Robust Channel Estimation Algorithm for Dual-Hop MIMO Relay Channels

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Abstract—In conventional two-phase channel estimation algorithms for dual-hop multiple-input multiple-output (MIMO) relay systems, the relay-destination channel estimated in the first phase is used for the source-relay channel estimation in the second phase. For these algorithms, the mismatch between the estimated and the true relay-destination channel affects the accuracy of the source-relay channel estimation. In this paper, we investigate the impact of such channel state information (CSI) mismatch on the performance of the two-phase channel estimation algorithm. By explicitly taking into account the CSI mismatch, we develop a robust algorithm to estimate the source-relay channel. Numerical examples demonstrate the improved performance of the proposed algorithm.

Index Terms—Channel estimation, MIMO relay, Robust.

I. INTRODUCTION

In recent years, there is a significant growth in the demand for reliable and high rate wireless communications. This led to great research efforts to improve the overall performance of wireless networks from both industry and academia. Multiple-input multiple-output (MIMO) relay channel has been identified to be one of the promising solutions, as it enhances channel capacity, network reliability and extends the network coverage [1].

For three-node two-hop MIMO relay systems where the direct source-destination link is omitted, the optimal relay precoding matrix is obtained in [2]-[3] to maximize the mutual information between the source and destination nodes. A unified framework has been established recently for optimizing the source and relay precoding matrices of two-hop MIMO relay systems with a broad class of commonly used objective functions [4].

For the MIMO relay systems [1]-[4] mentioned above, the instantaneous channel state information (CSI) knowledge of both the source-relay and relay-destination links is required at the destination node in order to retrieve the signals transmitted from the source node. However, in a real wireless relay system, the instantaneous CSI is unknown, and thus, estimation of channel matrices is required at the destination node. The estimation of channel matrices for single-hop MIMO systems can be found in [5]-[7]. However, the technique used to estimate the channel matrices for single-hop MIMO systems is not applicable for MIMO relay systems.

In [8], an algorithm based on the least-squares (LS) method was developed to estimate the channel matrices of MIMO relay networks. In particular, both the source-relay and the relay-destination channel matrices are estimated from the observed composite source-relay-destination channel matrix. A drawback from channel estimation using [8] is the scalar ambiguity of the estimated channel matrices. A two-phase channel estimation scheme based on linear minimum mean-squared error (LMMSE) was proposed in [9] for two-hop MIMO relay networks. In particular, in the first phase, the source node is silent while the relay node transmits a pilot matrix to the destination node to estimate the relay-destination channel matrix. In the second phase, the source transmits a source pilot matrix to the relay. The relay node linearly precodes its received signal and forward it to the destination node. Then the source-relay channel is estimated at the destination node making use of the relay-destination channel matrix estimated at the first phase. Compared with the approach in [8], there is no scalar ambiguity in this approach.

However, in practical relay systems, there is always mismatch between the estimated and the true relay-destination channel. Such CSI mismatch affects the accuracy of the source-relay channel estimation in [9]. In this paper, we investigate the impact of this CSI mismatch on the performance of the two-phase channel estimation algorithm [9]. By explicitly taking into account the CSI mismatch, we develop a robust algorithm to estimate the source-relay channel. Numerical examples demonstrate the improved performance of the proposed algorithm.

The rest of this paper is organized as follows. In Section II, we introduce the model of a two-hop MIMO relay communication system and the two-phase channel training algorithm. The impact of CSI mismatch on the performance of the two-phase channel estimation algorithm is investigated in Section III. A robust channel estimation algorithm is also developed in Section III. In Section IV, we show some numerical examples. Conclusions are drawn in Section V.

II. BACKGROUND

We consider a three-node two-hop MIMO relay system where the source node transmits information to the destination node through a relay node. The source, relay, and destination

Acknowledgments—The authors would like to thank the anonymous reviewers for their constructive comments. This work was supported by the Australian Research Council through the Discovery Project DP160100623.
nodes are equipped with \(n_S, n_R, \) and \(n_D\) antennas, respectively. We focus on the case where the direct link between the source and destination nodes is sufficiently weak to be ignored [8], [9]. This scenario occurs when the direct link is blocked by an obstacle such as a mountain. In fact, a relay plays a much more important role when the direct link is weak than when it is strong.

