Norm-Based Joint Transmit/Receive Antenna Selection Aided and Two-Tier Channel Estimation Assisted STSK Systems

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Abstract—We propose a simple yet effective norm-based joint transmit and receive antenna selection (NBJTRAS) assisted and two-tier channel estimation (TTCE) aided space-time shift keying (STSK) system. It is capable of significantly outperforming the conventional STSK system, while efficiently utilising available radio frequency (RF) chains. Specifically, the NBJTRAS carries out antenna selection based on the channel estimation (CE) generated using a low-complexity training based least square channel estimator by reusing RF chains. The selected sub-channel matrix is further refined by an efficient semi-blind CE and data detection scheme. Our simulation results show that only a few iterations are sufficient for the TTCE scheme to approach the optimal maximum-likelihood detection performance associated with perfectly channel state information.

Index Terms—Multi-input multi-output, joint transmit/receive antenna selection, space-time shift keying, channel estimation

I. INTRODUCTION

Although multi-input multi-output (MIMO) systems are capable of improving system’s reliability and capacity, they require large number of radio frequency (RF) chains, which leads to high power consumption and hardware costs as well as high complexity in channel estimation (CE). Antenna selection (AS) offers a low-cost alternative to reduce the number of RF chains utilised at transmitter and/or receiver, while retaining the significant advantages of MIMO systems. Generally, AS may be classified into three categories, namely, transmit AS (TxAS), receive AS (RxAS) and joint transmit and receive AS (JTRAS) [1]. The TxAS schemes for MIMO systems were studied in [2]–[4]. More explicitly, two TxAS techniques were proposed and compared in [2] for spatial modulation (SM) systems, where it was shown that the capacity optimised AS scheme outperformed the Euclidean distance optimised AS one. Three AS criteria were proposed for space-shift keying (SSK) systems in [3], which were the max-norm based AS (ASC1), the maximum norm difference based AS (ASC2), and the hybrid scheme combining ASC1 and ASC2. The simulation results of [3] showed that AS techniques were capable of improving the performance of SSK aided MIMO systems, and ASC1 outperformed both ASC2 and the hybrid design. The RxAS schemes for MIMO systems were studied in [5]–[8]. More specifically, the work [5] proposed an optimal RxAS scheme for space-time trellis codes, which selected receive antennas with the highest instantaneous signal-to-noise ratio (SNR). A RxAS method was proposed for V-BLAST systems in [6], where it was shown that the system performance was improved with the aid of AS in terms of block error rate.

As a hybrid version of TxAS and RxAS, JTRAS schemes were investigated in [9]–[17], where they were observed to be capable of improving the system performance while maintaining low transceiver hardware complexity. Moreover, it is well-known that the optimal capacity-based AS usually requires exhaustive search over all the possible subsets of the full channel matrix, which becomes impractical for the system with a large number of transmit and/or receive antennas [17]. Some sub-optimal capacity-based AS techniques were proposed in [13], [14], [17], which were capable of reducing the AS complexity at the cost of certain performance loss. As another efficient yet simple category of AS algorithms, norm-based AS (NBAS) techniques, were investigated in [12], [15], [16], where it was shown that NBAS algorithms were capable of approaching the performance of capacity based AS techniques, while imposing lower system complexity.

Most existing AS techniques [2]–[17] assume that the channel state information (CSI) is perfectly known at transmitter and/or receiver. However, the acquisition of accurate MIMO CSI imposes an excessive pilot-overhead, which not only significantly erodes the system’s achievable throughput but also results in an excessive CE complexity. The training based minimum mean square error (MMSE) channel estimator was employed in [18] for RxAS aided space-time coded MIMO systems, which only considered selecting a single receive antenna. In [19], the training based linear MMSE channel estimator was investigated for MIMO-OFDM systems with RxAS, where AS was only performed based on the received signal power occurring prior to channel estimation. As a unified MIMO architecture that includes SM [20] and SSK [21] as its special cases, the space-time shift-keying (STSK) was conceived in [22], and a low-complexity semi-blind scheme for STSK systems [23] is capable of accurately estimating the CSI without imposing high training overhead.

