A Novel Antenna Selection Scheme for Spatially Correlated Massive MIMO Uplinks with Imperfect Channel Estimation

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Abstract—We propose a new antenna selection scheme for massive multiple-input multiple-output (MIMO) uplinks with antenna spatial correlation and imperfect channel estimation, by exploiting the sparsity of channel gain vectors at the received end. The channel gain vectors are formulated by developing a minimisation problem of the received mean squared error, and iteratively calculated using the well known orthogonal matching pursuit (OMP) algorithm. Widely adopted approximation models of spatial correlation among the antennas and channel estimation errors are considered in this work, in order to investigate the proposed approach by taking realistic implementation situations into account. Simulation results demonstrate that when considerable impacts of spatial correlation and imperfect channel estimation introduced, our proposed scheme can significantly reduce implementation overhead and complexity, without degrading the system performance compared to the well-adopted optimal scheme.

I. INTRODUCTION

Multiuser multiple-input multiple-output (MU-MIMO) system equipped with large scale base station (BS) antennas has been recently developed as scalable advanced network architecture, also known as massive MIMO [1], [2], for next generation wireless communication systems [3], [4], with considerably improved performances of data rate and link reliability. Specifically, in [1], more than 10 fold throughput improvement by the massive MIMO can be achieved compared to LTE (Long Term Evolution). Despite such huge potential, in practice, the deployment of massive MIMO systems is hindered by several practical challenges that are not of concern in conventional MIMO systems. Firstly, there is an inherent problem of spatial correlation among the antennas due to insufficient spacing [2], [5], [6]. Specifically, for the uplink transmission, the antenna correlation is experienced across all diversity branches at the BS side, due to the nonisotropic BS antennas with decreased separation. In [2], it is illustrated that the severely limited antenna separation results in nearly negligible achievable capacity gains. Second, the channel state information (CSI) has to be estimated, and due to imperfection in channel estimation and the complicated fading environment, the accuracy of channel estimate can significantly degrade the system performance, especially for massive MIMO systems. Prior investigations show that the pilot contamination is a fundamental limitation of the massive MIMO [11], and the impact of channel estimation error can significantly reduce the capacity gain in massive MIMO systems [5], [6]. Therefore, from a very practical point of view, it is essential to take both spatial correlation and imperfect channel estimation into account for the massive MIMO system design.

For the massive MIMO uplinks, the performance with the consideration of antenna spatial correlation and imperfect channel estimation has been investigated in [1], [2], [5]–[7]. More specifically, in [1], it is shown that uplink combining schemes, such as maximum ratio combining (MRC), can have a reasonable performance, with knowledge of CSI for the entire combining branches. However, the price to pay for such performance is the significantly increased implementation overhead (e.g., the number of radio frequency chains) and the complexity of full transceiver design for the large scale BS antenna array [8], [9]. In [8], it is argued that cost-efficient antenna selection strategies can be employed to reduce the complexity and overhead of implementation, as well as to effectively maintain the reasonably high performance [9], but mainly for the downlink transmit antenna selection. The diversity selection combining (SC) of uplink receive antennas has been extensively studied in the literature [10], [11], in the context of conventional MIMO systems. For example, the effect of imperfect channel estimation on the SC systems is presented in [11], but not for the large scale antenna array network.

An analysis of the MRC in massive MIMO uplinks under imperfect channel estimation is presented in [1]. It is also suggested that other combining schemes can be further studied. In this direction, selection combining schemes can be considered. Exploiting sparsity, Lee and Naofal investigate antenna/relay selection for MIMO relay channels [12]. However, the work of [12] does not take into account spatial correlation among antennas, as well as the impacts of imperfect CSI acquisition. Considering the spatial correlation and imperfect channel estimation, spatially correlated channel models in [5], [13]–[15] are considered as a good approximation for large scale antenna correlation, and channel estimation errors in [5], [15]. [16] are applied to effectively model the imperfection caused by the practical channel estimation schemes.

The main contribution of this work is to propose an effective antenna selection combining scheme for spatially correlated massive MIMO uplinks under the imperfect channel estimation, by applying a sparsely structured channel gain vector at the BS side, which, to the best of the authors’ knowledge,
has not been studied in the literatures. Throughout this work, if a smaller number of antennas than the total number of antennas are selected for combining purpose, the resulting effective channel gain vector becomes sparse, in the sense that the corresponding entries to non-selected antennas are set to zero. This sparsely structured channel gain vector is obtained through sparse approximation operations. Simulation results indicate that the proposed antenna selection scheme can significantly reduce implementation complexity and overhead, e.g., Fig. 4 in Section V illustrates that only less than half number of antennas are required to retain closely approached error rate performance compared to MRC scheme, under high levels of imperfect channel estimation and spatial correlation.

