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A Low-Cost Decision-Aided Channel Estimation Method for Alamouti OSTBC

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Abstract In wireless communication systems, *Channel State Information* (CSI) acquisition is typically performed at the receiver side every time a new frame is received, without taking into account whether it is really necessary or not. Considering the special case of the 2×1 Alamouti Orthogonal Space-Time Block Code, this work proposes to reduce computational complexity associated to the CSI acquisition by including a decision rule to automatically determine the time instants when CSI must be again updated. Otherwise, a previous channel estimate is reused. The decision criterion has a very low computational complexity since it consists in computing the cross-correlation between preambles sent by the two transmit antennas. This allows us to obtain a considerable reduction on the complexity demanded by both supervised and unsupervised (blind) channel estimation algorithms. Such preambles do not penalize the spectral efficiency in the sense they are mandatory for frame detection as well as for time and frequency synchronization in current wireless communication systems.

Keywords CSI acquisition · Alamouti code · Supervised and unsupervised estimation · Hybrid adaptive algorithms · Batch learning

1 Introduction

A huge number of *Space-Time Coding* (STC) techniques have been proposed during the last decades in order to better exploit spatial diversity in recent wireless communication systems, which employ multiple antennas at the transmitter and/or the receiver [7]. Examples of wireless communication systems implementing such techniques are WiFi or WiMAX. A remarkable class of STC is the *Orthogonal Space-Time Block Coding* (OSTBC) since it provides full diversity gain with very simple encoding and decoding procedures [1, 10]. The basic premise of OSTBC is

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that the transmitted symbols are encoded to an orthogonal matrix which simplifies the optimum *Maximum Likelihood* (ML) decoder to a matched filter followed by a symbol-by-symbol detector.

In particular, the OSTBC code proposed by Alamouti [1], which considers two transmit antennas and a single receive antenna, is the only OSTBC capable of achieving full spatial rate using complex-valued constellations. Coherent detection in 2×1 Alamouti systems requires knowledge about two channel parameters, which is commonly achieved by means of using pilot symbols, also referred to as training sequences. However, the inclusion of such symbols reduces the system throughput (equivalently, it reduces the system spectral efficiency) and wastes transmission energy because these training sequences do not convey information.

The so-called *unsupervised techniques* –also known as *Blind Source Separation* (BSS) techniques [5]– are able to estimate the channel coefficients directly from the observations, without requiring pilot symbols. They only assume that the transmitted signals are statistically independent. Most BSS methods have been proposed considering the general problem of recovering signals from linear mixtures without the consideration of any specific application [2,4,9], although several authors have recently proposed algorithms in which the recovering matrix is computed taking into account the coding structure imposed by OSTBC [3,6,11].

Complexity of channel estimation algorithms is an important drawback in wireless communication systems since it implies power consumption and delay associated to the signal processing performed at the receiver side. In current standards, channel estimation is done every time a new frame is received but in general, such a channel estimate is only needed when there exists a significant variation in the channel fluctuations or in the *Signal–to–Noise Ratio* (SNR). Thus, the main goal of this work is to determine channel variations in wireless systems implementing the $2{\times}1$ Alamouti OSTBC by means of the cross-correlation between the preambles transmitted by both antennas. Remark that these preambles are absolutely necessary for such a proposal, which is not a restriction since they are usually included in a transmitted frame specially for synchronization tasks.

The time instant in which the channel parameters have significantly changed is determined by means of a simple comparison between current and previous channel parameters. Note that the channel estimation takes place only if the decision criterion decides that a significant channel variation have occurred, which leads to a considerable reduction of computational complexity without penalizing the performance in terms of *Symbol Error Rate* (SER).

This paper is structured as follows. Section 2 presents the signal model of a $2{\times}1$ Alamouti OSTBC and explains some supervised and unsupervised methods for channel estimation. Section 3 proposes the novel method to reduce the computational complexity and Section 4 shows some computer simulation results. The performance exhibited by this proposal is improved following the method explained in Section 5. Finally, Section 6 is devoted to the conclusions.

2 Alamouti Coded Systems

Figure 1 shows the baseband representation of a wireless communication system with two antennas at the transmitter and one antenna at the receiver, including Alamouti OSTBC. In general, if we let $f[n] = f(nT_{\mathrm{s}} + \Delta)$ denote samples of

$f(t)$ every T_s seconds with $\varDelta$ being the sampling delay and T_s the symbol time, then sampling $\boldsymbol{f}(t)$ every T_s seconds yields the aforementioned discrete time signal $\boldsymbol{f}[n] = \boldsymbol{f}(nT_\mathrm{s} + \varDelta)$, where $n = 0, 1, 2, \ldots$ corresponds to samples spaced with T_s. Taking into account this discrete time model equivalent to the continuous one, we have that $s_1[n]$ and $s_2[n]$, for $n = 2k + 1$ with $k = 0, 1, 2, \ldots$, are transmitted by the first and the second antenna, respectively, in the odd symbol times, while in the even symbol times, $-s_2^*[n]$ is transmitted by the first antenna and $s_1^*[n]$ by the second one. Here, $n = 2k$ with $k = 0, 1, 2, \ldots$ and the symbol sequence is assumed to be independent and identically distributed, so that $s_1[n]$ and $s_2[n]$ are statistically independent.