Against the above background, our novel contribution is twofold. Firstly, we propose a new norm-based JTRAS (NBJTRAS) aided STSK system, which significantly outperforms the conventional STSK system in terms of bit error rate (BER), given the CSI, while maintaining a low system complexity. In particular, we define the AS factor, which indicates the additional diversity order attained by the NBJTRAS aided STSK system. Secondly, we propose a novel two-tier CE (TTCE) scheme for assisting the NBJTRAS based STSK system.
Specifically, in tier one, a low-complexity training based least square CE (LSCE) with RF chain reuse is performed to obtain a rough CE of the full channel set by only utilizing a small number of training symbol blocks, for the sake of maintaining a high system throughput. The overhead of feedback and feedback in tier one is minimal as they only involve antenna indexes. The NBJTRAS is carried out based on this initial CE. In tier two, a semi-blind joint CE and data detection scheme [24] is used to further refine the CE of the selected channel subset. The low-complexity single-stream maximum likelihood (ML) data detection for the STSK system is carried out based on the selected channel subset found in the tier-one stage, and the detected data are re-modulated and used for further decision-directed CE (DDCE). Our simulation results show that with the aid of this proposed TTCE, the system’s performance converges in a few iterations to the optimal ML performance associated with perfect CSI.

II. SYSTEM OVERVIEW

Boldface capital and lower-case letters stand for matrices and column vectors, respectively. The inverse operation is given by \((\cdot)^{-1}\), while the transpose and conjugate transpose operators are given by \((\cdot)^T\) and \((\cdot)^H\), respectively. The norm and magnitude operators are denoted by \(\|\|\) and \(|\cdot|\), respectively. The \(M \times M\) identity matrix is denoted by \(I_M\), and \(H(i,j)\) is the \(i\)th-row and \(j\)th-column element of \(H\).

A. STSK System Model

We consider a frequency-flat Rayleigh fading environment. Let STSK(\(N_T, N_R, T_n, Q, L\)) be the STSK system employing \(L\)-phase shift keying (PSK) or \(L\)-quadrature amplitude modulation (QAM), where \(N_T\) and \(N_R\) are the numbers of transmit and receive antennas, respectively, while \(T_n\) is the number of time slots occupied by the STSK signal block and \(Q\) is the number of dispersion matrices employed. The numbers of transmit and receive RF chains are given by \(L_T\) and \(L_R\), respectively. Let \(i\) denote the STSK block index. At the STSK transmitter, the information bit sequence is firstly converted to the \(L\) numbers of dispersion matrices employed to choose the dispersion matrix \(A\) from the complex-valued Gaussian distribution of zero-mean and unit variance, denoted as \(\mathcal{CN}(0,1)\), while each element of the additive white Gaussian noise (AWGN) matrix \(V(i) \in \mathbb{C}^{N_T \times T_n}\) obeys the complex-valued Gaussian distribution of \(\mathcal{CN}(0,N_0)\) with \(N_0\) being the AWGN power. Define the equivalent transmitted signal vector \(k(i)\) as

\[
k(i) = \begin{bmatrix} 0 \cdots 0 & s(i) & 0 \cdots 0 \end{bmatrix}_T \in \mathbb{C}^{Q \times 1},
\]

where \(q\) indicates the corresponding dispersion matrix that is activated for the \(i\)th STSK block. The total number of legitimate signal transmitted vectors for \(k(i)\) is \(L \cdot Q\), and we have \(k(i) \in \{k_{q,l}, 1 \leq q \leq Q, 1 \leq l \leq L\}\) with

\[
k_{q,l} = \begin{bmatrix} 0 \cdots 0 & s_l & 0 \cdots 0 \end{bmatrix}_T,
\]