Similar to [9], the channel matrices are estimated in two phases, where the relay-destination channel matrix \(\mathbf{H}_2\) is estimated in phase one while the source-relay channel matrix \(\mathbf{H}_1\) is estimated in phase two. In phase one, the signal received by the destination node is given by

\[
\mathbf{Y}_D^{(1)} = \mathbf{H}_2 \mathbf{S}_R + \mathbf{N}^{(1)}
\]

where \(\mathbf{S}_R\) is the \(n_R \times n_R\) pilot matrix transmitted by the relay node to the destination node satisfying \(\mathbf{S}_R^H \mathbf{S}_R = \mathbf{I}_{n_R}\) [5], and \(\mathbf{N}^{(1)}\) is the \(n_D \times n_R\) noise matrix at the destination node during phase one. Here \(P_R\) is the power budget available at the relay node. \(\cdot^H\) stands for the matrix (vector) Hermitian transpose, and \(\mathbf{I}_n\) denotes an \(n \times n\) identity matrix. Note that we choose the length of \(\mathbf{S}_R\) to be \(n_R\) to maximize the overall system spectral efficiency.

A minimal variance unbiased (MVU) estimation [10] of \(\mathbf{H}_2\) can be obtained from (1) as

\[
\hat{\mathbf{H}}_2 = \frac{n_R}{P_R} \mathbf{Y}_D^{(1)} \mathbf{S}_R^H = \mathbf{H}_2 + \frac{n_R}{P_R} \mathbf{N}^{(1)} \mathbf{S}_R^H.
\]

It can be seen from (2) that due to the existence of the noise \(\mathbf{N}^{(1)}\), there is a mismatch \(\Delta_2 = \frac{n_R}{P_R} \mathbf{N}^{(1)} \mathbf{S}_R^H\) between \(\mathbf{H}_2\) and \(\hat{\mathbf{H}}_2\). Obviously, \(\Delta_2\) is a complex Gaussian random matrix with zero mean and the variance of its entries is \(n_R/P_R\). Therefore, \(\hat{\mathbf{H}}_2\) is a complex Gaussian matrix with the following distribution

\[
\mathbf{H}_2 \sim \mathcal{CN}(\hat{\mathbf{H}}_2, \beta \mathbf{I}_{n_R} \otimes \mathbf{I}_{n_D})
\]

where \(\beta \triangleq n_R/P_R\) and \(\otimes\) denotes the matrix Kronecker product [11]. It can be seen from (3) that the variance of \(\hat{\mathbf{H}}_2\) decreases when \(P_R\) increases.

In phase two, the source node transmits an \(n_S \times n_S\) pilot matrix \(\mathbf{S}_S\) to the relay node. Here we choose the length of \(\mathbf{S}_S\) to be \(n_S\) to maximize the overall system spectral efficiency. The relay node applies an \(n_R \times n_R\) precoding matrix \(\mathbf{F}\) and retransmits the linear precoded signal matrix

\[
\mathbf{X}_R = \mathbf{F} \mathbf{H}_1 \mathbf{S}_S + \mathbf{F} \mathbf{V}
\]

to the destination node, where \(\mathbf{V}\) is the \(n_R \times n_S\) noise matrix at the relay node. The signal received at the destination node can be written as

\[
\mathbf{Y}_D = \mathbf{H}_2 \mathbf{F} \mathbf{H}_1 \mathbf{S}_S + \mathbf{H}_2 \mathbf{F} \mathbf{V} + \mathbf{N}
\]

where \(\mathbf{N}\) is the \(n_D \times n_S\) noise matrix at the destination node during phase two.

By vectorizing both sides of (5), we obtain

\[
\mathbf{y}_D = (\mathbf{S}_S^T \otimes \mathbf{H}_2 \mathbf{F}) \mathbf{h}_1 + (\mathbf{I}_{n_S} \otimes \mathbf{H}_2 \mathbf{F}) \mathbf{v} + \mathbf{n}
\]

where \(\mathbf{y}_D \triangleq \text{vec}(\mathbf{Y}_D), \mathbf{h}_1 \triangleq \text{vec}(\mathbf{H}_1), \mathbf{v} \triangleq \text{vec}(\mathbf{V}), \mathbf{n} \triangleq \text{vec}(\mathbf{N}), (\cdot)^T\) denotes matrix transpose, and vec(\cdot) denotes the vectorization operator which stacks all column vectors of a matrix on top of each other. To obtain (6) from (5), we use the property of vec(ABC) = (C^T \otimes A)vec(B) [11].