According to Figure 1, the transmitted symbols arrive at the receive antenna through the fading paths $h_1[q]$ and $h_2[q]$, so that the signals received during the first and the second symbol times are, respectively, $z_1[n] = s_1[n]\ h_1[q] + s_2[n]\ h_2[q] + v_1[n]$ and $z_2[n] = s_1^*[n]\ h_2[q] - s_2^*[n]\ h_1[q] + v_2[n]$, where $v_1[n]$ and $v_2[n]$ represent the *Additive White Gaussian Noise* (AWGN) in each symbol time. Note that the index q denotes the time slot and it is introduced to indicate that the channels remain unchanged during several symbol times (i.e.. a block-fading channel is considered). Defining the observation vector as $\boldsymbol{x}[n] = [x_1[n]\ x_2[n]]^\mathrm{T} = [z_1[n]\ z_2^*[n]]^\mathrm{T}$, we obtain that the relationship between the observation vector $\boldsymbol{x}[n]$ and the source vector $\boldsymbol{s}[n] = [s_1[n]\ s_2[n]]^\mathrm{T}$ is given by

$$\boldsymbol{x}[n] = \boldsymbol{H}[q]\ \boldsymbol{s}[n] + \boldsymbol{v}[n], \tag{1}$$

where $\boldsymbol{H}[q]$ is the 2×2 effective channel matrix defined as

$$\boldsymbol{H}[q] = \begin{bmatrix} h_1[q] & h_2[q] \\ h_2^*[q] & -h_1^*[q] \end{bmatrix}, \tag{2}$$

and $\boldsymbol{v}[n] = [v_1[n]\ v_2^*[n]]^\mathrm{T}$ is modeled as a vector of two uncorrelated zero-mean, complex-valued, circularly-symmetric, and Gaussian-distributed random processes. It is interesting to note that $\boldsymbol{H}[q]$ is an orthogonal matrix, i.e. $\boldsymbol{H}[q]\boldsymbol{H}^\mathrm{H}[q] = \boldsymbol{H}^\mathrm{H}[q]\boldsymbol{H}[q] = ||\boldsymbol{h}[q]||^2\ \boldsymbol{I}_2$, where $||\boldsymbol{h}[q]||^2 = |h_1[q]|^2 + |h_2[q]|^2$ is the squared Euclidean norm of $\boldsymbol{h}[q]$. As a consequence, the transmitted signals can be recovered using

$$\boldsymbol{y}[n] = \boldsymbol{H}^\mathrm{H}[q]\boldsymbol{x}[n] = ||\boldsymbol{h}[q]||^2 \boldsymbol{s}[n] + \tilde{\boldsymbol{v}}[n], \tag{3}$$

where $\tilde{\boldsymbol{v}}[n] = \boldsymbol{H}^\mathrm{H}[q]\boldsymbol{v}[n]$ is the output noise vector, with the same statistical properties as the input noise. It is apparent from Eq. (3) that the correct detection of the transmitted symbols $\boldsymbol{s}[n]$ requires an accurate estimate of the channel matrix $\boldsymbol{H}[q]$ from the received data $\boldsymbol{x}[n]$.

2.1 Channel Estimation Approach

For channel estimation, we consider a linear system that generates the signal $\boldsymbol{y}[n] = \boldsymbol{W}^\mathrm{H}[n]\boldsymbol{x}[n]$ at its output, where $\boldsymbol{W}[n]$ is the 2×2 mixing matrix. Notice that the connection between that mixing matrix and the channel in Eq. (2) is given by $\boldsymbol{W} = \boldsymbol{H}$ since $\boldsymbol{H}^{-1} = \boldsymbol{H}^\mathrm{H}$. The classical way to estimate this matrix is to minimize the *Mean Squared Error* (MSE) between the outputs $\boldsymbol{y}[n]$ and the desired signals $\boldsymbol{s}[n]$ [8]. Mathematically, the cost function is defined as

$$\mathrm{J_{MSE}} = \sum_{i=1}^{N} \mathrm{E}\left[|y_i[n]-s_i[n]|^2\right] = \mathrm{E}\left[\mathrm{tr}\left((\boldsymbol{W}^{\mathrm{H}}[n]\boldsymbol{x}[n]-\boldsymbol{s}[n])(\boldsymbol{W}^{\mathrm{H}}[n]\boldsymbol{x}[n]-\boldsymbol{s}[n])^{\mathrm{H}}\right)\right], \tag{4}$$

where N is the number of transmit antennas, two for the case of a $2{\times}1$ Alamouti coded system. The gradient of this cost function is obtained as

$$\nabla_{\boldsymbol{W}} \mathrm{J_{MSE}} = \mathrm{E}\left[\boldsymbol{x}[n](\boldsymbol{W}^{\mathrm{H}}[n]\boldsymbol{x}[n]-\boldsymbol{s}[n])^{\mathrm{H}}\right]. \tag{5}$$

