Tensor-Based Joint Channel and Symbol Estimation for Two-Way MIMO Relaying Systems

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***Abstract*—In this letter, we present two closed-form semiblind receivers for a two-way amplify-and-forward relaying system. The proposed receivers jointly estimate the symbol and channel matrices involved in the two-way relaying system by exploiting tensor structures of the received signals at the relay and the destination, and without using training sequences, in contrast to previous works. Differently from competing receivers, one of the proposed receivers does not require channel reciprocity between uplink and downlink phases, which can be of interest in frequency division duplexing relaying systems. Parameter identifiability and computational complexity are analysed, and simulation results are provided to corroborate the effectiveness of the proposed semiblind receivers in scenarios with and without channel reciprocity.**

***Index Terms*—two-way relaying, closed-form semiblind receiver, tensor space-time code (TSTC), Tucker-2 model.**

I. Introduction

Cooperative wireless communication systems are gaining attention nowadays due to signal propagation effects mitigation, leading to increased capacity and coverage [1], [2]. In such context, the usefulness of tensor decompositions to derive semiblind receivers for multiple input multiple output (MIMO) systems has been demonstrated in several works in the literature (see e.g. [3]–[5] and references therein). Recently, tensor-based receivers have been proposed for one-way MIMO relaying, considering scenarios with two-hop [6]–[9] or multi-hop relaying [10]. In [6], training sequence based channel estimation using parallel factor analysis is addressed, while [7], [8] propose semiblind joint channel and symbol estimation algorithms without resorting to training sequences by exploiting different space-time coding (STC) structures. However, the literature on tensor-based two-way MIMO relaying systems is scarce. In [11], authors propose a supervised tensor-based channel estimation algorithm for a two-way amplify-and-forward (AF) relaying system. The authors assume channel reciprocity between uplink and downlink phases for self-interference cancellation. In [12], the problem of channel estimation for a MIMO multi-relay system using a tensor approach is considered. However, both works deal with supervised channel estimation schemes, where the user terminals need to send training sequences, which decreases the spectrum efficiency. In addition, the channel estimation algorithms in [11] and [12] cannot be applied in scenarios where the assumption of channel reciprocity fails.

In this letter, by considering a two-way MIMO relaying wireless communication system, we propose two semiblind receivers for joint channel and symbol estimation that avoid the use of bandwidth-consuming training sequences. Our transmission scheme makes use of a third-order tensor space-time coding (TSTC), as introduced in [13], with the AF relaying protocol. We show that the received signals follow a block Tucker-2 model at the relay, and a Tucker-2 one at the sources. We address both the scenarios with and without the channel reciprocity assumption, and a tensor-based semiblind receiver is proposed for each one. Thanks to the tensor modeling, our closed-form receivers yield joint estimates of the channel and symbol matrices. Furthermore, in contrast to traditional two-way schemes that require training sequences and a two-step channel estimation, our tensor approach is unsupervised. Numerical results show that the proposed receivers offer remarkable symbol error rate (SER) performances with or without channel reciprocity.

