Blind channel identification for Alamouti's coding systems based on eigenvector decomposition

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***Abstract*— This paper focuses on blind channel estimation in multiple antenna systems that make use of the well known Alamouti orthogonal space time code to attain full transmit diversity. The channel matrix is estimated from the eigenvalue decomposition of a square matrix formed by either second-order statistics (SOS) or by fourth-order cumulants of the observations. We will show that, unlike other coding strategies, the orthogonality property of the Alamouti scheme allows to estimate the channel using only SOS. Simulation results show that the SOS-based approach needs less observation symbols to obtain a good channel estimation.**

I. Introduction

Wireless communication systems that employ multiple antennas at both transmission and reception are commonly referred to as Multiple Input Multiple Output (MIMO) systems. One of the major advantages of MIMO systems is their ability to provide spatial diversity gains to decrease the Symbol-Error-Rate (SER) in multipath fading channels [1]. Diversity gain results from combining signals that experience independent signal fades.

Achieving the promised performance gains, even in practical operating conditions, requires for specific Space-Time Coding (STC) techniques that spread the transmitted symbols over the space and time dimensions. A large number of STCs have been proposed in the literature (see [2] and references therein). A remarkable example is orthogonal Space Time Block Coding (STBC) because it is easy to encode and decode [3]. The basic premise of orthogonal STBCs is the encoding of the transmitting symbols into an unitary matrix to spatially decouple their Maximum Likelihood (ML) detection. Orthogonal STBCs are very attractive because they provide full transmit diversity with linear decoding complexity.

For the case of two transmitting antennas, the orthogonal STBC is known as the Alamouti code [4]. Alamouti coding consists in transmitting a pair of symbols in a time-slot and the same pair with a different phase in the next time-slot. Although it does not provide any coding gain, Alamouti coding is very attractive because it provides full transmit diversity with linear decoding complexity and, for this reason, it is currently part of both the W-CDMA and CDMA-2000 standards [5].

The performance of Alamouti's coding scheme, as most other coding strategies, depends on the accurate estimation of the channel between the transmitter and the receiver. The transmission of pilot symbols, referred to as training symbols, is often used to perform channel estimation [6]. However, training symbols reduce the throughput and such schemes are inadequate when the bandwidth is scarce. Recently, a blind technique has been proposed to estimate the channel directly from the observations by using Higher Order Statistics (HOS) [7]. The basic idea is to compute the eigenvectors of the fourth-order cross-cumulant matrix of the observations. This approach, however, requires that the channel remains constant during a large number of symbol periods. In this paper, we will show that the performance of this method can be improved by averaging several cross-cumulant matrices.

We will also show that the channel matrix in the Alamouti's coding scheme can be estimated by performing an eigenvalue decomposition of the autocorrelation matrix of the observations. The only condition is that the transmitted signals have different powers. The advantages of this approach are remarkable: SOS can be estimated with less symbols than HOS, the computational cost is low and it presents a good performance in block fading channels.

This paper is structured as follows. Section II presents an overview of STC techniques, including a description of the Alamouti's codification scheme. Section III is devoted to introduce the idea of blind algorithms as powerful solutions to estimate the channel without using training sequences. In Section IV we present a novel method based on performing an eigenvalue decomposition of a square matrices containing SOS or HOS. Section V presents the results of several computer simulations carried out to compare the algorithms performance. Finally, section VI is devoted to the conclusions.

II. STC schemes

Space-time Coding (STC) has recently emerged as a powerful technique to exploit the spatial diversity in systems with multiple elements at both transmission and reception (MIMO wireless systems). In general, STC consists in transmitting several (redundant) copies of the original data through several transmitting antennas. The STC encoder must be designed in order to maximize the diversity gain and to combat fading, noise and interferences in MIMO channels [8], [2].

The development of the STC concept was originally presented in [9] with the form of trellis codes, so-called Space-Time Trellis Codes (STTC), where the transmitting symbols are obtained using a trellis (or convolutive) code. The STTC provides a diversity gain equal to the number of transmitting antennas in addition to a coding gain that depends on the number of states in the trellis. The limitation of this scheme is the high computational cost associated to the Viterbi algorithm used at the receiver to recover the original data.

The other kind of STC is the called Space-Time Block Codes (STBC) where different versions of the original data are transmitted through several transmitting antennas across several time-slots. Although STBC gives the same diversity gain as the STTC for the same number of transmitting antennas, they provides less coding gain. In contrast to STTC, the decoding method used in STBC is very simple and it can be performed using linear processing.