In general, the expectation in $\nabla_{\boldsymbol{W}} \mathrm{J_{MSE}}$ is unknown so it must be estimated from the available data. In particular, by considering only one sample, we obtain the *Least Mean Squares* (LMS) algorithm, also called *delta rule* of *Widrow-Hoff* [8] in the context of Artificial Neural Networks, which adapts the coefficients by means of using

$$\boldsymbol{W}[n+1] = \boldsymbol{W}[n] - \mu\boldsymbol{x}[n](\boldsymbol{W}^{\mathrm{H}}[n]\boldsymbol{x}[n]-\boldsymbol{s}[n])^{\mathrm{H}}, \tag{6}$$

where μ is the step-size parameter. The classical stability analysis is based on the study of the point where $\nabla_{\boldsymbol{W}} \mathrm{J_{MSE}} = 0$ so that it can be demonstrated that the stationary points of this rule are obtained for the mixing matrix

$$\boldsymbol{W} = \boldsymbol{C}_{\boldsymbol{x}}^{-1}\boldsymbol{C}_{\boldsymbol{xs}}, \tag{7}$$

which is termed as *Widrow-Hoff solution*. Note that $\boldsymbol{C}_{\boldsymbol{x}} = \mathrm{E}[\boldsymbol{x}[n]\boldsymbol{x}^{\mathrm{H}}[n]]$ is the autocorrelation of the observations and $\boldsymbol{C}_{\boldsymbol{xs}} = \mathrm{E}[\boldsymbol{x}[n]\boldsymbol{s}^{\mathrm{H}}[n]]$ is the cross–correlation between the observations and the desired signals. In practice, the desired signals are considered as known only during a finite number of instants (pilot symbols).

Such a pilot transmission can be avoided taking advantage of BSS approaches, which estimate the matrix $\boldsymbol{H}[q]$ directly from the observation vector $\boldsymbol{x}[n]$, assuming for that purpose that the transmitted signals and the channel parameters are completely unknown at the receiver side. An interesting family of BSS methods based on diagonalizing matrices is formed by the so-called *high-order cumulants*. In particular, its utilization for the 2×1 Alamouti code of the popular *Joint Approximate Diagonalization of Eigenmatrices* (JADE) batch learning algorithm proposed by Cardoso et al. [4] consists in a joint diagonalization of four 2×2 matrices whose coefficients are the fourth-order cross-cumulants. Recently, Dapena et al. [6] have proposed a JADE's simplification, referred to as *Blind Channel Estimation based on Eigenvalue Spread* (BCEES), which is based on diagonalizing only the matrix with maximum eigenvalue spread. This adaptive learning procedure is detailed in the pseudocode of Table 1.

Table 2 shows the total number of operations needed to compute the Widrow-Hoff solution in Eq. (7) given a pilot sequence of N_P symbols and $N=2$ transmit antennas. From this table, it can be concluded that the computational complexity is $O(N_P)$. Table 3 shows the computational complexity of BCEES considering a total of N_U user data symbols. Since the number of user symbols is higher than the number of pilots, the computational complexity of BCEES is considerable higher than that obtained with the Widrow-Hoff solution explained above.

Given the current observation vector $\boldsymbol{x} = [x_1, x_2]^{\mathrm{T}}$, do the following steps.
Step 1. Compute the cumulants

$$c_4 = \mathrm{cum}(x_1, x_1^*, x_2, x_2^*) \quad \text{and} \quad c_2 = \mathrm{cum}(x_1, x_1^*, x_1, x_2^*).$$

Step 2. Obtain the positive-valued parameter

$$|\beta| = \frac{c_4}{|c_2|} = \frac{\mathrm{cum}(x_1, x_1^*, x_2, x_2^*)}{|\mathrm{cum}(x_1, x_1^*, x_1, x_2^*)|}.$$

Step 3. If $|\beta| < 1$ **then**
compute the cumulants

$$c_1 = \mathrm{cum}(x_1, x_1^*, x_1, x_1^*) \quad \text{and} \quad c_3 = \mathrm{cum}(x_1^*, x_1, x_1^*, x_2),$$

and form the matrix

$$\boldsymbol{C} = \begin{bmatrix} c_1 & c_2 \\ c_3 & c_4 \end{bmatrix}$$

else
compute the cumulants

$$c_5 = \mathrm{cum}(x_1, x_2^*, x_1, x_2^*) \quad \text{and} \quad c_6 = \mathrm{cum}(x_1, x_2^*, x_2, x_2^*),$$

and form the matrix

$$\boldsymbol{C} = \begin{bmatrix} c_2 & c_5 \\ c_4 & c_6 \end{bmatrix}.$$

Step 4. Compute the eigenvectors of $\boldsymbol{C}$, denoted by $\boldsymbol{U}$.
Step 5. Recover the sources $\boldsymbol{s} = \boldsymbol{U}^{\mathrm{H}} x$.

