtained, with the scale and sign indeterminacy, as the channel providing an estimated weighted output signal with maximum variance.

Here it is interesting to point out that the selection of the weights λ_k offers a degree of freedom that can be exploited in different ways.

Initialize the learning rate μ and the estimated channel $\hat{\tilde{\mathbf{h}}}[0] \neq \mathbf{0}$.
for $n = 1, 2, \ldots$ **do**
  for $k = 1, 2, \ldots, N$ **do**
    Obtain $\hat{y}_k[n] = \lambda_k \tilde{\mathbf{x}}^T[n] \tilde{\mathbf{G}}_k \hat{\tilde{\mathbf{h}}}[n-1]$.
    Update $\hat{\tilde{\mathbf{h}}}[n] = \hat{\tilde{\mathbf{h}}}[n-1] + \mu \lambda_k \tilde{\mathbf{G}}_k^T \tilde{\mathbf{x}}[n] \hat{y}_k[n]$.
    Normalize $\hat{\tilde{\mathbf{h}}}[n] = \hat{\tilde{\mathbf{h}}}[n] / \|\hat{\tilde{\mathbf{h}}}[n]\|$.
    Obtain $\hat{s}_k[n] = \tilde{\mathbf{x}}^T[n] \tilde{\mathbf{F}}_k \hat{\tilde{\mathbf{h}}}[n]$
  end for
end for

Algorithm 1: Summary of the proposed adaptive algorithm.

For instance, the trivial selection $\mathbf{\Lambda} = \mathbf{I}$ reduces (6) to (4), which implies that the ambiguities are given by (5). A better alternative consists on selecting the weights such that if $\sigma_k^2 > \sigma_l^2$ then $\lambda_k^2 > \lambda_l^2$, in particular, we can select $\mathbf{\Lambda} = \mathbf{\Sigma}$ following the idea of the matched filter [8]. As can be seen later, this selection of the parameters provides a decoding algorithm with good performance.

4.2. Generalization to correlated source signals

Considering that the correlation matrix $E[\mathbf{s}[n]\mathbf{s}^T[n]] = \mathbf{Q}\mathbf{\Sigma}^2\mathbf{Q}^T$ is known, the eigenvectors associated to the N largest eigenvalues of $\mathbf{R}_{\tilde{\mathbf{x}}}$, which are given by the columns of the matrix $\tilde{\mathbf{W}}(\mathbf{h})\mathbf{Q}$, can be seen as the equalizers $\tilde{\mathbf{v}}_k(\mathbf{h})$ of a different OSTBC code with code matrices

$$\mathbf{D}_k = \sum_{l=1}^{N} q_{lk} \mathbf{C}_l, \qquad k = 1, \ldots, N,$$

where q_{lk} is the l-th row and k-th column element of the matrix $\mathbf{Q}$. Thus, the criterion to be maximized is

$$J_3(\hat{\mathbf{h}}) = \mathrm{Tr}\left(\mathbf{\Lambda} \tilde{\mathbf{V}}^T(\hat{\mathbf{h}}) \mathbf{R}_{\tilde{\mathbf{x}}} \tilde{\mathbf{V}}(\hat{\mathbf{h}}) \mathbf{\Lambda}\right), \tag{8}$$

where $\mathbf{V}(\hat{\mathbf{h}}) = [\mathbf{v}_1(\hat{\mathbf{h}}) \cdots \mathbf{v}_N(\hat{\mathbf{h}})]$, $\mathbf{v}_k(\hat{\mathbf{h}}) = \mathbf{D}_k \hat{\mathbf{h}}$, $\tilde{\mathbf{v}}_k(\hat{\mathbf{h}}) = \tilde{\mathbf{G}}_k \hat{\tilde{\mathbf{h}}}$ and $\mathbf{G}_k = [\mathbf{D}_k \quad j\mathbf{D}_k]$. Following a similar development to that of the previous subsection, the final criterion to be maximized is

$$J_3(\hat{\mathbf{h}}) = \hat{\tilde{\mathbf{h}}}^T \left(\sum_{k=1}^{N} \lambda_k^2 \tilde{\mathbf{G}}_k^T \mathbf{R}_{\tilde{\mathbf{x}}} \tilde{\mathbf{G}}_k \right) \hat{\tilde{\mathbf{h}}}, \tag{9}$$

and the ambiguity problem is restricted to the codes and sources satisfying

$$\mathrm{range}(\tilde{\mathbf{V}}_k(\hat{\mathbf{h}})) = \mathrm{range}(\tilde{\mathbf{V}}_k(\mathbf{h})), \qquad k = 1, \ldots, N,$$

where $\tilde{\mathbf{V}}_k(\hat{\mathbf{h}})$ and $\tilde{\mathbf{V}}_k(\mathbf{h})$ are defined as the matrices containing the equalization vectors $\tilde{\mathbf{v}}_l(\hat{\mathbf{h}})$ and $\tilde{\mathbf{v}}_l(\mathbf{h})$ respectively, for $\sigma_l^2 = \sigma_k^2$ or $\lambda_l^2 = \lambda_k^2$.