In addressing the issue of decoding complexity, Alamouti has proposed in [4] a remarkable STBC scheme for transmission with two antennas, that is currently part of both the W-CDMA and CDMA-2000 standards [5]. This code achieves a transmission rate equal to one by transmitting a pair of symbols in a time-slot and the same pair with a different phase in the next time-slot. This scheme supports Maximum-Likelihood (ML) detection based only on linear processing at the receiver.

More recently, Tarokh et al. [10], [11] has developed a theory to design STBC which also supports ML decoding with linear processing. For any number of transmitting antennas, these codes achieve the maximum possible transmission rate when the symbols correspond to any arbitrary real constellation and rate $1/2$ for complex constellations. For the specific case of three or four transmitting antennas, it is possible to achieve $3/4$ of the maximum transmission using any complex constellation. The simulation results presented in [11] show that significant gains can be achieved by increasing the number of transmitting antennas with very little decoding complexity.

The most popular STBCs (including [4] and [10]) are designed in order to guarantee that the transmission matrices have orthogonal columns. However, in the literature [12] it has been also proposed quasi-orthogonal STBCs where the orthogonality holds between some columns of the transmission matrix. Using this design it is possible to achieve full rate for any constellation using, like orthogonal STBC, linear processing at the receiver, although the decoding process is slightly more complex than for orthogonal STBCs. Results presented in [12] show that these quasi-orthogonal STBCs outperform orthogonal STBCs over a wide range of Signal to Noise Ratios (SNR). However, at high SNRs orthogonal STBCs provide better performance.

A. Alamouti's coding scheme

In this paper, we focus on the Alamouti's coding scheme proposed in [4]. Figure 1 shows the baseband representation for Alamouti STBC with two antennas at the transmitter and one antenna in the receiver. Each pair of symbols $\{s_1, s_2\}$ is transmitted in two adjacent periods using a simple strategy: in the first period s_1 and s_2 are transmitted from the first and the second antenna, respectively, and in the second period $-s_2^*$ is transmitted from the first antenna and s_1^* from the second one. In this paper, we will consider that the exact probability density function of s_i is unknown. We also assume that they are complex-valued, zero-mean, stationary, non-Gaussian distributed and statistically independent.

The transmitted symbols arrive at the receiving antenna through the fading paths h_1 and h_2, i.e, the signal received in the first period has the form

$$x_1 = s_1 \ h_1 + s_2 \ h_2 \tag{1}$$

where h_i denotes the path form the i-th transmitting antenna to the receiving one. If the channel remains constant during two periods, the observation in the second period is given by

$$x_2 = s_1^* \ h_2 - s_2^* \ h_1 \tag{2}$$

Alamouti's coding scheme can be also expressed in matrix form as follows

$$\left[\begin{array}{c} x_1 \\ x_2 \end{array} \right] = \left[\begin{array}{c} h_1 s_1 + h_2 s_2 \\ -h_1 s_2^* + h_2 s_1^* \end{array} \right] + \left[\begin{array}{c} n_1 \\ n_2 \end{array} \right] \tag{3}$$

where n_i is additive white Gaussian noise. A more convenient form of writing this coding strategy consists of considering the observation vector $\mathbf{x} = [x_1 \ x_2^*]^T$. The relationship between the observation vector $\mathbf{x}$ and the source vector $\mathbf{s} = [s_1 \ s_2]^T$ is given by

$$\mathbf{x} = \mathbf{H} \ \mathbf{s} + \mathbf{n} \tag{4}$$

where $\mathbf{H}$ is the 2×2 channel matrix,

$$\mathbf{H} = \left[\begin{array}{cc} h_1 & h_2 \\ h_2^* & -h_1^* \end{array} \right] \tag{5}$$

It is interesting to note that $\mathbf{H}$ is an orthogonal matrix, i.e.,

$$\mathbf{H} \ \mathbf{H}^H = \mathbf{H}^H \ \mathbf{H} = ||\mathbf{h}||^2 \ \mathbf{I}_2 \tag{6}$$

where $||\mathbf{h}||^2 = |h_1|^2 + |h_2|^2$ is the squared Euclidean norm, $\mathbf{I}_2$ is the 2×2 identity matrix and ^{H} is the Hermitian operator. As a result, the transmitted symbols can be recovered using $\hat{\mathbf{s}} = \mathbf{H}^H \ \mathbf{x}$.

Although in this paper we only consider the Alamouti's coding scheme, it is straightforward to show that the model in (4) is also adequate for the half-rate STBC schemes presented in [10] where N complex-valued signals are transmitted in $2N$ time-slots.