Given the random variables x_i, x_j, x_l, and x_k, the fourth-order cumulants are defined as

$$\mathrm{cum}(x_i, x_j^*, x_k, x_l^*) = \mathrm{E}[x_i x_j^* x_k x_l^*] - \mathrm{E}[x_i x_j^*]\,\mathrm{E}[x_k x_l^*] - \mathrm{E}[x_i x_l^*]\,\mathrm{E}[x_j x_k^*] - \mathrm{E}[x_i x_k]\,\mathrm{E}[x_j^* x_l^*].$$

Table 1 Procedure of the algorithm Blind Channel Estimation based on Eigenvalue Spread (BCEES). Since the equivalent channel matrix in the 2×1 Alamouti OSTBC is orthogonal, it can be shown that the eigenvector matrix $\boldsymbol{U}$ is an estimation of the channel matrix $\boldsymbol{H}$ (see [4] for more information).

Compute $\boldsymbol{C_x}$ (or $\boldsymbol{C_{xs}}$)	$N^2 \times N_P$ multiplications $N^2 \times (N_P - 1)$ summations
Matrix inversion $\boldsymbol{C_x}^{-1}$	$O(N^3)$ for the Gauss-Jordan method
Compute $\boldsymbol{C_x}^{-1}\boldsymbol{C_{xs}}$	N^3 complex multiplications $N^2 \times (N-1)$ complex summations

Table 2 Computational complexity of the Widrow-Hoff solution ($N = 2$ for 2×1 Alamouti OSTBC).

3 Decision-Aided Criterion

This section proposes a novel method to automatically track wireless channel variations taking into account that wireless communication standards define the transmission of preambles before the data symbols. The basic structure of a frame consists of the following parts: the preamble, which is used to perfectly correct phase shift and power, to synchronize in time/frequency, and to estimate the sig-

Compute $\boldsymbol{C}$	$N^2 \times ((N-1)^2 \times N_U + 3)$ multiplications $N^2 \times (7 \times N_U - 4)$ summations
Compute β	1 division
Compute eigenvectors of a 2×2 matrix	6 multiplications 11 summations 3 squared roots

Table 3 Computational complexity of BCEES ($N = 2$ for 2×1 Alamouti OSTBC).

nal power; pilot symbols, which are used for supervised channel estimation; and finally, user data symbols, which represent the information to be recovered.

Denoting by $p_1[n]$ and $p_2[n]$ the preambles respectively transmitted by the first and the second antenna, and considering that only a single antenna is simultaneously transmitting at every instant, the received signals at odd and at even instants have the form

$$\begin{aligned} \text{Odd time instant} &\rightarrow x_1[n] = h_1[q]\ p_1[n] + v_1[n], \\ \text{Even time instant} &\rightarrow x_2[n] = h_2[q]\ p_2[n] + v_2[n]. \end{aligned} \tag{8}$$

Therefore, the cross-correlation between the signals in the above equation has the form

$$c_{12}[q] = \mathrm{E}[x_1[n]x_2^*[n]] = h_1[q]h_2^*[q]\,\mathrm{E}[p_1[n]p_2^*[n]] + \mathrm{E}[v_1[n]v_2^*[n]]. \tag{9}$$

In order to guarantee that $\mathrm{E}[p_1[n]p_2^*[n]] \neq 0$, we will consider non-orthogonal preamble sequences (i.e. $p_1[n]$ and $p_2[n]$) or equivalently, only a portion of non-orthogonal symbols included inside both of them. The distance between the value of this cross-correlation operation obtained from two consecutive frames is computed by means of the following difference measure, which considers the real and imaginary parts of such cross-correlations in the way

$$\begin{aligned} \Re\text{-Difference}[q] &= 1 - \frac{\min\{|\Re\{c_{12}[q]\}|, |\Re\{c_{12}[q-1]\}|\}}{\max\{|\Re\{c_{12}[q]\}|, |\Re\{c_{12}[q-1]\}|\}}, \\ \Im\text{-Difference}[q] &= 1 - \frac{\min\{|\Im\{c_{12}[q]\}|, |\Im\{c_{12}[q-1]\}|\}}{\max\{|\Im\{c_{12}[q]\}|, |\Im\{c_{12}[q-1]\}|\}}. \end{aligned} \tag{10}$$

Note that this value is a real number restricted to the interval $[0, 1]$. Finally, we decide if the channel has significantly changed using the decision rule

If ($\Re$-Difference$[q] > t$) **OR** ($\Im$-Difference$[q] > t$) $\rightarrow$ Estimated CSI is required
else A previous channel estimate is used.

The parameter t included in the decision rule is a real-valued threshold. The inclusion of this decision rule allows us to reduce the computational complexity as well as the average power consumption of the estimation algorithm since the channel matrix is estimated only when a significant variation is detected. During the rest of the time, a previous channel estimate is used to recover the transmitted symbols.