Notation: Scalars, column vectors, matrices and tensors are denoted by lower-case, boldface lower-case, boldface upper-case, and calligraphic letters, e.g., $a, \mathbf{a}, \mathbf{A}, \mathcal{A}$, respectively. The Kronecker product is denoted by $\otimes$. The identity and all-zeros matrices of dimensions $N \times N$ are denoted as $\mathbf{I}_N$ and $\mathbf{0}_N$, respectively. We use the superscripts ${}^T, {}^*, {}^H, {}^{-1}, {}^\dagger$ for matrix transposition, complex conjugation, Hermitian transposition, inversion, and Moore-Penrose pseudo inversion, respectively. A Tucker decomposition of a Nth-order tensor $\mathcal{X} \in \mathbb{C}^{I_1 \times \cdots \times I_N}$ is defined in terms of n-mode products as $\mathcal{X} = \mathcal{G} \times_1 \mathbf{A}^{(1)} \times_2 \cdots \times_N \mathbf{A}^{(N)}$, with $\mathcal{G} \in \mathbb{C}^{R_1 \times \cdots \times R_N}$ and $\mathbf{A}^{(n)} \in \mathbb{C}^{I_n \times R_n}, n = 1, \cdots, N$. A flat n-mode unfolding of the tensor $\mathcal{X}$ is given by $\mathbf{X}_n = \mathbf{A}^{(n)} \mathbf{G}_n \left(\bigotimes_{m \neq n} \mathbf{A}^{(m)} \right)^T \in \mathbb{C}^{I_n \times I_1 I_2 \cdots I_{n-1} I_{n+1} \cdots I_N}$. Defining $\mathcal{G} = \text{blockdiag}(\mathcal{G}_1, \cdots, \mathcal{G}_K)$, then $\mathcal{X} = \sum_{k=1}^{K} \mathcal{G}_k \times_1 \mathbf{A}_k^{(1)} \times_2 \cdots \times_N \mathbf{A}_k^{(N)}$ follows a Nth-order block-Tucker decomposition.

II. System Model

We consider a two-way MIMO relaying system composed of two sources and one relay, as illustrated by means of Figure 1, where the number of antennas at the sources i, j and the relay are M_{s_i}, M_{s_j} and M_r, respectively. We assume $M_{s_i} = M_{s_j} = M_s$. The sources and relay are assumed to operate in a half-duplex mode. Each source aims to estimate the information signals sent by the other source. During the uplink phase of the relaying protocol, both sources transmit

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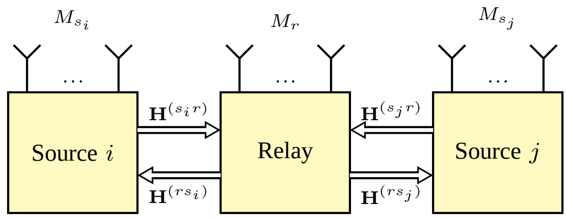

Fig. 1. Two-way model with a pair of sources i and j.

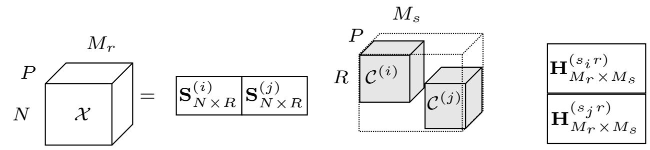

Fig. 2. 3-D illustration of a block Tucker-2 tensor.

their signals to the relay. In the downlink phase, the relay retransmits the received signals to the sources following an AF relaying protocol. Due to the symmetry of the problem, we will present the analysis just for source i, the solution for source j being similar.

The matrix $\mathbf{H}^{(s_i r)} \in \mathbb{C}^{M_r \times M_s}$ representing the channel between the source i and the relay is assumed flat-fading and quasi-static during the total transmission time. The matrix $\mathbf{H}^{(rs_i)} \in \mathbb{C}^{M_s \times M_r}$ represents the channel in the opposite direction. When channel reciprocity is assumed, we have $\mathbf{H}^{(rs_i)T} = \mathbf{H}^{(s_i r)}$. We assume that $\mathbf{H}^{(s_i r)}$ and $\mathbf{H}^{(rs_i)}$ have complex Gaussian entries with zero-mean and variance chosen to make the received symbol energy to noise spectral density ratio (E_s/N_0) independent on the number of transmit antennas.

Define the symbol matrix transmitted by source i as $\mathbf{S}^{(i)} \in \mathbb{C}^{N\times R}$ containing N data symbols in R data-streams. The sources and relay encode the signals to be transmitted with tensor space-time code (TSTC) $\mathcal{C}^{(i)} \in \mathbb{C}^{R\times M_s \times P}$ and $\mathcal{G} \in \mathbb{C}^{M_r \times M_s \times J}$, respectively. The parameters P and J are time spreading lengths of the codes at sources and relay, respectively.