where \(s_l\) is the \(l\)th symbol in the \(L\)-PSK/QAM. By defining

\[
\overline{y}(i) = \text{vec}(Y(i)) \in \mathbb{C}^{N_n T_n \times 1},
\]

\[
\overline{H} = H_{Tn} \otimes H \in \mathbb{C}^{N_n T_n \times N_T T_n},
\]

\[
Y = \{\text{vec}(A_1) \cdot \text{vec}(A_2) \cdots \text{vec}(A_Q)\} \in \mathbb{C}^{N_T T_n \times Q},
\]

\[
\overline{v}(i) = \text{vec}(V(i)) \in \mathbb{C}^{N_T T_n \times 1},
\]

the equivalent system model is given as [22]

\[
\overline{y}(i) = \overline{HY} k(i) + \overline{v}(i).
\]

Given \(H\), a low-complexity single-stream-based ML detector can be applied, since the equivalent system model (9) is free from interchannel interference [22]. Let \((q,l)\) be the input index of the dispersion matrix and modulated symbol that have been selected at the transmitter for the \(i\)th STSK signal block, the ML estimate of \((q,l)\) is given by

\[
(q,l) = \arg\min_{1 \leq q \leq Q, 1 \leq l \leq L} \|\overline{y}(i) - \overline{HY} k_{q,l}\|^2.
\]

B. NBJTRAS Aided STSK System

The proposed NBJTRAS aided STSK system is depicted in Fig. 1, where for the time being we assume that the full channel matrix \(H\) is known. Since the numbers of the RF chains at the transmitter and receiver are \(L_T < N_T\) and \(L_R < N_R\), respectively, the resulting STSK system has the configuration STSK(\(L_T, L_R, T_n, Q, L\)) with the communication occurring on the selected subset channel matrix \(H_{\text{sub}} \in \mathbb{C}^{L_R \times L_T}\).

Generally speaking, larger channel gain yields better system performance. This leads to the NBAS approach which selects the transmit and receive antennas related to the subset channel matrix with the highest channel norm. Let \(H_{\text{sub}} \in \mathbb{C}^{L_R \times L_T}\) be the subset candidates of the full channel matrix \(H\). The selected subset \(H_{\text{sub}}\) based on the NBAS criterion is found by solving the optimization

\[
H_{\text{sub}} = \arg\max_{H_{\text{sub}}} \sum_{n_{t}=1}^{L_T} \sum_{n_{r}=1}^{L_R} \|H_{\text{sub}}(n_{t}, n_{r})\|^2.
\]

Solving the above optimization by exhaustive search requires to evaluate the norms of the \(\mathbb{C}^{L_n N_R} \times \mathbb{C}^{L_T N_T}\) candidate subset matrices, where \(\mathbb{C}^{\alpha} = \frac{k!}{\alpha! (k - \alpha)!}\). \(\mathbb{C}^{L_n N_R}\) and \(\mathbb{C}^{L_T N_T}\) are the
Applying (14) to all the row-dimension and column-dimension combinations of \( H_{\text{sub}} \), respectively. We now present a novel NBJTRAS scheme to solve the optimization (11) at a much lower complexity. Given the full channel matrix \( H \in \mathbb{C}^{N_R \times N_T} \), without loss of generality, assume \( C_{NR}^{L_R} < C_{NR}^{L_T} \). Our NBJTRAS algorithm accomplishes the optimization in the following two steps.