B. Relationship between Alamouti' scheme and BSS

It is interesting to note that the Alamouti's coding scheme corresponds to the classic problem in Blind Source Separation (BSS) where a set of unknown signals $\mathbf{s} = [s_1, s_2, \ldots, s_N]^T$ must be recovered from their observed mixtures $\mathbf{x} = [x_1, x_2, \ldots, x_M]^T$, which are typically measured at the output of a sensor array [13], [14]. The mixtures can often be considered as instantaneous and linear, so that the mixing process may be expressed mathematically as the matrix transformation

$$\mathbf{x} = \mathbf{H}\mathbf{s} + \mathbf{n} \tag{7}$$

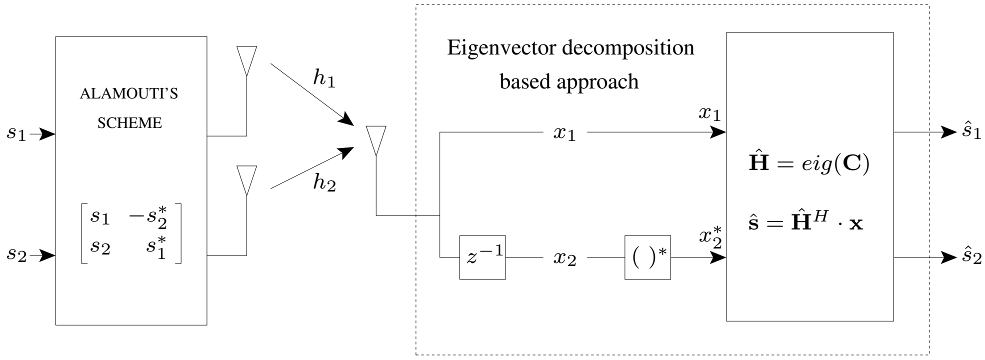

Fig. 1. Alamouti's coding scheme

where $\mathbf{n}$ typically corresponds to additive Gaussian noise.

The goal of BSS is to estimate the mixing matrix $\mathbf{H}$ and the realizations of the source vector $\mathbf{s}$ from the corresponding realizations of the observed vector $\mathbf{x}$. The term *blind* (or unsupervised) refers to the fact that little or nothing is known or assumed about the sources and the mixing matrix structure. This lack of prior knowledge may limit the achievable performance, but makes the BSS approach more robust to calibration errors (i.e., deviations of model assumptions from reality) than conventional array processing techniques [15]. Since the seminal work of [16], [17], the arousing research interest in BSS has been motivated by the great variety of application areas where model (7) appears. In particular, Alamouti's coding scheme can also be cast in the BSS model.

Obviously, the linear inversion of $\mathbf{H}$ requires that $M \geq N$. In such a case, one deals with overdetermined, or undercomplete, mixtures. The so-called underdetermined or overcomplete mixture scenario, in which $M < N$, is certainly more challenging, but has only begun to receive attention recently (see, e.g., [18] and references therein).

Without further assumptions on the sources or the mixture, the reconstruction of model (7) can at most be carried out up to an ambiguity in the ordering and scale of the sources and the associated columns of the mixing matrix. These indeterminacies are inherent to blind techniques and are thus considered as acceptable in BSS.

Most approaches to BSS are property recovering techniques: an unmixing transformation (the inverse of the mixing matrix) is sought such that it recovers a known property of the sources. Under certain conditions, recovering the property amounts to recovering the sources, and thus the mixing matrix, up to the ambiguities mentioned above. A property commonly exploited is the statistically independence of the sources. Depending on the degree of independence considered, two main group of techniques can be distinguished: SOS-based approaches and HOS-based approaches. A number of techniques in both SOS and HOS approaches are based on the eigen-decomposition of certain matrix or tensor structures. Particular instances are the techniques proposed and analyzed later in this paper to perform blind channel estimation in the context of Alamouti's space-time coding.

III. Decoding algorithms for orthogonal STBC

The major advantage of orthogonal STBCs is that they provides full diversity gain with a low decoding complexity. If the Channel State Information (CSI) is available at the receiver, the optimal ML decoder is a simple linear receiver followed by a symbol-by-symbol detector. Although training approaches [6] can be used to obtain the CSI at the receiver, training bits degrade the transfer rate.

In those situations where CSI at the receiver is unavailable, blind algorithms can be used to estimate the channel without using training sequences. When the sources are temporally white, like occurs in most digital communication applications, it is needed to exploit higher-order independence of the source signals. Independence is typically measured by means of HOS such as the higher-order cumulants: the absolute value of the marginal cumulants is to be maximized or, equivalently, that of the cross-cumulants minimized, subject to the appropriate constraints. Interestingly, very similar HOS criteria are obtained from a variety of apparently disparate information-theoretical principles such as negentropy, mutual information or maximum likelihood [19], [20]. Totally analogous cumulant-based criteria such as kurtosis maximization [21], [22] were developed years before in the context of blind deconvolution [23], [24]. Indeed, this latter problem may be seen as the blind separation of a single source from time-delayed versions of itself.