In this paper, we assume that the channel matrices \(\mathbf{H}_1\) and \(\mathbf{H}_2\) satisfy the well-known Kronecker correlation model [12]

\[
\mathbf{H}_i = \mathbf{C}_i \mathbf{H}_{w,i} \mathbf{C}_i^T, \quad i = 1, 2
\]

where \(\mathbf{C}_i\) and \(\mathbf{C}_{w,i}\), \(i = 1, 2,\) are channel correlation matrices at the transmit side and the receive side of \(\mathbf{H}_i\), respectively, and \(\mathbf{H}_{w,i}, i = 1, 2,\) are Gaussian random matrices with independent and identically distributed (i.i.d.) entries having zero mean and unit variance. We also assume that all noises are i.i.d. additive white Gaussian noise (AWGN) with zero mean and unit variance.

### III. Robust Channel Estimation Algorithm

In this section, we derive the optimal \(\mathbf{S}_S\) and \(\mathbf{F}\) that minimize the MSE of estimating \(\mathbf{H}_1\). Using a linear estimator, the estimated \(\mathbf{h}_1\) is given by

\[
\mathbf{h}_1 = \mathbf{W} \mathbf{y}_D
\]

where \(\mathbf{W}\) is the weight matrix of the linear estimator. Using (8), the MSE of estimating \(\mathbf{h}_1\) can be written as

\[
J_1 = E[tr((\mathbf{h}_1 - \mathbf{h}_1)(\mathbf{h}_1 - \mathbf{h}_1)^H)] = tr(\mathbf{R}_{\mathbf{h}_1} - \mathbf{R}_{\mathbf{h}_1}) W^H - \mathbf{W} \mathbf{R}_{\mathbf{h}_1} W^H (10)
\]

where \(tr(\cdot)\) denotes the matrix trace, \(E[\cdot]\) stands for statistical expectation, and from (6) we have

\[
\mathbf{R}_{\mathbf{h}_1} = E[\mathbf{h}_1 \mathbf{h}_1^H] = (\mathbf{C}_1 \mathbf{S}_S^T) \otimes (\mathbf{C}_{r_1} \mathbf{F}^H \mathbf{H}_2^H) + \mathbf{I}_{n_S} \otimes (\mathbf{H}_2 \mathbf{F} \mathbf{F}^H \mathbf{H}_2^H) + \mathbf{I}_{n_D} (11)
\]

\[
\mathbf{R}_{\mathbf{y}_D} = E[\mathbf{y}_D \mathbf{y}_D^H] = (\mathbf{S}_S^T \mathbf{C}_1 \mathbf{S}_S^T) \otimes (\mathbf{C}_{r_2} \mathbf{F}^H \mathbf{H}_2^H) + \mathbf{I}_{n_S} \otimes (\mathbf{H}_2 \mathbf{F} \mathbf{F}^H \mathbf{H}_2^H) + \mathbf{I}_{n_D} (12)
\]

Here \(\cdot^*\) stands for complex conjugate, and we use \(\mathbf{h}_1 = (\mathbf{C}_1^T \otimes \mathbf{C}_{r_1}^T) \mathbf{h}_{w_1}\) with \(\mathbf{h}_{w_1} \triangleq \text{vec}(\mathbf{H}_{w_1}).\)

From (10)-(12), it can be seen that the CSI of \(\mathbf{H}_2\) is needed in order to minimize \(J_1\). However, the exact \(\mathbf{H}_2\) is unknown in the second phase. In fact, it is shown in (3) that \(\mathbf{H}_2\) is a complex Gaussian random matrix with the mean matrix of \(\hat{\mathbf{H}}_2\). Obviously, the mismatch between \(\hat{\mathbf{H}}_2\) and \(\mathbf{H}_2\) affects the accuracy of the estimation of \(\mathbf{H}_1\). To take such mismatch into account, we adopt a statistically robust objective function through averaging \(J_1\) in (9) with respect to the distribution of \(\mathbf{H}_2\) as

\[
E_{\mathbf{H}_2}[J_1] = tr(\mathbf{R}_{\mathbf{h}_1} - \mathbf{E}_{\mathbf{H}_2}[\mathbf{R}_{\mathbf{h}_1}]) W^H - \mathbf{W} \mathbf{E}_{\mathbf{H}_2}[\mathbf{R}_{\mathbf{h}_1} W^H (13)
\]