**Step 1: Row Dimension Operations.**

Let \( i_r \in \{1, 2, \ldots, C_{NR}^{L_R} \} \) be the row combination index, and the row indices corresponding to the \( i_r \)th sub-matrix \( H_{i_r} \in \mathbb{C}^{L_R \times N_T} \) be given by \( l_{i_r} = [l_{i_r}^1, l_{i_r}^2, \ldots, l_{i_r}^{N_T}]^T \). Then

\[
H_{i_r} = \begin{bmatrix} h_{i_r}^1 \bar{H}_{i_r} \\ h_{i_r}^2 \bar{H}_{i_r} \\ \vdots \\ h_{i_r}^{N_T} \bar{H}_{i_r} \end{bmatrix} = \begin{bmatrix} H_{i_r}(1, 1) & \cdots & H_{i_r}(1, N_T) \\ H_{i_r}(2, 1) & \cdots & H_{i_r}(2, N_T) \\ \vdots & \vdots & \vdots \\ H_{i_r}(L_R, 1) & \cdots & H_{i_r}(L_R, N_T) \end{bmatrix},
\]

(12)

where \( h_{i_r}^x \) is the \( x \)th row of \( H \). Computing

\[
m_{i_r}^x = \sum_{j=1}^{L_R} |H_{i_r}(j, x)|^2, \quad 1 \leq x \leq N_T,
\]

(13)

where \( m_{i_r}^x \) represents the magnitude of the \( x \)th column in \( H_{i_r} \), yields the norm metric vector

\[
m_{i_r}^T = \begin{bmatrix} m_{i_r}^1 \\ m_{i_r}^2 \\ \vdots \\ m_{i_r}^{N_T} \end{bmatrix}.
\]

(14)

Applying (14) to all the \( C_{NR}^{L_R} \) possible combinations leads to the norm metric matrix \( M \in \mathbb{C}^{C_{NR}^{L_R} \times N_T} \) given by

\[
M = \begin{bmatrix} m_1^T \\ m_2^T \\ \vdots \\ m_{C_{NR}^{L_R}}^T \end{bmatrix} = \begin{bmatrix} m_1^1 & m_2^1 & \cdots & m_{C_{NR}^{L_R}}^1 \\ m_1^2 & m_2^2 & \cdots & m_{C_{NR}^{L_R}}^2 \\ \vdots & \vdots & \vdots & \vdots \\ m_1^{N_T} & m_2^{N_T} & \cdots & m_{C_{NR}^{L_R}}^{N_T} \end{bmatrix}.
\]

(15)

**Step 2: Column Dimension Operations.**

Find the largest \( L_T \) elements in the \( i_r \)th row of \( M \) and sum them up, which is denoted as \( m_{i_r}^{\text{max}} \), as well as record the column indices of these \( L_T \) elements in the index vector \( l_{i_r} \), \( i_r \)th row of \( l_{i_r} \). Then the largest \( L_T \) elements in the \( i_r \)th row of \( M \) is the \( i_r \)th row combination index, \( r_i \).

\[
\hat{l}_{i_r} = \frac{\bar{H}_{i_r}^T \bar{H}_{i_r}}{\bar{H}_{i_r}^T \bar{H}_{i_r}}.
\]

Next find

\[
\hat{l}_{i_r} = \arg \max s.t. \quad \hat{l}_{i_r} = \frac{\bar{H}_{i_r}^T \bar{H}_{i_r}}{\bar{H}_{i_r}^T \bar{H}_{i_r}}.
\]

(16)

Then selected transmit and receive antenna indices are specified by \( l_{i_r} \hat{l}_{i_r} \) and \( \hat{l}_{i_r} \), respectively, and the corresponding subset channel matrix \( H_{\text{sub}} \) is the optimal solution of (11). The complexity of the NBJTRAS is \( C_{\text{NBJTRAS}} \approx O \left( (N_T \cdot L_R) \cdot C_{NR}^{L_R} \right) \), which is much smaller than \( C_{\text{ES}} \approx O \left( (L_T \cdot L_T) \cdot (L_T \cdot C_{NR}^{L_T}) \right) \) of the exhaustive search. If \( C_{NR}^{L_R} > C_{NR}^{L_T} \), the NBJTRAS starts with **Step 1** of Column Dimension Operations followed by **Step 2** of Row Dimension Operations, and the complexity of this algorithm is \( O \left( (N_T \cdot L_T) \cdot C_{NR}^{L_T} \right) \).