In Comon's pioneering BSS contribution [25], the initial source estimates provided by SOS are further processed via Givens rotations aiming at maximizing the 4th-order independence of the transformed signals. The optimal rotation angles are obtained by rooting a low-degree polynomial whose coefficients are computed from the 4th-order cumulants of the signal pair. Several sweeps over all signal pairs are necessary for convergence. This pairwise scheme can be seen as the generalization to 4th-order cumulant tensors (higher-order arrays) of the well-known Jacobi technique for matrix diagonalization.

Higher-order eigen-based approaches began to be investigated since Cardoso's early work on the so-called quadricovariance, a folded version of the 4th-order moment array [26]. This line of research culminated with the popular method known as joint approximate diagonalization of eigenmatrices (JADE) [15].

Another strategy based on HOS has been proposed in [7] by considering the specific properties of the channel matrix in systems with orthogonal STBC. In this case, the channel matrix is computed by performing an eigenvalue decomposition of matrices containing the fourth-order cross-cumulant of the observations. The simulation results reported in [7] show that a large number of symbols are needed to obtain a good performance.

In general, HOS-based methods present a high computational cost and may require long streams of data to obtain accurate channel estimates. For this reasons, SOS-based methods are preferable in practice. Recently, reduced-complexity SOS-based algorithms have been developed for blind channel estimations in orthogonal STBC transmissions [27], [28]. These methods are based on finding the eigenvectors of a matrix computed from the SOS of the observations. The channel matrix is identifiable when this matrix have distinct principal eigenvalues. In practice, when the methods in [27], [28] are used for the Alamouti's coding scheme, the condition over the principal eigenvalues is traduced in including a precoder before the STBC encoder, which considerably increases the complexity of both the encoder and the decoder.

IV. Proposed channel estimation method

In this section, we will propose blind strategies to estimate the channel matrix (see Figure 1). The basic idea is to find a 2×2 matrix $\mathbf{C}$ that can be decomposed as $\mathbf{C} = \mathbf{H}\mathbf{\Delta}\mathbf{H}^H$ where $\mathbf{\Delta} = diag(\delta_1, \delta_2)$. Note that if $\delta_1 \neq \delta_2$, the channel matrix corresponds to the eigenvectors of $\mathbf{C}$, up to a single phase ambiguity [29].

A. SOS-based approach

First, we will consider the feasibility of using SOS to estimate the channel matrix. In this case, the matrix $\mathbf{C}$ is the autocorrelation matrix of the observations, i.e.,

$$\mathbf{C}_{SOS} = E[\mathbf{x}\mathbf{x}^H] = \mathbf{H}\ \mathbf{R_s}\ \mathbf{H}^H + \sigma_n^2 \mathbf{I}_2 \tag{8}$$

where σ_n^2 is the noise power and $\mathbf{R_s} = E[\mathbf{s}\mathbf{s}^H]$ is the correlation matrix of the transmitted signals. Since $\mathbf{H}$ is orthogonal, from (6), we obtain

$$\mathbf{C}_{SOS} = \mathbf{H}\ \left(\mathbf{R_s} + \frac{\sigma_n^2}{||\mathbf{h}||^2}\mathbf{I}_2\right)\ \mathbf{H}^H \tag{9}$$

Note that $\mathbf{C}_{SOS}$ is diagonal when the two transmitted signals have the same power, $E[|s_1|^2] = E[|s_2]^2] = \sigma_s^2$, and the system is not identifiable using an eigenvalue decomposition.

We will consider now that the transmitted signals have different power,

$$E[|s_2|^2] = \gamma^2 E[|s_1|^2] = \gamma^2\ \sigma_s^2, \quad \gamma^2 \neq 1 \tag{10}$$

where $\sigma_s^2 = E[|s_1|^2]$ is the power associated to the s_1 symbols. In this case, it is straightforward to obtain

$$\mathbf{C}_{SOS} = \sigma_s^2\ \mathbf{H}\ \mathbf{\Delta}_{SOS}\ \mathbf{H}^H \tag{11}$$

where

$$\mathbf{\Delta}_{SOS} = \begin{bmatrix} 1+\sigma_h^2 & 0 \\ 0 & \gamma^2+\sigma_h^2 \end{bmatrix} \tag{12}$$

where $\sigma_h^2 = \frac{\sigma_n^2}{\sigma_s^2||\mathbf{h}||^2}$. As a result, the matrix $\mathbf{H}$ is identifiable if the transmitter adapts the signal power in order to guarantee (10). The proposed approach can be used only when $\mathbf{H}$ is an orthogonal matrix, as occurs in Alamouti's coding scheme.