The estimator \(\mathbf{W}\) which minimizes (13) is the linear MMSE estimator [10] given by

\[
\mathbf{W} = \mathbf{E}_{\mathbf{H}_2} [\mathbf{R}_{\mathbf{h}_1} W^H] (\mathbf{E}_{\mathbf{H}_2}[\mathbf{R}_{\mathbf{y}_D} W^H])^{-1}
\]
where \((\cdot)^{-1}\) denotes matrix inversion. Substituting (14) back into (13), we have
\[
E_{H_2}[J_1] = \text{tr}(R_{h_2}h_2^H - E_{H_2}[R_{h_2},y_{y_2}^H])(E_{H_2}[R_{y_2,y_2}^H])^{-1}
\]
\[
\times E_{H_2}[R_{y_2,y_2}^H].
\] (15)

It can be easily seen from (10) that
\[
E_{H_2}[R_{y_2,y_2}^H] = (C_r,S_r^\ast) \otimes (C_r,F^H\tilde{H}_2^H).
\] (16)

Using the property that for a complex Gaussian random matrix \(H \sim CN(\mathbf{H},\Theta \otimes \Phi)\), \(E_{H}[AH\Gamma] = \hat{H}\hat{A}\Gamma + \text{tr}(A\Theta \Phi)\mathbf{I}\) [13], we have from (3) that
\[
E_{H_2}[R_{y_2,y_2}^H] = (S_t^T C_r, S_r^\ast) \otimes (\tilde{H}_2 FC_r, F^H\tilde{H}_2^H + \text{tr}(\beta FC_r, F^H)I_n).n)
\]
\[
+ I_n \otimes (\tilde{H}_2 FF^H\tilde{H}_2^H + \text{tr}(\beta FF^H)I_n) + I_{n,n}.n)
\] (17)

Substituting (16) and (17) back into (15), we obtain that
\[
E_{H_2}[J_1] = \text{tr}(C_t \otimes C_r - (S_t^T C_r, S_r^\ast) \otimes (\tilde{H}_2 FC_r, F^H\tilde{H}_2^H + \text{tr}(\beta FC_r, F^H)I_n)
\]
\[
\times [S_t^T C_r, S_r^\ast] \otimes (\tilde{H}_2 FC_r, F^H\tilde{H}_2^H + \text{tr}(\beta FC_r, F^H)I_n)
\]
\[
+ I_n \otimes (\tilde{H}_2 FF^H\tilde{H}_2^H + \text{tr}(\beta FF^H)I_n) + I_{n,n}.n)
\] (18)

The transmission power consumed at the relay node during phase two can be calculated from (4) as
\[
p_r = E_{H_2}[J_1] = \text{tr}(F[H_1 S_t S_t^H S_t^H (H_1^2 + n_s I_n) + n_s I_n]
\]
\[
= \text{tr}(S_t^T C_r, S_r^\ast) \text{tr}(FC_r, F^H) + n_s \text{tr}(FF^H).
\] (19)

Using (18) and (19), the optimal robust \(S_S\) and \(F\) can be found as the solution to the following problem
\[
\min_{S_S,F} E_{H_2}[J_1]
\]
\[
s.t. \text{tr}(S_t^T S_r^\ast) \leq P_S
\]
\[
\text{tr}(S_t^T C_r, S_r^\ast) \text{tr}(FC_r, F^H) + n_s \text{tr}(FF^H) \leq P_R
\] (22)

where (21) and (22) are the transmission power constraint at the source and the relay node, respectively, and \(P_S\) is the power budget available at the source node. The problem (20)- (22) is complicated with matrices variables. We first show the optimal structure of \(S_S\) and \(F\).

Let us define the following eigenvalue decompositions (EVDs)
\[
S_t^T C_r, S_r^\ast = U_S A_S U_S^H
\] (23)
\[
\tilde{H}_2 FC_r, F^H\tilde{H}_2^H = U_F A_F U_F^H
\] (24)
\[
C_t = U_t A_t U_t^H
\] (25)
\[
C_r = U_r A_r U_r^H
\] (26)

where \(U_S, U_F, U_t,\) and \(U_r\) are the unitary eigenvector matrices, and \(A_S, A_F, A_t,\) and \(A_r\) are the diagonal eigenvalue matrices with descending diagonal elements. From (23)-(24), we can obtain that
\[
S_t^T C_r^\ast U_S^H A_S^2 Q_S, \quad \tilde{H}_2 FC_r^\ast U_F A_F^2 Q_F
\] (27)

where \(Q_S\) and \(Q_F\) are unitary matrices. Here \(C_r^\ast\) and \(C_r^\ast\) are defined based on (25) and (26) as
\[
C_t^\ast = U_t A_t^\dagger, \quad C_r^\ast = U_r A_r^\dagger
\] (28)