Given \( L_R \) and \( L_T \), the achievable multiplexing gain of the STSK system is fixed. We now define the AS factor as

\[
\gamma_{\text{AS}}(N_T, N_R) = \frac{N_T + N_R}{L_T + L_R},
\]

(18)

which is the diversity order attained, compared with the conventional STSK \( (L_T, L_R, N_T, Q, L) \) without AS.

**III. TWO-TIER CHANNEL ESTIMATION FOR NBJTRAS**

The TTCE scheme consists of Tier-One training based CE (TBCE) and Tier-Two DDCE as illustrated in Fig. 1. **A. Tier One: TBCE**

We adopt the training based LSCE with a very small number of training blocks in tier one to maintain a high throughput at the cost of a poor CE. According to the study [25], AS is relatively insensitive to CE error and, therefore, this inaccurate CE is adequate for the NBJTRAS scheme to carry out the AS task. Because the numbers of the RF chains available at transmitter/receiver are smaller than those of transmit/receive...
antennas, RF chains are reused in the estimation of the full channel matrix \( \mathbf{H} \in \mathbb{C}^{N_T \times N_R} \). For simplicity and without loss of generality, we assume that both the ratios of \( \frac{N_T}{T} \) and \( \frac{N_R}{R} \) are integers. Then the number of the subset channel matrices that need to be estimated is \( \frac{N_T}{T} \times \frac{N_R}{R} \). Specifically, we need to estimate the subset channel matrices \( \mathbf{H}_{est}^{(i,j)} \in \mathbb{C}^{L_i \times L_T} \) for \( i \in \{1, 2, \ldots, \frac{N_T}{T} \} \) and \( j \in \{1, 2, \ldots, \frac{N_R}{R} \} \).

Assume that the number of the available training blocks is \( M_T \) and the training data for \( \mathbf{H}_{est}^{(i,j)} \) are arranged as

\[
\begin{align*}
\mathbf{Y}_{t,i,j}^{(i,j)} & = \left[ \mathbf{Y}^{(i,j)}(1) \mathbf{Y}^{(i,j)}(2) \ldots \mathbf{Y}^{(i,j)}(M_T) \right], \\
\mathbf{S}_{t,i,j}^{(i,j)} & = \left[ \mathbf{S}^{(i,j)}(1) \mathbf{S}^{(i,j)}(2) \ldots \mathbf{S}^{(i,j)}(M_T) \right].
\end{align*}
\]

Typically, \( M_T \) is very small. The LSCE of \( \mathbf{H}_{est}^{(i,j)} \) based on the training data of (19) and (20) is given by

\[
\mathbf{H}_{est}^{(i,j)} = \mathbf{Y}_{t,i,j}^{(i,j)} \left( \mathbf{S}_{t,i,j}^{(i,j)} \right)^{T} \left( \mathbf{S}_{t,i,j}^{(i,j)} \right)^{-1},
\]

and the estimate of \( \mathbf{H} \in \mathbb{C}^{N_T \times N_R} \) is expressed as

\[
\mathbf{\tilde{H}} = \begin{bmatrix}
\mathbf{H}_{est}^{(1,1)} & \mathbf{H}_{est}^{(1,2)} & \cdots & \mathbf{H}_{est}^{(1,\frac{N_R}{R})} \\
\mathbf{H}_{est}^{(2,1)} & \mathbf{H}_{est}^{(2,2)} & \cdots & \mathbf{H}_{est}^{(2,\frac{N_R}{R})} \\
\vdots & \vdots & \ddots & \vdots \\
\mathbf{H}_{est}^{(\frac{N_T}{T},1)} & \mathbf{H}_{est}^{(\frac{N_T}{T},2)} & \cdots & \mathbf{H}_{est}^{(\frac{N_T}{T},\frac{N_R}{R})}
\end{bmatrix}.
\]

Then the NBJTRAS is carried out based on this estimated full channel matrix \( \mathbf{\tilde{H}} \in \mathbb{C}^{N_T \times N_R} \), which also yields the rough estimate \( \mathbf{\tilde{H}}_{sub} \) of the selected subset channel matrix.