B. HOS-based approach

In [7], Beres and Adve have presented a method to identify the channel matrix by computing the eigenvectors of the fourth-order cross-cumulants of the observations vector given by

$$\begin{aligned} \mathbf{C}_{HOS}^{[k]} &= c_4(\mathbf{x}, \mathbf{x}^*, x_k, x_k^*) \qquad (13) \\ &= \begin{bmatrix} c_4(x_1, x_1^*, x_k, x_k^*) & c_4(x_1, x_2^*, x_k, x_k^*) \\ c_4(x_2, x_1^*, x_k, x_k^*) & c_4(x_2, x_2^*, x_k, x_k^*) \end{bmatrix} \end{aligned}$$

where $k = 1, 2$ denotes the time-slot and

$$\begin{aligned} c_4(x_1, x_2, x_3, x_4) = E[x_1x_2x_3x_4] - E[x_1x_2]E[x_3x_4] \\ -E[x_1x_3]E[x_2x_4] - E[x_1x_4]E[x_2x_3] \end{aligned} \tag{14}$$

Assuming that s_1 and s_2 have the same kurtosis, $\rho_4 = c_4(s_1, s_1^*, s_1, s_1^*) = c_4(s_2, s_2^*, s_2, s_2^*)$, in [7] it has been proved that equation (13) can be written as

$$\mathbf{C}_{HOS}^{[k]} = \rho_4 \mathbf{H}\ \mathbf{\Delta}_k\ \mathbf{H}^H \tag{15}$$

where $\mathbf{\Delta}_k$ depend on the time-slot,

$$\mathbf{\Delta}_1 = \begin{bmatrix} |h_1|^2 & 0 \\ 0 & |h_2|^2 \end{bmatrix} \quad \mathbf{\Delta}_2 = \begin{bmatrix} |h_2|^2 & 0 \\ 0 & |h_1|^2 \end{bmatrix} \tag{16}$$

From equation (15) we conclude that the channel matrix $\mathbf{H}$ can be identified by computing the eigenvectors of $\mathbf{C}_4^{[1]}$ or $\mathbf{C}_4^{[2]}$ when $|h_1| \neq |h_2|$. The simulation results reported in [7] show that the channel must remain constant during a large number of symbol periods to obtain an adequate estimation.

In order to improve the idea presented above, we propose to compute the eigenvectors of the matrix

$$\mathbf{C}_{HOS}^{\lambda} = C_4^{[1]} + \lambda\ C_4^{[2]} \tag{17}$$

where λ is a real valued parameter. Using equation (15), it is straightforward to obtain

$$\mathbf{C}_{HOS}^{\lambda} = \rho_4 \mathbf{H}\ \mathbf{\Delta}_{HOS}\ \mathbf{H}^H \tag{18}$$

where

$$\mathbf{\Delta}_{HOS} = \begin{bmatrix} |h_1|^2 + \lambda|h_2|^2 & 0 \\ 0 & |h_2|^2 + \lambda|h_1|^2 \end{bmatrix} \tag{19}$$

Note that for $\lambda = 1$ the matrix $\mathbf{C}_{HOS}^{\lambda=1}$ takes the form

$$\begin{aligned} \mathbf{C}_{HOS}^{\lambda=1} &= \mathbf{C}_{HOS}^{[1]} + \mathbf{C}_{HOS}^{[2]} \\ &= \rho_4\ (|h_1|^2 + |h_2|^2)\ \mathbf{H}\ \mathbf{H}^H \\ &= \rho_4\ ||\mathbf{h}||^2\ \mathbf{I}_2 \end{aligned} \tag{20}$$

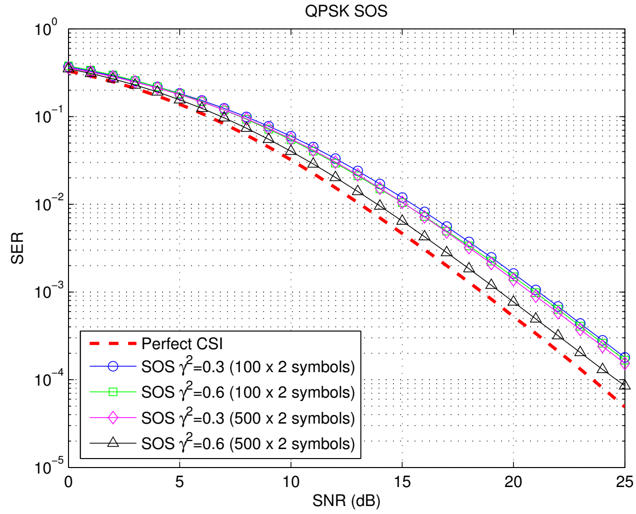

Fig. 2. SER vs SNR obtained with the SOS-based approach for QPSK signals.