Finally, it is easy to realize that the particular case of $\mathbf{Q} = \mathbf{I}$ implies $\mathbf{D}_k = \mathbf{C}_k$ and $\tilde{\mathbf{G}}_k = \tilde{\mathbf{F}}_k$, and then (6) can be seen as a particular case of (9). Analogously, in the case of $\mathbf{\Lambda} = \mathbf{I}$ (8) is equivalent to (4).

4.3. Final remarks and implementation

The results of the previous subsection show that the estimation technique is reduced to the solution of a PCA problem, i.e. the extraction of the main eigenvector of the $2Q \times 2Q$ correlation matrix

$$\sum_{k=1}^{N} \lambda_k^2 \tilde{\mathbf{G}}_k^T \mathbf{R}_{\tilde{\mathbf{x}}} \tilde{\mathbf{G}}_k.$$

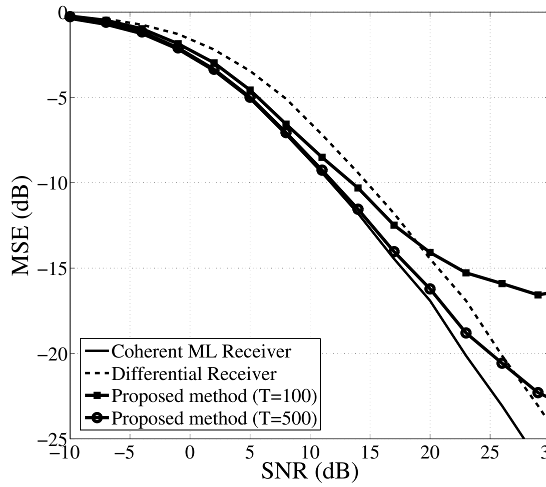

Fig. 1. MSE of a duobinary signal for the Alamouti code.

In practice, the true correlation matrix $\mathbf{R}_{\tilde{\mathbf{x}}}$ is unavailable and we must estimate the sample covariance matrix

$$\hat{\mathbf{R}}_{\tilde{\mathbf{x}}} = \frac{1}{T} \sum_{n=1}^{T} \tilde{\mathbf{x}}[n] \tilde{\mathbf{x}}^T[n],$$

where T is the number of available received blocks. An alternative to this implementation of the algorithm is the direct application of the Oja's rule [7]

$$\hat{\tilde{\mathbf{h}}}[n] = \hat{\tilde{\mathbf{h}}}[n-1] + \mu \lambda_k \tilde{\mathbf{G}}_k^T \tilde{\mathbf{x}}[n] \hat{y}_k[n],$$

where μ is the learning rate, and $\hat{y}_k[n] = \lambda_k \tilde{\mathbf{x}}^T[n] \tilde{\mathbf{G}}_k \hat{\tilde{\mathbf{h}}}[n-1]$ is the estimate of the rotated and weighted version of the source signal $s_k[n]$. Finally, the overall adaptive algorithm is summarized in Algorithm 1.

5. SIMULATION RESULTS

In this section the performance of the proposed algorithm is evaluated through some simulation examples. In all the simulations, the results of 1000 independent realizations are averaged. The elements of the flat fading MISO channels are zero-mean, circular, complex Gaussian random variables with unit variance, the SNR is defined as $10 \log_{10}(\eta_s^2/\eta^2)$, where η_s^2 is the total transmitted energy and η^2 is the noise variance.

The source signals are binary i.i.d signals precoded by a filter with response $H(z) = 1 + z^{-1}$, which is the filter used in duobinary modulation, then at its output we have a correlated symbol sequence drawn from the alphabet $\{-2, 0, +2\}$ with probabilities 1/4, 1/2 and 1/4 respectively. Two duobinary signals are the real and imaginary parts of the complex symbols which are the input of the OSTBC coder. In this way, the elements of the matrix $E[\mathbf{s}[n]\mathbf{s}^T[n]]$ are 2 in its main diagonal, 1 in its first diagonals above and below the main diagonal, and zeros elsewhere. In all the simulations, the weighting matrix has been selected as $\mathbf{\Lambda} = \mathbf{\Sigma}$.