B. Tier Two: DDCE

With a small training blocks \( M_T \), the accuracy of the estimate \( \mathbf{\tilde{H}}_{sub} \) is poor. Note that data detection is more sensitive to the CE error than the NBJTRAS. In the tier two, we use the semi-blind joint CE and data detection scheme of [24] which applies the DDCE to refine the initial TBCE \( \mathbf{\tilde{H}}_{sub} \).

Let the observation data at the receiver be

\[
\mathbf{Y}_d = [\mathbf{Y}(1) \mathbf{Y}(2) \ldots \mathbf{Y}(\tau)],
\]

where \( \tau \) is the number of the received data blocks per frame. Given the maximum number of DDCE iterations \( I_{max} \), the tier-two DDCE is summarized as follows.

1) Set the DDCE iteration index as \( i_{te} = 0 \) and the initial CE as the TBCE of \( \mathbf{\tilde{H}}_{sub} \); \( \mathbf{\tilde{H}}_{sub} = \mathbf{\tilde{H}}_{sub} \).

2) Perform the ML data detection for \( \mathbf{Y}_d \) based on the CE \( \mathbf{\tilde{H}}_{sub}^{(ite)} \), and re-modulate the detected data into the symbol sequence given by

\[
\hat{\mathbf{S}}_d^{(ite)} = \left[ \hat{\mathbf{S}}_d^{(ite)}(1) \hat{\mathbf{S}}_d^{(ite)}(2) \ldots \hat{\mathbf{S}}_d^{(ite)}(\tau) \right].
\]

Then the DDCE is updated according to

\[
\mathbf{\tilde{H}}_{sub}^{(ite+1)} = \mathbf{Y}_d \left( \hat{\mathbf{S}}_d^{(ite)} \right)^{T} \left( \hat{\mathbf{S}}_d^{(ite)} \right)^{-1}.
\]

3) If \( i_{te} = I_{max} \), stop; else, set \( i_{te} = i_{te} + 1 \) and go to 2). \( I_{max} \leq 4 \) is sufficient for this DDCE process to converge.

IV. SIMULATION RESULTS

A quasi-static Rayleigh fading STSK \( L_T = 2, L_R = 2, T_n = 2, Q = 4, L = 4 \) was simulated. Various values of \( N_T \) and \( N_R \) were used to yield different AS factors \( f_{AS}(N_T, N_R) \). The transmitted signal power was normalized to unity and thus the SNR was given by \( \frac{T}{\tau} \). The frame length was set to 1,000 bits, yielding \( \tau = 250 \) STSK \( (2, 2, 2, 4, 4) \) symbol blocks. Two metrics were used to assess the achievable performance, and they were the BER and the mean channel error (MCE) of the CE defined by

\[
J_{MCE}(\mathbf{\tilde{H}}_{sub}) = \| \mathbf{H}_{sub} - \mathbf{\tilde{H}}_{sub} \|^2 / \| \mathbf{H}_{sub} \|^2.
\]

All the results were averaged over 10,000 channel realizations.

![Fig. 2: BER performance of the proposed NBJTRAS aided STSK(2,2,2,4,4) given three AS factors \( f_{AS}(N_T, N_R) \), in comparison to performance of the conventional STSK(2,2,2,4,4) without AS, assuming the perfect CSI at both transmitter and receiver.](image)
the TBCE based NBJTRAS aided STSK system outperforms the TBCE aided conventional STSK in comparison to the TBCE aided conventional STSK system employing the tier-one TBCE scheme, in comparison to the perfect CSI case. When the number of the training blocks increases to \( M_T = 30 \), the BER performance gap between the case of perfect CSI and the TBCE based system is smaller than 0.1 dB.