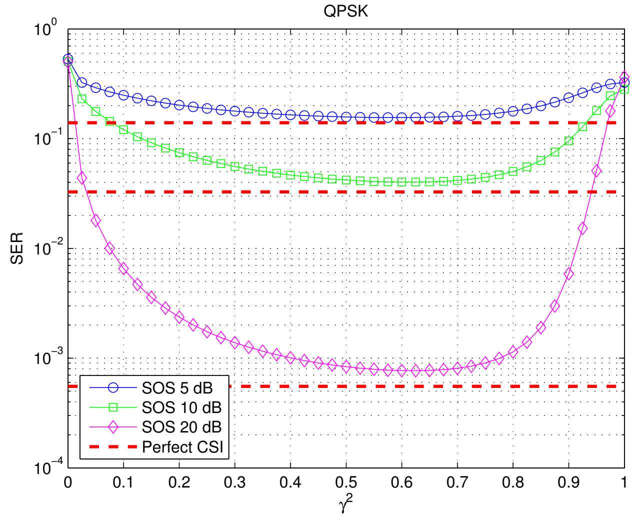

Fig. 3. SER obtained with the SOS-based approach for QPSK signals varying the parameter γ. The curves corresponds to SNR of 5, 10 and 20 dB. The horizontal dashed lines represent the SER obtained with perfect CSI.

As a consequence, the channel cannot be identified when $\lambda = 1$. On the contrary, when $\lambda = -1$, we obtain

$$\begin{aligned} \mathbf{C}_{HOS}^{\lambda=-1} &= \mathbf{C}_{HOS}^{[1]} - \mathbf{C}_{HOS}^{[2]} \\ &= \rho_4 \mathbf{H} \begin{bmatrix} |h_1|^2 - |h_2|^2 & 0 \\ 0 & |h_2|^2 - |h_1|^2 \end{bmatrix} \mathbf{H}^H \\ &= \rho_4 (|h_1|^2 - |h_2|^2) \mathbf{H} \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \mathbf{H}^H \end{aligned} \tag{21}$$

In this case, the channel matrix corresponds to the eigenvectors of $\mathbf{C}_{HOS}^{\lambda=-1}$. Again, this modification fails if $|h_1| = |h_2|$.

We note that using $\mathbf{C}_{HOS}^{\lambda}$ instead of $\mathbf{C}_{HOS}^{[k]}$ increases the complexity of the algorithm. However, simulation results show that the performance of the estimation is significantly improved.

V. Simulation Results

This section presents the results of several computer simulations carried out to verify the estimation algorithms proposed in Section IV. The experiments have been performed by using QPSK signals and flat fading channels. We consider the Rayleigh-distributed randomly generated channel and additive white Gaussian noise. We assume block fading, i.e., the channel remains constant during the transmission of a block of K symbols. The statistics in (8) and (13) have been calculated for each block by sample averaging over the block symbols. The performance has been measured in terms of the Symbol Error Rate (SER). For comparison purposes we also present the SER obtained with Perfect Channel Side Information (Perfect CSI).

In the first computer experiment, two QPSK signals have been transmitted in blocks of $K = 100$ and $K = 500$ symbols. The energy of the signal s_2 has been adapted according to (10) with $\gamma^2 = 0.3$ and $\gamma^2 = 0.6$. Figure 2 shows the SER versus the SNR obtained by averaging the results over 100,000 different channel realizations. Note that the performance with $\gamma^2 = 0.6$ and $K = 500$ is closer to that obtained with Perfect CSI.

We have also evaluated the performance of the SOS-based approach for several values of γ. Figure 3 shows the SER versus γ^2 for SNR values of 5, 10 and 20 dB. The autocorrelation matrix has been estimated with $K = 500$ symbols. This figure also plots the SER obtained with Perfect CSI (horizontal dashed lines). It is apparent that the SOS-based channel estimation approach fails for $\gamma^2 = 1$ because this case corresponds to signals with the same power. The same occurs when $\gamma^2 = 0$ which corresponds to the limiting case where only s_1 is transmitted. Note also that the best performance is obtained with $\gamma^2 \approx 0.6$ which implies that the power of s_1 is approximately two times the power of s_1, i.e, $E[|s_2|^2] = \gamma^2 \sigma_s^2 \approx \sigma_s^2/2$.