Let us introduce the singular value decomposition (SVD) of \(\tilde{H}_2\) as
\[
\tilde{H}_2 = U_{H_2} \Sigma_{H_2} V_{H_2}^H
\] (29)

where \(U_{H_2}\) and \(V_{H_2}\) are the singular vector matrices and \(\Sigma_{H_2}\) is the singular value matrix with descending diagonal elements. From (27) and (29) we have
\[
S_t^T = U_S A_S^2 Q_S C_t^\ast, \quad F = V_{H_2} \Sigma_{H_2} U_{H_2}^H U_F A_F^2 Q_F C_r^\ast.
\] (30)

Using (23)-(30), \(J_1 = E_{H_2}[J_1] - \text{tr}(C_t \otimes C_r)\) can be written as
\[
J_1 = -\text{tr}([A_S \otimes (\Lambda_F + a I_{n_d})] + I_{n_d} \otimes (A_r^2 Q_F \Lambda_f - Q_F^2 A_r^2 F) + 1(\text{tr}(S_S^T S_r^\ast) - \text{tr}(FC_r, F^H) + n_s \text{tr}(FF^H))/n_s.)
\] (31)

where
\[
a = \text{tr}(\beta A_F U_H^2 U_2 \Sigma_{H_2}^2 U_H^2 U_2 F)
\]
\[
b = \text{tr}(\beta U_F A_F^2 Q_F^2 A_r^2 Q_F^2 A_r^2 U_H^2 U_2 \Sigma_{H_2}^2 U_H^2 U_2 F + 1)/n_s.
\]

The power constraints (21) and (22) can be rewritten as
\[
\text{tr}(A_S Q_S A_t^{-1} Q_H^2) \leq P_S
\] (32)
\[
\text{tr}(A_S A_t U_F A_F U_F^H U_H^2) + n_s \text{tr}(S_S^T S_r^\ast U_F A_F^2 Q_F A_r^2 Q_F^2 A_r^2 U_H^2 U_2 \Sigma_{H_2}^2 U_H^2 U_2 F) \leq P_R
\] (33)

From (31), we see that the mismatch between \(H_2\) and \(\hat{H}_2\) is considered by matrices \(a I_{n_d}\) and \(b I_{n_d} I_n\). In fact, the objective function in [9] can be viewed as a special case of (31) where \(a = b = 0\). It can be proven similar to [9] that if \(C_t = \alpha I_{n_t}\), then at the optimal \(S_S\), there is \(Q_S = I_{n_t}, Q_F = I_{n_d}, U_F = U_{H_2},\) and \(U_S = I_{n_t}\) Therefore, the optimal structure of \(S_S\) and \(F\) can be written as
\[
S_t^T = A_S^2 C_t^\ast, \quad F = -\frac{1}{\alpha^2} V_{H_2} \Sigma_{H_2}^2 A_r^2 F
\] (34)

Substituting (34) back into (31)-(33) and let \(\lambda_{S,t}, \lambda_{F,j},\) \(\lambda_{t,i},\) \(\lambda_{r,i},\) and \(\lambda_{H_2,j}\) be the ith diagonal element of \(A_S, A_F, A_t,\) \(A_r\), and \(\Sigma_{H_2}\), respectively, the problem (20)-(22) is converted to the following problem with scalar variables
\[
\min_{\lambda_{S,t}, \lambda_{F,j},\lambda_{t,i},\lambda_{r,i}} \sum_{\lambda_{S,t}, \lambda_{F,j}} \lambda_{S,t} \lambda_{F,j} \leq P_S
\] (35)
\[
\sum_{\lambda_{S,t}, \lambda_{F,j}} \lambda_{S,t} \lambda_{F,j} + \sum_{\lambda_{H_2,j}} \lambda_{H_2,j} \lambda_{r,i} \leq P_R
\] (37)
\[
\lambda_{S,t} \geq 0, \quad i = 1, \ldots, n_S
\] (38)
\[
\lambda_{F,j} \geq 0, \quad j = 1, \ldots, n_D
\] (39)
where
\[ c_{i,j} \triangleq \lambda_{S,i}\lambda_{r_1,j}\lambda_{F,j}\lambda_{r_1,j} \]
\[ d_{i,j} \triangleq \lambda_{S,i}\lambda_{F,j} + \sum_{j=1}^{n_D} \frac{\beta\lambda_{S,i}\lambda_{F,j}}{\sigma_{H_{r_1,j}}^{2}} + \frac{\lambda_{S,i}}{\lambda_{r_1,j}\sigma_{H_{r_1,j}}^{2}} + 1 \]
\[ \{\lambda_{S,i}\} \triangleq \{\lambda_{S,i}, i = 1, \ldots, n_S\} \]
\[ \{\lambda_{F,j}\} \triangleq \{\lambda_{F,j}, j = 1, \ldots, n_D\} \]