In the first example, the Alamouti [1] code has been selected, and the performance of the proposed batch algorithm is compared

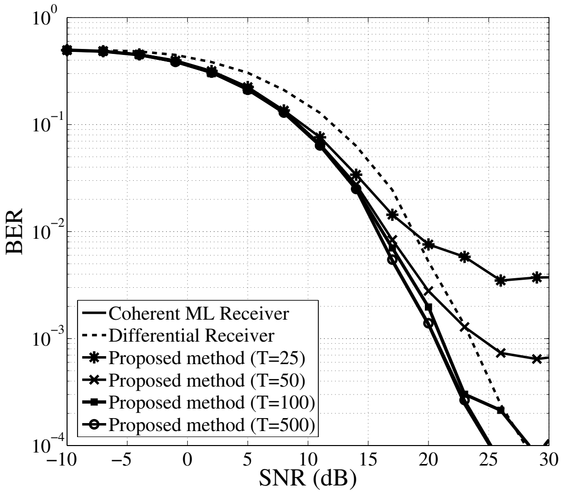

Fig. 2. BER of a duobinary signal for the rate=3/4 code.

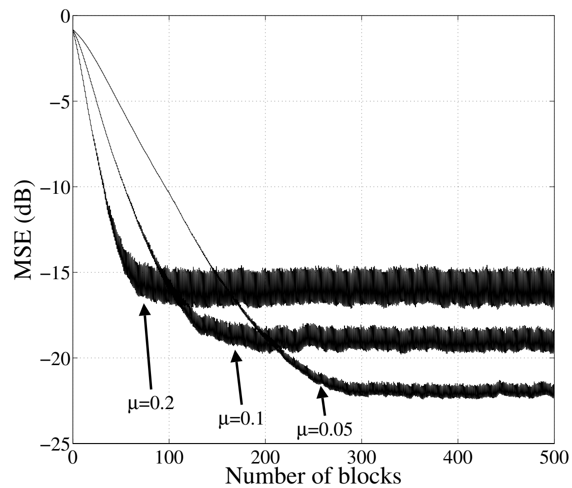

Fig. 3. Performance of the proposed adaptive algorithm. SNR=20dB.

with the coherent ML receiver and the differential receiver proposed in [3]. Figure 1 shows the mean squared error (MSE) in the signal estimate for $T = 100$ and $T = 500$ received blocks. As can be seen, the proposed blind decoder outperforms the differential receiver at low and moderate SNRs. The noise floor present in the proposed method can be attributed to the difference between the true correlation matrix and its sample mean (this noise floor rapidly decreases with the number of available blocks).

In the second example, we have tested the 3/4 OSTBC code for $M = 3$ complex symbols, $P = 4$ time slots and $Q = 3$ transmit antennas, which is presented in eq. (7.4.9) of [3]. Figure 2 shows the final BER after decoding, where we can see that the proposed method again outperforms the differential receiver in low and moderate SNRs.

Finally, the proposed adaptive version of the algorithm has been tested with the 3/4 OSTBC code. The MSE of the channel estimate for SNR=20dB and three different learning rates ($\mu = 0{,}05$, $\mu = 0{,}1$ and $\mu = 0{,}2$) is shown in Fig. 3. As can be seen, the tradeoff between the speed of convergence and the final residual error is determined by the learning rate.

6. CONCLUSIONS

In this paper, a new method for blind channel estimation and decoding of OSTBC systems with only one receive antenna have been presented. The proposed method is based solely on second order statistics (SOS) and the main idea consists on exploiting the correlation of the source signals, which is assumed to be known. We have proved that, if at least one of the eigenvalues of this correlation matrix has multiplicity one, then the channel and source signals can be extracted unambiguously, up to a sign and scale factor, by means of a simple principal component analysis (PCA) procedure. The simulation results have shown that, for low and moderate SNRs, the proposed batch and adaptive algorithms are better than the differential receiver and very similar to the coherent receiver. As further lines we can cite the theoretical study of the optimum selection of the weighting matrix, as well as the analysis of some linear precoding techniques which can reduce or avoid the noise floor due to the finite sample problem.

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