With these experiments we have evaluated the performance in terms of averaged SER between s_1 and s_2. Figure 4 separately shows, for a SNR of 20 dB, the SER for s_1, s_2, the mean SER and finally, the difference between the two SERs. Obviously, SER of s_1 is better than SER of s_2 but we can see that it is approximately between two and three times around $\gamma^2 = 0.6$. Note that it is important to choose an adequate value of γ to have a good trade-off between mean SER and the magnitude of decompensation for two signals. Figure 5 shows the SER for s_1 and s_2 for $\gamma^2 = 0.6$ which is the value that achieves lower mean error.

In order to validate the HOS-based method, two QPSK signals with the same energy have been transmitted in blocks of $K = 500$ and $K = 5000$ symbols. Figure 6 shows the SER versus the SNR obtained for $\lambda = 0$ which corresponds to the method proposed in [7] and for $\lambda = -1$. In this case, the results have been obtained by averaging the SER obtained with 10,000 different channels. Note that the selection of $\lambda = -1$ improves the performance of the system.

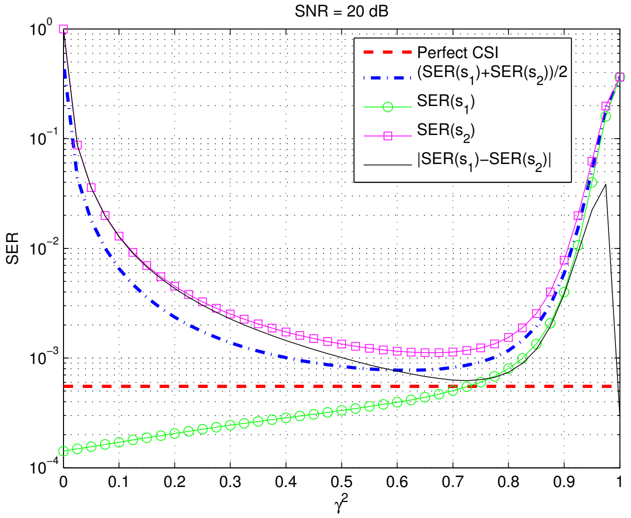

Fig. 4. SER for s_1 and s_2 obtained with the SOS-based approach for QPSK signals varying the parameter γ with SNR of 20 dB.

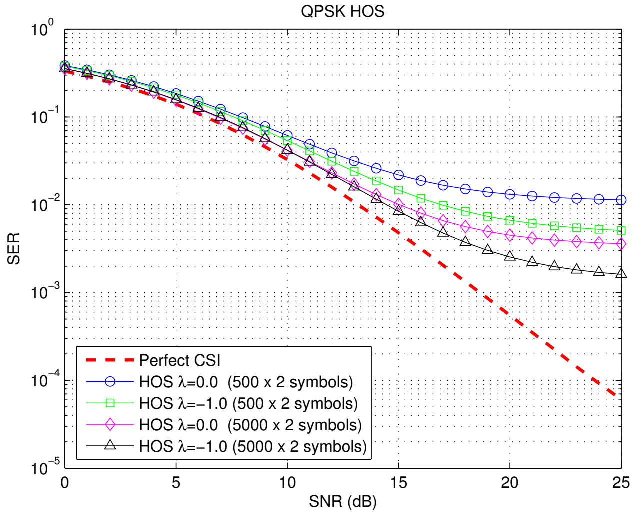

Fig. 6. SER vs SNR obtained with the HOS-based approach for QPSK signals.

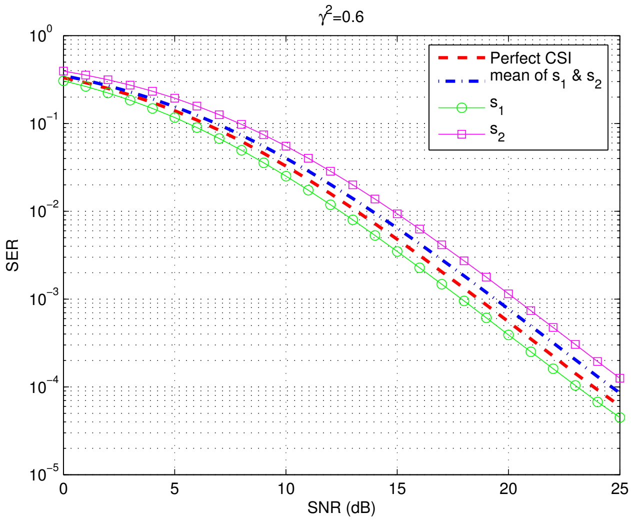

Fig. 5. SER for s_1 and s_2 vs SNR obtained with the SOS-based approach for QPSK signals.