The problem (35)-(39) is non-convex. However, as the optimization of \{\lambda_{F,j}\} is convex when \{\lambda_{S,i}\} is fixed, and vice versa, (at least) a local optimum solution can be found by iteratively optimize \{\lambda_{F,j}\} and \{\lambda_{S,i}\}. These two sub-optimizations problem are formulated as follows.

1. **Optimizing \{\lambda_{F,j}\} with fixed \{\lambda_{S,i}\}**. The power constraint at the source node is irrelevant as \{\lambda_{S,i}\} is fixed. Therefore, the Karush-Kuhn-Tucker (KKT) conditions of optimizing \{\lambda_{F,j}\} can be written as

\[ \frac{n_S}{d_{i,j}} \lambda_{S,i}\lambda_{r_1,j} \left( \frac{\lambda_{S,i}}{\lambda_{r_1,1}} + \frac{1}{\lambda_{r_1,1}} \right) + 1 = \mu \left[ \sum_{i=1}^{n_S} \frac{\lambda_{S,i}}{\sigma_{H_{r_1,j}}^{2}} + \sum_{j=1}^{n_D} \frac{n_S\lambda_{F,j}}{\sigma_{H_{r_1,j}}^{2}} \right] \]

2. **Optimizing \{\lambda_{S,i}\} with fixed \{\lambda_{F,j}\}**. The KKT conditions of this subproblem can be written as

\[ \frac{n_D}{d_{i,j}} \lambda_{F,j}\lambda_{r_1,j} \left( \frac{\lambda_{F,j}}{\lambda_{r_1,j}} + \frac{1}{\lambda_{r_1,j}} \right) = \frac{\nu_1}{\lambda_{r_1,1}} + \frac{\nu_2}{\sigma_{H_{r_1,j}}^{2}} + \sum_{i=1}^{n_S} \frac{\lambda_{S,i}}{\lambda_{r_1,j}} \]

![Fig. 1. Normalized MSE versus P. N = 2 and \( \rho = 0.2 \)](image)

In this section, we study the performance of the proposed channel estimation algorithm through numerical simulations. We compare the proposed approach with the algorithm developed in [9] (denoted as “imperfect \( H_2 \)” where \( H_2 \) is used in the second phase to estimate \( H_1 \)). As a benchmark, the performance of channel estimation algorithm with exactly known \( H_2 \) is also studied.

In the simulations, for simplicity, we set \( n_S = n_R = n_D = N \). The channel correlation matrices are modelled as \( |C_{i,j}|_{m,n} = \rho^{|m-n|} \), \( i = 1, 2, |C_{i,j}|_{m,n} = \rho^{|m-n|} \), where \( \rho \) is the correlation coefficient, and \( C_{r_1} = I_{n_R} \). For each channel realization, the normalized MSE (NMSE) of channel estimation for all three algorithms is calculated as \( \|H_1 - \hat{H}_1\|^2_2 / n_Sn_B \). All simulation results are averaged over 100 random channel realizations.
node $P_R$ is varied from $5\text{dB}$ to $30\text{dB}$. The number of antennas and the normalized correlation coefficient are set to be $N = 2$ and $\rho = 0.8$ respectively.

From the simulation results, it is obvious that by considering the mismatch between $\mathbf{H}_3$ and $\mathbf{H}_2$ in the algorithm, the performance of the algorithm has been improved without the need of greater computation effort. The simulations are executed with different parameters to examine the effectiveness of the algorithm, and all results show an improvement in the estimation of channel matrices.

V. Conclusions

The effect of the mismatch between the estimated and true relay-destination channel on the performance of the LMMSE-based MIMO relay channel estimation algorithm has been investigated in this paper. It has been proven that the robust channel estimation algorithm performs better compared to the channel estimation algorithm proposed in [9] that does not take the mismatch into the consideration. Moreover, the robust channel estimation algorithm does not require greater computational effort.

References