With channel reciprocity, we set the flat 3-mode unfoldings $\mathbf{C}_3^{(i)} \in \mathbb{C}^{P\times RM_s}$ and $\mathbf{G}_3 \in \mathbb{C}^{J\times M_r M_s}$ of the code tensors $\mathcal{C}^{(i)}$ and $\mathcal{G}$, as discrete Fourier transform (DFT) matrices. When the channel reciprocity is not assumed, $\mathbf{C}_3^{(i)}, \mathbf{C}_3^{(j)}$ are chosen as two blocks extracted from a $P \times 2RM_s$ DFT matrix and $\mathbf{G}_3$ as a DFT matrix of dimension $J \times M_r M_s$, such that, $\mathbf{C}_3^{(j)H}\mathbf{C}_3^{(i)} = \mathbf{0}_{RM_s}$, $\mathbf{C}_3^{(j)H}\mathbf{C}_3^{(j)} = \mathbf{I}_{RM_s}$, and $\mathbf{G}_3^H\mathbf{G}_3 = \mathbf{I}_{M_r M_s}$. Such an orthogonal design of the code tensors unfoldings allows to derive closed-form semiblind receivers.

III. Proposed Receivers

Let $\tilde{\mathcal{X}} = \mathcal{X} + \mathcal{N}$ be the noisy tensor of signals received at the relay and $\tilde{\mathcal{Y}}^{(i)} = \mathcal{Y}^{(i)} + \mathcal{V}^{(i)}$ the noisy tensor of signals received at the source i from the relay. The entries of the noise tensors $\mathcal{N}$ and $\mathcal{V}^{(i)}$ are zero-mean circularly symmetric complex-valued Gaussian random variables. During the uplink transmission phase, the signals received from the sources i and j at the relay form a tensor $\tilde{\mathcal{X}} \in \mathbb{C}^{N\times M_r \times P}$ which follows a block Tucker-2 decomposition given by

$$\tilde{\mathcal{X}} = \mathcal{C}^{(i)} \times_1 \mathbf{S}^{(i)} \times_2 \mathbf{H}^{(s_i r)} + \mathcal{C}^{(j)} \times_1 \mathbf{S}^{(j)} \times_2 \mathbf{H}^{(s_j r)} + \mathcal{N}. \quad (1)$$

This decomposition is illustrated in Figure. 2, disregarding the noise. The flat 3-mode unfolding of $\tilde{\mathcal{X}}$ satisfies the following equation

$$\begin{aligned}\tilde{\mathbf{X}}_{P\times NM_r} &= \mathbf{C}_3^{(i)}\left(\mathbf{S}^{(i)} \otimes \mathbf{H}^{(s_i r)}\right)^T \\ &\quad + \mathbf{C}_3^{(j)}\left(\mathbf{S}^{(j)} \otimes \mathbf{H}^{(s_j r)}\right)^T + \mathbf{N}_{P\times NM_r}.\end{aligned} \quad (2)$$

We now consider two approaches. The first one assumes channel reciprocity between the uplink and downlink phases, while for the second one this assumption is disregarded.

1) Two-way relaying with reciprocity: During the downlink phase, the relay reencodes the received signals given by Eq. (2) using the code tensor $\mathcal{G} \in \mathbb{C}^{M_r\times M_s \times J}$ and sends the coded signals to the sources in a broadcast fashion.