Note that other metrics could be defined like, for instance, to use the absolute value squared of such cross-correlations in the way

$$\text{Difference}[q] = 1 - \frac{\min\{|c_{12}[q]|^2, |c_{12}[q-1]|^2\}}{\max\{|c_{12}[q]|^2, |c_{12}[q-1]|^2\}}. \tag{11}$$

The decision rule takes the form

If (Difference[q] $> t$) $\rightarrow$ Estimated CSI is required
else A previous channel estimate is used.

From now on, the approaches using the proposed decision rules are referred to as *DA*, i.e. *DA-Supervised* and *DA-BCEES*.

4 Simulation Results

In order to evaluate the performance of the proposed schemes in Eqs. (10) and (11), we will consider the transmission of QPSK signals over Rayleigh-distributed and randomly-generated channels affected by AWGN. The channel coefficients are adapted following the model

$$h_i[q] = \frac{(1-\alpha)h_i[q-1] + \alpha\ r_i[q]}{\sqrt{(1-\alpha)^2 + \alpha^2}},\ \text{with}\ i = 1, 2, \tag{12}$$

where $r_i[q]$ has a Gaussian distribution and α is a random variable with uniform distribution. The preambles have been randomly generated also using a QPSK modulation. We have chosen such a preamble structure for simplicity reasons and moreover because, at first, we are not interested in evaluating the impact of the preamble structure on the system performance, and secondly the preamble structure is typically imposed by wireless communication standards.

4.1 Training Procedure

The first question is to determine the threshold t to be used for both decision rules proposed in previous section, i.e. the decision-aided criterion based on real and imaginary parts of cross-correlations and the one based on the absolute value squared. Towards this aim, we have measured the difference defined in Eqs. (10) and (11) in those time instants when the channel changes and when it remains constant. Since both the real and the imaginary difference measures described in Eq. (10) have the same distribution, all the values are collected in the same random variable.

In order to obtain a considerable number of values, we have considered transmit SNR values ranged from -5 to 15 dB (i.e. 21 different values). Starting from 25 000 different channel realizations, each channel realization is varied once for each SNR value following Eq. (12), yielding 25 000 channel variations and 50 000 channel realizations per SNR value in total. Figure 2 shows the number of occurrences corresponding to the evaluation of the decision rule based on Eq. (10) for time variant (i.e. the current channel realization has changed with respect to the previous one) as well as for unchanged channels (i.e. when the same channel realization is repeated). Such a figure shows curves corresponding to preamble sizes of 10 and 100 symbols. In both cases, it is observed that the decision criterion has an uniform distribution in those situations where the channel changes (non-dashed curves), which is a consequence of the uniform distribution of α. Also note that small values of the decision criterion are more likely when the channel remains unchanged. From these results, we can set the threshold to $t = 0.2951$ for preambles of 10 symbols and to $t = 0.1550$ for preambles of 100 symbols. As it can be seen in Figure 3, the same experiment is performed for the second criterion introduced in this subsection, obtaining as a result a threshold value of $t = 0.3650$ for preambles of 10 symbols and of $t = 0.1950$ for preambles of 100 symbols.

Figure 4 shows the results for preamble sizes in the interval $[10, 110]$ considering both criteria. Note that the threshold values are very similar in both cases, independently from the preamble size.

4.2 Performance Evaluation

Considering the threshold values obtained above for both decision rules, we evaluate the SER of supervised and *Decision-Aided supervised* (DA-Supervised) approaches. We have transmitted 50 000 frames with 50 pilot symbols and 250 user symbols per frame. The channel changes every 5 frames (i.e. there is a 20% of channel changes).

Figure 5 (a) shows the results obtained for preamble sizes of 10 and 100 symbols. As a reference, we also plot the curves corresponding to the supervised approach in which the channel is estimated for all frames. From this figure, it is clear that the decision-aided criterion depending on absolute values causes a significant loss in SER performance, especially for medium and high SNR values. Figure 6 shows the comparison of the number of CSI estimation factor (evaluated as the ratio between the number of frames in which the channel has been estimated and the total number of transmitted frames) obtained after applying both decision rules. As expected, the CSI estimation factor using the absolute value squared is considerably less than that obtained by means of using the real and the imaginary parts as described in Eq. (10). Obviously, in such a case a cross-correlation phase loss has happened, and therefore the channel estimate was not requested –according to the threshold value– even though phases did significantly change. As a result, we can conclude that the decision-aided criterion of difference measures based on real and imaginary parts of the cross-correlations offers an adequate compromise between SER performance and channel updating.

We have also evaluated the SER of BCEES, and DA-BCEES using the criterion in Eq. (10). Figure 5 (b) shows the results obtained for preamble sizes of 10 and 100 symbols, whereas Figure 6 plots the CSI estimation factor (i.e. the number of times the channel is estimated according to the decision rule). Although there is no penalization in terms of SER (according to Figure 5 (b)), reducing the number of preamble symbols also reduces the computational complexity. Note also that the unsupervised approaches have a loss in SER with respect to the supervised approaches (Figure 5 (a)) due to that in general, a correct estimation of the fourth-order cumulants in BCEES requires more symbols than the estimation of the second-order statistics in supervised approaches (i.e. the autocorrelation matrix).