Fig. 4 shows the MCE performance of the NBJTRAS aided STSK system employing the tier-one TBCE scheme, in comparison to the TBCE aided conventional STSK(2, 2, 2, 4, 4) without AS. It can be seen from Fig. 4 that for the cases of \( M_T = 2 \) and SNR < -1 dB as well as \( M_T = 3 \) and SNR < -3 dB, the MCE of the training based NBJTRAS aided STSK system is slightly worse than that of the non-AS based conventional STSK system. However, when the SNR is larger than -1 dB, the TBCE based NBJTRAS aided STSK outperforms the TBCE assisted conventional STSK without AS. Moreover, when the training length increases to \( M_T \geq 5 \), the TBCE based NBJTRAS aided STSK system outperforms the conventional STSK without AS over the entire SNR range tested. This clearly demonstrates that with the aid of the NBJTRAS scheme, the CE accuracy is improved.

3) Proposed TTCE for NBJTRAS Aided STSK: The BER of the proposed TTCE assisted NBJTRAS aided STSK system with \( M_T = 5 \) is shown in Fig. 5. It is seen that in the low SNR region of SNR < 3 dB, the TTCE assisted system fails to converge to the perfect CSI bound. However, for SNR > 3 dB, the BER of the TTCE assisted system is capable of converging to the perfect CSI case. Fig. 5 also shows that the performance of the TBCE aided NBJTRAS aided STSK system with \( M_T = 10 \) is unable to attain the BER of the NBJTRAS aided STSK system associated with perfect CSI.

Fig. 6 illustrates the MCE convergence behaviour of the proposed TTCE scheme for the NBJTRAS aided STSK system with \( M_T = 5 \), where it is seen that three iterations are sufficient for the TTCE to converge.

Fig. 7 compares the MCE of the proposed TTCE scheme with \( M_T = 5 \) training blocks with those of the conventional TBCE scheme given various numbers of training blocks. As expected, the TBCE assisted NBJTRAS aided STSK system with \( M_T = 5 \) training blocks has the same MCE performance.
as the initial CE of the proposed TTCE assisted NJTRAS aided STSK system with the same \( M_T = 5 \) training blocks. From Fig. 7, it can be seen that the MCE of the TTCE assisted NJTRAS aided STSK system with only \( M = 5 \) training blocks is capable of converging in three iterations to the MCE of the conventional TBCE scheme for the NJTRAS aided STSK system with \( M_T = 250 \) training blocks for SNR > 6 dB. For SNR > 6 dB, the BER of the TTCE assisted NJTRAS aided STSK system is below \( 10^{-3} \), as can be seen from Fig. 5, and all the \( \tau = 250 \) decisions become reliable. Therefore, the proposed TTCE scheme with \( \tau \) blocks per frame is capable of approaching the performance bound of TBCE with \( M_T = \tau \) training blocks in high SNR region.

V. CONCLUSIONS

We have proposed a simple yet efficient NJTRAS aided STSK system which is capable of significantly outperforming the conventional STSK system without AS, given CSI. Additionally, we have proposed a novel TTCE scheme for assisting the NJTRAS aided STSK system. The proposed TTCE scheme only requires a very small number of training blocks in the tier one to provide a rough CE for the NJTRAS to carry out the AS. In the tier two, the selected subset training based CE is used for initial data detection, and the detected data are re-modulated for further DDCE. Our simulation results have showed that typically 3 iterations are sufficient for this DDCE to converge. Our results have also demonstrated that the proposed TTCE assisted NJTRAS aided system with a very small number of training blocks is capable of approaching the optimal ML performance bound associated with perfect CSI, provided that the SNR is over certain threshold.

REFERENCES