The signals received at the source i form a third-order tensor satisfying a Tucker-2 model

$$\tilde{\mathcal{Y}}^{(i)} = \mathcal{G} \times_1 \tilde{\mathbf{X}}_{PN\times M_r} \times_2 \mathbf{H}^{(rs_i)T} + \mathcal{V}^{(i)} \in \mathbb{C}^{PN\times M_r\times J}. \quad (3)$$

Assuming the channel reciprocity, i.e., $\mathbf{H}^{(rs_i)T} = \mathbf{H}^{(s_i r)}$, a flat 3-mode unfolding of $\tilde{\mathcal{Y}}^{(i)}$, is given by

$$\tilde{\mathbf{Y}}^{(i)}_{J\times PNM_r} = \mathbf{G}_3\left(\tilde{\mathbf{X}}_{PN\times M_r} \otimes \mathbf{H}^{(s_i r)}\right)^T + \mathbf{V}^{(i)}_{J\times PNM_r}. \quad (4)$$

For simplicity of presentation and due to space limitation, we consider a noiseless formulation from now on. Exploiting the column orthonormality of the code tensor unfolding $\mathbf{G}_3$, the least square (LS) estimate of the Kronecker product can be calculated as

$$\mathbf{Z}^{(i)}_{M_r M_s\times PNM_r} = \mathbf{G}_3^H \mathbf{Y}^{(i)}_{J\times PNM_r} \cong \left(\mathbf{X}_{PN\times M_r} \otimes \mathbf{H}^{(s_i r)}\right)^T. \quad (5)$$

Once $\mathbf{Z}^{(i)}$ estimated, the factors $\left(\mathbf{X}_{PN\times M_r}, \mathbf{H}^{(s_i r)}\right)$ of the Kronecker product can be obtained by applying the rank-one approximation algorithm described in [5], the so-called Kronecker product least-square (KPLS) algorithm. Reformate the estimate $\hat{\mathbf{X}}_{PN\times M_r}$ as a flat 3-mode unfolding $\hat{\mathbf{X}}_{P\times NM_r}$, deduced from Eq. (2) as

$$\hat{\mathbf{X}}^{(i)}_{P\times NM_r} \cong \underbrace{\mathbf{C}_3^{(i)}\left(\mathbf{S}^{(i)} \otimes \mathbf{H}^{(s_i r)}\right)^T}_{\text{self-interference of source } i} + \underbrace{\mathbf{C}_3^{(j)}\left(\mathbf{S}^{(j)} \otimes \mathbf{H}^{(s_j r)}\right)^T}_{\text{desired signal for source } i}. \quad (6)$$

This equation gives an estimate, at source i, of the signals received at the relay. It is composed of two parts, one containing the signals sent by source j and to be estimated by source i, while the other represents a self-interference for source i. The same approach is used to estimate at the source j the signals received at the relay, i.e. $\hat{\mathbf{X}}^{(j)}_{P\times NM_r}$.

The symbol matrix $\mathbf{S}^{(i)}$ and the code tensor $\mathcal{C}^{(i)}$ being known at the source i, we can use the estimates of $\mathbf{X}_{PN\times M_r}$ and $\mathbf{H}^{(s_i r)}$ obtained from Eq. (5), to eliminate the

TABLE I
CLOSED-FORM SEMIBLIND RECEIVERS.

Inputs: $\tilde{\mathcal{X}}$, $\tilde{\mathcal{Y}}^{(i)}$, $\mathcal{C}^{(i)}$, $\mathcal{C}^{(j)}$ and $\mathcal{G}$.

(A) With reciprocity
- (1.1) Compute the LS estimate of $\mathbf{Z}^{(i)} = \left(\mathbf{X}_{PN\times M_r} \otimes \mathbf{H}^{(s_i r)}\right)^T$ using (5).
- (1.2) Use the KPLS algorithm to estimate $\mathbf{X}_{PN\times M_r}$ and $\mathbf{H}^{(s_i r)}$.
- (1.3) Remove the scaling ambiguities of $\hat{\mathbf{X}}_{PN\times M_r}$ and $\hat{\mathbf{H}}^{(s_i r)}$.
- (1.4) Eliminate the self-interference of the source i using (7).
- (1.5) Compute the LS estimate of $\mathbf{V}^{(i)} = \left(\mathbf{S}^{(j)} \otimes \mathbf{H}^{(s_j r)}\right)^T$ using (9).
- (1.6) Use the KPLS algorithm to estimate $\mathbf{S}^{(j)}$ and $\mathbf{H}^{(s_j r)}$.
- (1.7) Remove the scaling ambiguities of $\hat{\mathbf{S}}^{(j)}$ and $\hat{\mathbf{H}}^{(s_j r)}$, and project the estimated symbols onto the alphabet.