5 Refined Decision-Aided Criterion

The results presented in the previous section show that the decision-aided criterion is an interesting strategy to mitigate the computational complexity of the channel estimation algorithms by reducing the number of times the channel is estimated. However, the CSI estimation factor is still high for low SNR values, which means that the criterion detects false channel variations. As a consequence, it is needed to modify the proposed criterion trying to avoid those unnecessary channel estimates in low SNR regime.

The SNR estimation is a common procedure in current wireless communication systems. In particular, for the 2×1 Alamouti OSTBC, we have for each receive antenna

$$\mathrm{SNR}_i[q] = \frac{\mathrm{E}[|x_i[n]|^2] - \mathrm{E}[|v[n]|^2|}{\mathrm{E}[|v[n]|^2]}, \text{ with } i = 1, 2.$$

The average SNR at the receiver is then given by

$$\mathrm{SNR}_{\mathrm{RX}}[q] = \frac{\mathrm{SNR}_1[n] + \mathrm{SNR}_2[n]}{2}.$$

The SNR estimation is included in the decision rule as follows (notice that we are assuming a lazy evaluation for the conditionals)

If $((\mathrm{SNR}_{\mathrm{RX}}[q] > t_{\mathrm{SNR}})$ **AND** $((\Re\text{-Difference}[q] > t)$ **OR** $(\Im\text{-Difference}[q] > t)))$
$\rightarrow$ Estimated CSI is required,
else A previous channel estimate is used.

Considering preambles of 100 symbols, frames of 50 pilot symbols, and 250 user symbols, Figures 7 and 8 compare the results obtained with this refined decision rule, which is referred to as *R*efined Decision-Aided (RDA) criterion, considering an SNR threshold value of $t_{\mathrm{SNR}} = 0\,\mathrm{dB}$, to those obtained with the decision-aided approach. As it is shown in these figures, we can clearly conclude that applying the refined algorithm described in this section leads to a reduction in the CSI estimation factor for low SNR values and without penalizing the SER.

6 Conclusions

The computational complexity and the power consumption of the channel estimation methods are important drawbacks in wireless communication systems. The main contribution of this work is to propose a novel channel tracking method so that the channel is only estimated when it is really necessary (i.e. when the channel parameters suffer significant variations). Otherwise, the data recovering is performed using a previous channel estimate. The channel variations are detected by computing the cross-correlation between the preambles transmitted just before the payload. Such preambles are needed for other usual operations performed in wireless communication systems, as for example time and frequency synchronization. Computer simulations show that, for preamble sizes about 100 symbols, our proposal obtains a considerable reduction in terms of computational complexity without penalizing the symbol error rate.

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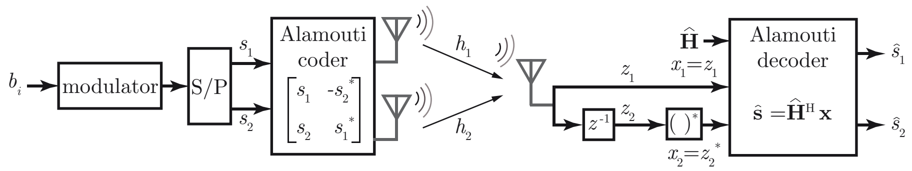

Fig. 1 Alamouti coded scheme.

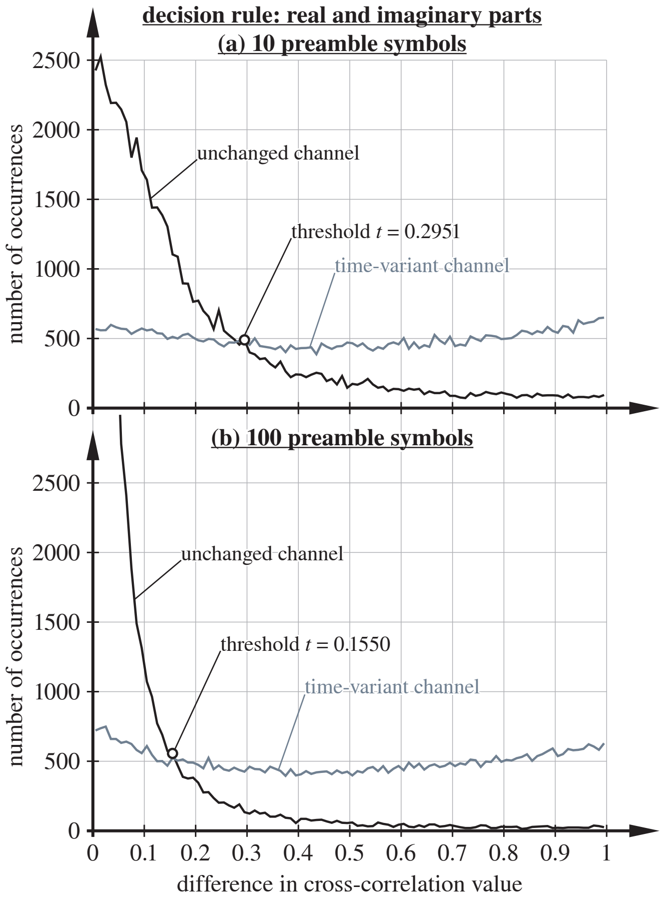

Fig. 2 Training step: Number of occurrences versus difference in cross-correlation between measured and transmitted preambles using real and imaginary parts of such cross-correlations for a preamble size of 10 symbols (top subfigure) and 100 symbols (bottom subfigure).