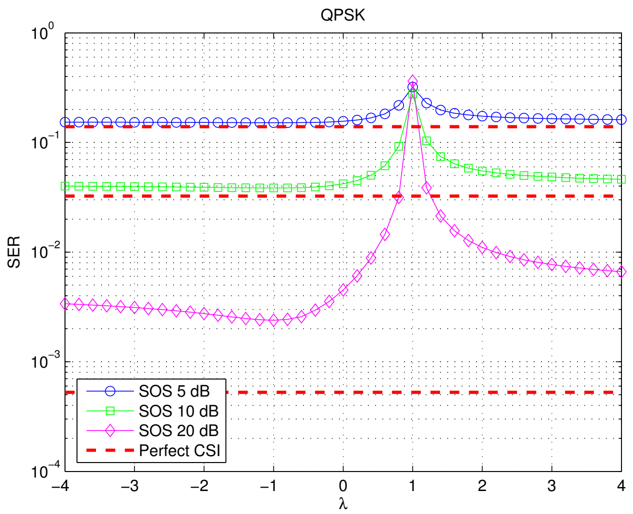

Fig. 7. SER obtained with the HOS-based approach for QPSK signals varying the parameter λ. The curves correspond to SNR of 5, 10 and 20 dB. The horizontal dashed lines represent the SER obtained with perfect CSI.

Figure 7 shows the dependence of SER versus λ for SNR of 5, 10 and 20 dB SNR of 20 dB, and blocks of $K = 5000$ symbols. Note that the HOS are insufficient to estimate the channel when $\lambda = 1$ because it corresponds to equation (20). The best performance is achieved when $\lambda \approx -1$.

Figure 8 compares the performance obtained with the two approaches for blocks of 500 and 5000 symbols. The other parameters have been: $\gamma^2 = 0.6$ for the SOS-based approach and $\lambda = -1$ for the HOS-based approach. From these results, we conclude that the SOS-based approach needs less symbols to achieve a good performance.

VI. Conclusions

This paper shows that the channel parameters of a multiple antenna transmission system with Alamouti's coding can be estimated by calculating the eigenvalue decomposition of a square matrix formed by either second order statistics or fourth-order cross-cumulants. The estimation is blind because it is performed without the aid of training sequences. The SOS-based approach consists of computing the eigenvectors of the autocorrelation matrix of the observations. Since the channel matrix is orthogonal, the eigenvectors directly correspond to the channel matrix when the transmitted signals have different power. In contrast, the system is not identifiable when both signals have the same power because the autocorrelation matrix is diagonal. Simulation results show that this approach allows one to estimate the channel with a small number of symbols (about 500 symbols for QPSK signals). As a

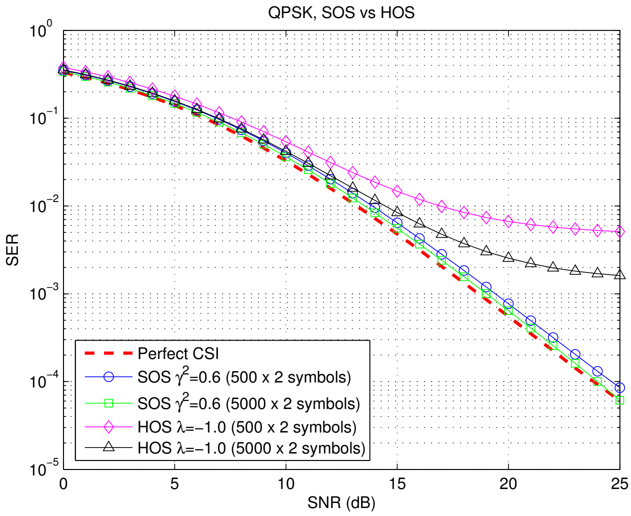

Fig. 8. Comparison of SOS-approach and HOS-approach for QPSK signals with 500 and 5000 symbols.

result, the computational cost is reduced and it is adequate for flat-fading block channels. The other approach is based on the algorithm proposed in [7]. The channel matrix is determined by calculating the eigenvectors of an average of fourth-order cross-cumulants matrices. Simulations show that this approach presents a flooring effect for high SNR due to higher finite-sample estimation errors in HOS. In addition, the computational cost is considerably increased.

Acknowledgement

This work has been supported by Xunta de Galicia, Ministerio de Educación y Ciencia of Spain and FEDER funds of the European Union under grants number PGIDT05PXIC10502PN and TEC2004-06451-C05-01.

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