(B) Without reciprocity
- (1.1) Compute the LS estimate of $\mathbf{Z}^{(i)} = \left(\mathbf{X}_{PN\times M_r} \otimes \mathbf{H}^{(rs_i)T}\right)^T$ using (11).
- (1.2) Use the KPLS algorithm to estimate $\mathbf{X}_{PN\times M_r}$ and $\mathbf{H}^{(rs_i)T}$.
- (1.3) Reformate $\hat{\mathbf{X}}_{PN\times M_r}$ and compute the LS estimate of $\mathbf{V}^{(i)} = \left(\mathbf{S}^{(j)} \otimes \mathbf{H}^{(s_j r)}\right)^T$ using (12).
- (1.4) Use the KPLS algorithm to estimate $\mathbf{S}^{(j)}$ and $\mathbf{H}^{(s_j r)}$.
- (1.5) Remove the scaling ambiguities of $\hat{\mathbf{S}}^{(j)}$ and $\hat{\mathbf{H}}^{(s_j r)}$, and project the estimated symbols onto the alphabet.

self-interference term as

$$\mathbf{W}^{(i)}_{P\times NM_r} \cong \hat{\mathbf{X}}^{(i)}_{P\times NM_r} - \underbrace{\mathbf{C}_3^{(i)}\left(\mathbf{S}^{(i)} \otimes \hat{\mathbf{H}}^{(s_i r)}\right)^T}_{\text{self-interference cancellation}} \quad (7)$$

$$\cong \mathbf{C}_3^{(j)}\left(\mathbf{S}^{(j)} \otimes \mathbf{H}^{(s_j r)}\right)^T. \quad (8)$$

The matrix $\mathbf{W}^{(i)}_{P\times NM_r}$ contains the information signals received at the relay from the source j, which can be exploited at the source i to estimate $\mathbf{S}^{(j)}$.

Assuming the knowledge of the coding tensor $\mathcal{C}^{(j)}$ at the source i, and using the column orthonormality property of its matrix unfolding $\mathbf{C}_3^{(j)}$, the LS estimate of the Kronecker product $\left(\mathbf{S}^{(j)} \otimes \mathbf{H}^{(s_j r)}\right)^T$ is then given by

$$\mathbf{V}^{(i)}_{RM_s\times NM_r} = \mathbf{C}_3^{(j)H}\mathbf{W}^{(i)}_{P\times NM_r} \cong \left(\mathbf{S}^{(j)} \otimes \mathbf{H}^{(s_j r)}\right)^T. \quad (9)$$

Once $\mathbf{V}^{(i)}_{RM_s\times NM_r}$ estimated, the matrix pair $\left(\mathbf{S}^{(j)}, \mathbf{H}^{(s_j r)}\right)$ can be obtained by applying the KPLS algorithm.

2) Two-way relaying without reciprocity: In this case, the flat 3-mode unfolding (4) of $\mathcal{Y}^{(i)}$ becomes

$$\mathbf{Y}^{(i)}_{J\times PNM_r} = \mathbf{G}_3\left(\mathbf{X}_{PN\times M_r} \otimes \mathbf{H}^{(rs_i)T}\right)^T, \quad (10)$$

and the LS estimate of the Kronecker product is given by

$$\mathbf{Z}^{(i)}_{M_rM_s\times PNM_r} = \mathbf{G}_3^H\mathbf{Y}^{(i)}_{J\times PNM_r} \cong \left(\mathbf{X}_{PN\times M_r} \otimes \mathbf{H}^{(rs_i)T}\right)^T. \quad (11)$$