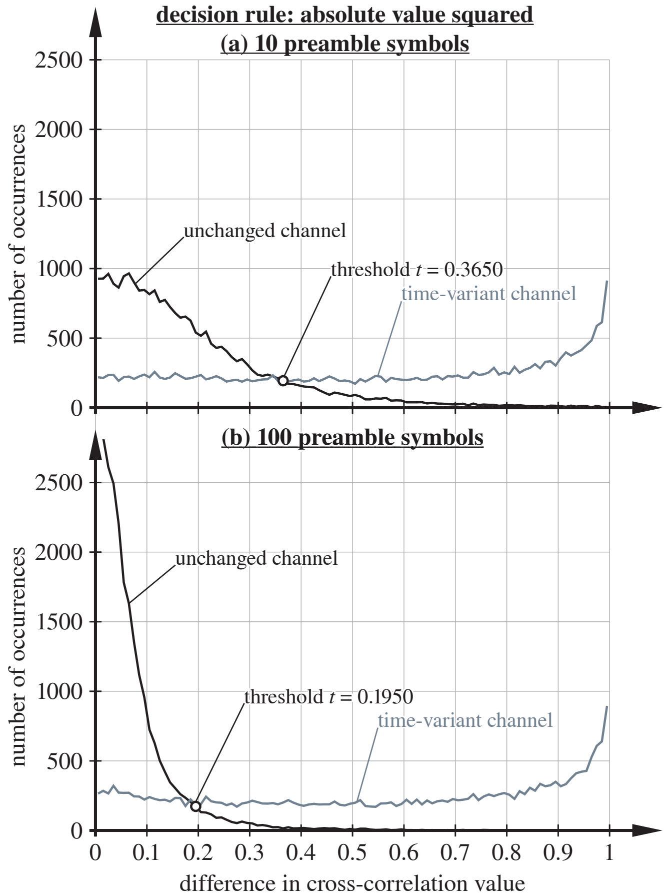

Fig. 3 Training step: Number of occurrences versus difference in cross-correlation between measured and transmitted preambles using the absolute value squared of such cross-correlations for a preamble size of 10 symbols (top subfigure) and 100 symbols (bottom subfigure).

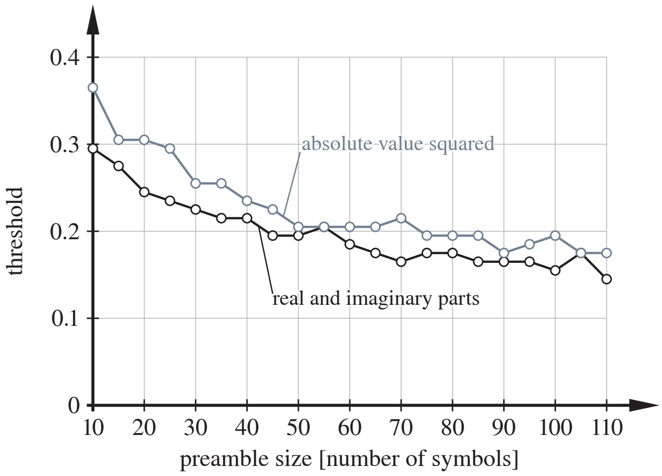

Fig. 4 Training step: Threshold versus preamble size for the decision-aided criteria based on real and imaginary parts and absolute value squared of preamble cross-correlations.