Contrary to the case with reciprocity, the self-interference can not be eliminated anymore by means of Eq. (7). The trick is now to exploit the property of the matrix unfolding codes $\mathbf{C}_3^{(i)}$ and $\mathbf{C}_3^{(j)}$, i.e., $\mathbf{C}_3^{(j)H}\mathbf{C}_3^{(i)} = \mathbf{0}_{RM_s}$, combined with the column orthonormality of $\mathbf{C}_3^{(j)}$, i.e.,$\mathbf{C}_3^{(j)H}\mathbf{C}_3^{(j)} = \mathbf{I}_{RM_s}$ to deduce, from (6), the following estimate of the Kronecker products whose factors are obtained by applying the KPLS algorithm

$$\mathbf{V}^{(i)}_{RM_s\times NM_r} = \mathbf{C}_3^{(j)H}\hat{\mathbf{X}}^{(i)}_{P\times NM_r} \cong \left(\mathbf{S}^{(j)} \otimes \mathbf{H}^{(s_j r)}\right)^T. \quad (12)$$

Note that the source i estimates also the uplink channel of the source j. The same approach is used at the source j to estimate $\mathbf{S}^{(i)}$.

The two-way MIMO system transmits $2NR$ information symbols during the uplink and downlink phases, of respective duration NP and NPJ. Then, the transmission rate is given by $\frac{2R}{P(J+1)}\log_2\mu$, where μ is the alphabet cardinality.

IV. IDENTIFIABILITY AND COMPLEXITY

For the source i, the system parameter identifiability is linked to the uniqueness of the LS estimates of the Kronecker products $\mathbf{Z}^{(i)}$ and $\mathbf{V}^{(i)}$, i.e. the full column rank property of the matrices $\mathbf{G}_3$, $\mathbf{C}_3^{(j)}$ (and $\mathbf{C}_3^{(i)}$ for source j), to ensure the uniqueness of their left inverse, in Eqs. (5), (9) and (12). In the reciprocity case, that implies the necessary conditions $J \geq M_rM_s$ and $P \geq RM_s$. When no reciprocity is assumed, a DFT matrix of dimensions $P\times 2RM_s$ is used to construct the code tensors unfoldings $\mathbf{C}_3^{(i)}$ and $\mathbf{C}_3^{(j)}$, implying the necessary conditions $P \geq 2RM_s$ and $J \geq M_rM_s$.

Disregarding the noise, the matrices $(\mathbf{H}^{(s_i r)}, \mathbf{H}^{(rs_i)}, \mathbf{S}^{(i)})$ are estimated at source i, up to column scaling ambiguities (permutation ambiguity does not exist due to the knowledge of the coding tensors). For eliminating these scaling ambiguities, we assume that the elements $h_{1,1}^{(rs_i)}$ and $s_{1,1}^{(j)}$ are known. Then, the final estimates of the channels and symbol matrices are given by

$$\hat{\mathbf{H}}^{(s_i r)} \leftarrow \hat{\mathbf{H}}^{(s_i r)}\lambda_{\mathbf{H}^{(s_i r)}},\ \hat{\mathbf{X}}_{PN\times M_r} \leftarrow \hat{\mathbf{X}}_{PN\times M_r}\lambda^{-1}_{\mathbf{H}^{(s_i r)}}$$
$$\hat{\mathbf{S}}^{(j)} \leftarrow \hat{\mathbf{S}}^{(j)}\lambda_{\mathbf{S}},\ \hat{\mathbf{H}}^{(s_j r)}_{M_r\times M_s} \leftarrow \hat{\mathbf{H}}^{(s_j r)}_{M_r\times M_s}\lambda^{-1}_{\mathbf{S}},$$

where $\lambda_{\mathbf{H}^{(s_i r)}} = h_{1,1}^{(rs_i)}/\hat{h}_{1,1}^{(rs_i)}$ and $\lambda_{\mathbf{S}} = s_{1,1}^{(j)}/\hat{s}_{1,1}^{(j)}$. The closed-form receivers with and without the reciprocity assumption, are summarized in Table I.

The dominant complexity is associated with the singular value decomposition (SVD) applied to compute the factors of the Kronecker products, which are rewritten as rank-one matrices. Note that, for a matrix of dimensions $J \times K$, the complexity of its SVD computation is $\mathbb{O}(\min(J,K)JK)$. So, for the proposed semiblind receivers, the computational complexity is concentrated in the application of the KPLS algorithm, at both sources, i.e., in steps (1.2) and (1.6) for the case with reciprocity, and steps (1.2) and (1.4) for the case without reciprocity. For both receivers, step (1.2) has complexity $\mathbb{O}(\min(PNM_r, M_rM_s)PNM_r^2M_s)$, while step (1.6) (with reciprocity) and (1.4) (without reciprocity) have complexity $\mathbb{O}(\min(NR, M_rM_s)NRM_rM_s)$.

V. SIMULATION RESULTS

Simulation results are provided to evaluate the performance of the proposed semiblind receivers, in terms of SER and normalized mean square error (NMSE) of the estimated channels, which are plotted as a function of the symbol energy to noise spectral density ratio (E_s/N_0). Each SER and NMSE curve represents an average over at least 4×10^4 Monte Carlo runs. Each run corresponds to different realizations of the channels, transmitted symbols and noise. The symbols are randomly drawn from a unit energy quadrature amplitude modulation (QAM) alphabet, chosen as 16-QAM for the case with reciprocity and 256-QAM for the case without reciprocity, to insure the same transmission rate for both cases and thus allowing a fair comparison. On the other hand, the number R of data streams and the spreading length P are adjusted to ensure the same transmission rate, equal to $4/5$ bits per channel use, for all the configurations compared in a same figure. The remaining design parameters are fixed with the following values: $N = 10$, $M_s = M_r = 2$ and $J = 4$. Recall that the code tensors follow a DFT structure defined in section II for their 3-mode unfoldings.

Fig. 3 compares the SER performance of the proposed receivers, with and without the channel reciprocity. As a reference for comparison, we also show the performance of the Zero-Forcing (ZF) receiver with reciprocity, providing the symbols estimate $\hat{\mathbf{S}}^{(j)} = \mathbf{W}^{(i)}_{N\times M_r P}\left[\mathbf{C}_1^{(j)}\left(\mathbf{H}^{(s_j r)} \otimes \mathbf{I}_P\right)^T\right]^\dagger$, $\mathbf{C}_1^{(j)} \in \mathbb{C}^{R\times M_s P}$ being the 1-mode unfolding of the code tensor $\mathcal{C}^{(j)} \in \mathbb{C}^{R\times M_s \times P}$. As expected, the performance of the proposed receiver without channel reciprocity is improved when P is increased, thanks to higher coding gains. Moreover, we can notice that the same SER is obtained without reciprocity using $P = 80$ than with the reciprocity assumption and $P = 4$.

Fig. 4 depicts the NMSE for the estimated channels. Note that the receiver with reciprocity estimates the channels $\mathbf{H}^{(s_i r)}$ and $\mathbf{H}^{(s_j r)}$ at source i, whereas the channels $\mathbf{H}^{(r s_i)}$ and $\mathbf{H}^{(s_j r)}$ are estimated in the case without reciprocity. From this figure and as expected, one can remark that the channels NMSE linearly vary as a function of the SNR. Note also that, in all cases, the estimation of $\mathbf{H}^{(s_j r)}$ is worse due to an error propagation, this channel being estimated in the second KPLS factorization step (see Table I). Finally, one observes that increasing P yields a better channel estimation performance, which is in agreement with the SER results of Fig. 3.