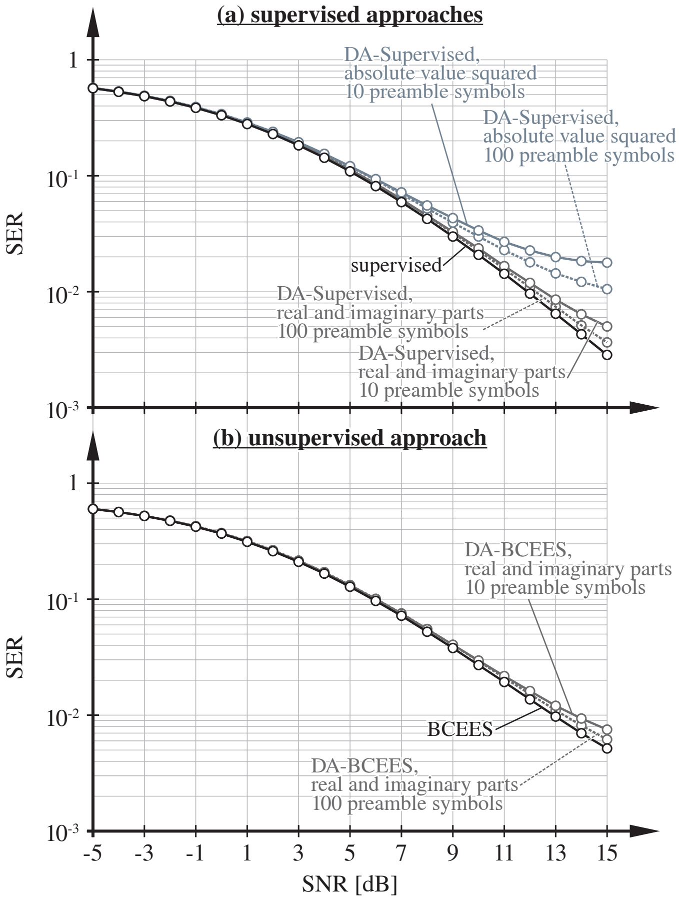

Fig. 5 Algorithm performance: SER versus SNR for supervised (with real and imaginary parts as well as absolute value squared criteria) and unsupervised approaches.

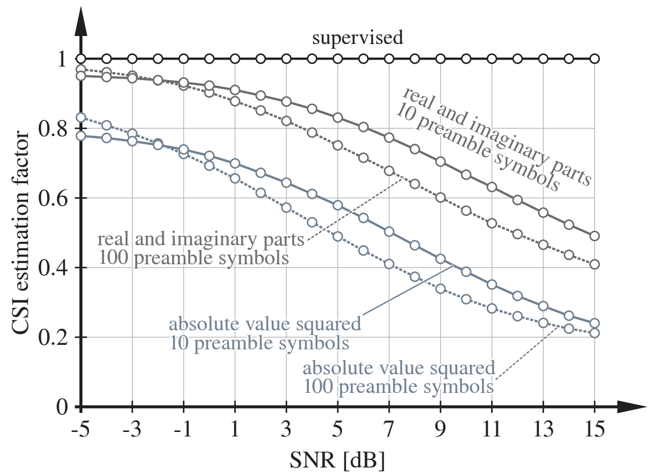

Fig. 6 Algorithm performance: CSI estimation factor versus SNR. The CSI estimation factor is evaluated as the ratio between the frames in which the channel is estimated and the total number of frames transmitted.

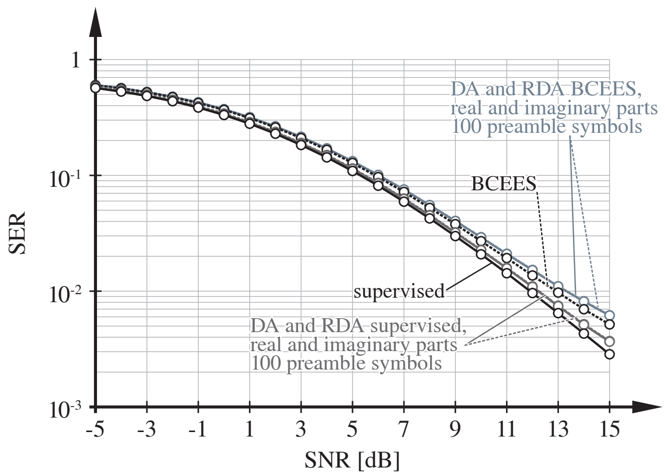

Fig. 7 Algorithm performance: Comparison in terms of SER versus SNR between DA and Refined-DA (RDA) criteria. Notice that DA and RDA curves for supervised approaches match each other. The same is true also for the DA and RDA curves for the BCEES unsupervised method.

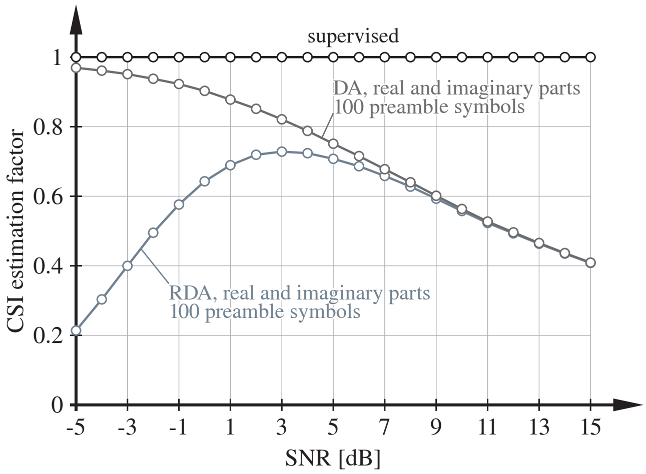

Fig. 8 Algorithm performance: Comparison in terms of CSI estimation factor between DA and Refined-DA (RDA) criteria.