In Fig. 5, the channels NMSE performance obtained with the proposed semiblind receivers is compared with that of the so-called tensor-based channel estimation (TENCE) algorithm [11] which is a supervised channel estimator, assuming channel reciprocity. For a fair comparison, the number of training symbols transmitted by the sources and the relay, as well as the number of antennas at the sources and destination are set to the same value for TENCE and for the proposed semiblind receivers. That leads to the following design parameters. With reciprocity: $N = 4$, $P = 4$, $R = 2$, $J = 4$, $M_s = M_r = 2$; without reciprocity: $N = 2$, $P = 8$, $R = 2$, $J = 4$, $M_s = M_r = 2$, and for TENCE: $M_s = 8$,$M_r = 4$. From Fig. 5, one can conclude that the proposed semiblind receivers outperform TENCE in most of the cases, while avoiding the use of training sequences and the channel reciprocity assumption.

VI. Conclusion

We have presented two closed-form semiblind receivers for two-way MIMO AF relaying systems. Two scenarios with and without the uplink-downlink channel reciprocity have been considered. Simulation results have illustrated the good performance of the proposed receivers in terms of SER and channel estimation. Perspectives of this work include the multisource case, Orthogonal Frequency Division Multiplexing (OFDM) relay systems, other relaying protocols like decode-and-forward (DF) [9], and Minimum Mean Square Error (MMSE)-based receivers.

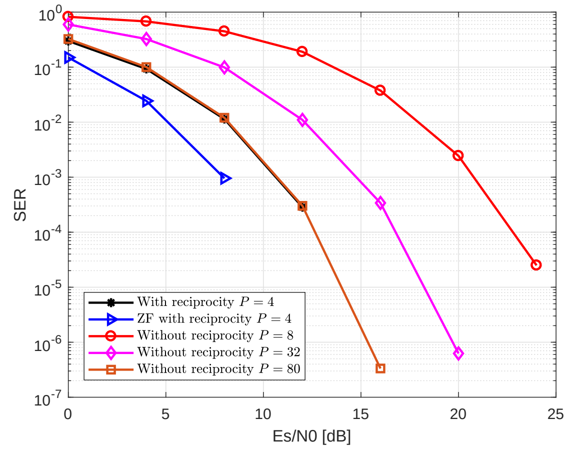

Fig. 3. SER performance.

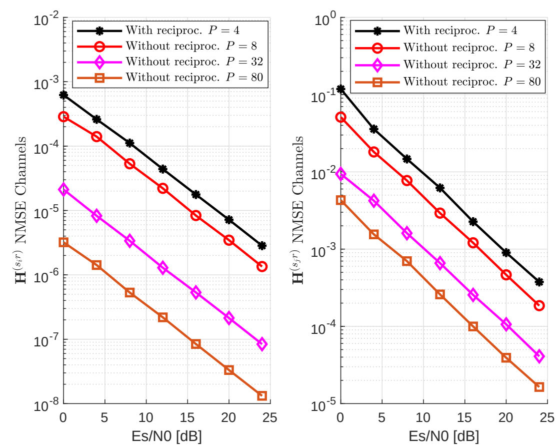

Fig. 4. NMSE of the estimated channels.

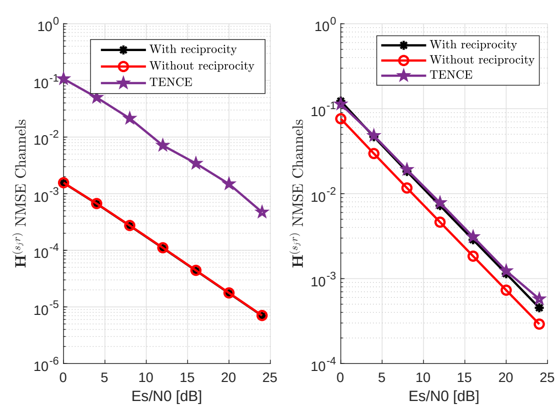

Fig. 5. Comparison with the TENCE receiver of [11].

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