The rest of this paper is organised as follows. In Section II we present the system model for this work. The iterative antenna selection algorithm is discussed in Section III. The proposed selection algorithm is then generalised to the spatially correlated channel model with imperfect channel estimation, in Section IV. Performance of the proposed scheme and the relevant discussions are given in Section V and VI respectively.

II. SYSTEM MODEL

We consider a single-cell system consisting of a single user terminal (UT) and one BS with large scale antennas. Due to space limitations, we present our system model here as single user systems, and it is being considered to emphasise upon MU-MIMO in the journal version of this work, although the extension to multiuser uplink systems is straightforward. The focus of this paper is on the antenna selection combining at the UT side, and the relevant discussions are given in Section V and VI respectively.

A. Spatially Correlated Channel Model

The spatially correlated channel $H$ in the (1) can be characterised as following Kronecker model [13]

$$H = \Phi_{Rs}^{1/2} H_c \Phi_{Tx}^{1/2},$$

where the $N_{Rx} \times N_{Tx}$-dimensional $H_c$ is an uncorrelated complex channel matrix whose entries are independent identically distributed (i.i.d) circularly symmetric complex Gaussian random variables with zero mean and unit variance. The $N_{Rx} \times N_{Rx}$ matrix $\Phi_{Rs}$ and the $N_{Tx} \times N_{Tx}$ matrix $\Phi_{Tx}$ determine the correlation between receiver antennas, and between transmitter antennas, respectively. Note that $(\cdot)^{1/2}$ in the (2) represents the Hermitian square root of a matrix. Hereafter we assume that correlation matrices $\Phi_{Rs}$ and $\Phi_{Tx}$ are known, due to the fact that they are supposed to be less frequently varying than the channel matrix. Furthermore, the distribution of the uncorrelated matrix $H_c$ is known to the receiver [14], and the channel matrix $H_c$ stays constant and is independent of the transmitted signal vector $x$ and noise vector $v$ during one transmission period.

B. Imperfect Channel Estimation

In practice, the channel (i.e., the channel matrix $H$ here) is estimated at the receiver, by applying different channel estimation schemes such as MMSE-based pilot signalling estimation, which can introduce estimation errors. Since the correlation matrices are assumed to be available, the channel estimation can be applied for the uncorrelated channel component $H_c$. The imperfect estimate $\hat{H}_c$ of the $H_c$ can be modelled as [16]

$$H_c = \sqrt{1-\tau} \hat{H}_c + \sqrt{\tau} E_i,$$

where $E_i$ is the estimation error. It is suggested that $E_i$ can be a white error matrix independent of $H_c$, due to the property of the MMSE estimator [5], whose entries are i.i.d zero mean circularly symmetric complex Gaussian random variables. Here the estimation variance parameter $\tau \in [0, 1]$ represents the estimation accuracy, i.e., $\tau = 1$ reflects that the completely uncorrelated estimate to the original channel, whereas $\tau = 0$ corresponds to the perfect channel estimation [5]. Considering the antenna spatial correlation in this work as well, the channel matrix $H$ can be further expressed as [5], [15]

$$H = \Phi_{Rs}^{1/2} \left( \sqrt{1-\tau} \hat{H}_c + \sqrt{\tau} E_i \right) \Phi_{Tx}^{1/2},$$

$$= \hat{H} + E,$$

where $\hat{H} = \sqrt{1-\tau} \Phi_{Rs}^{1/2} H_c \Phi_{Tx}^{1/2}$ and $E = \sqrt{\tau} \Phi_{Rs}^{1/2} E_i \Phi_{Tx}^{1/2}$. Then, the effect of both antenna spatial correlation and imperfect channel estimation can be investigated, by substituting the structure in the (4) or (5) for $H$ in the (1).
we introduce a $N_{Rx} \times 1$-dimensional channel gain vector $h_{s,i}$, which can also be considered as a antenna selection vector, due to the fact that each receiver antenna is weighted by a corresponding channel gain in the vector $h_{s,i}$. The expression of received signal in Equation (1) can be revised as $\hat{y}$, after we apply the channel gain vector, as

$$\hat{y} = h_{s,i}^H (x + v).$$

(6)

Based on the revised signal structure, an optimisation problem of multiple antenna selection with the channel gain vector for minimising the received mean squared error (MSE) can be developed. Specifically, we define the received signal error as

$$e = x - \hat{y} = x - h_{s,i}^H (h_i x + v).$$

(7)

By exploiting the structure of the error signal, the MSE can be formulated as

$$\text{MSE} := E[|e|^2] = \sigma_e^2 - h_{s,i}^H \sigma_e^2 h_{s,i} + h_{s,i}^H \sigma_s^2 h_{s,i}^H h_{s,i} + h_{s,i}^H \sigma^2 I_{N_{Rx}} h_{s,i},$$

(8)

where “::” is the definition sign. We then let

$$\tilde{h}_i = \sigma_s^2 h_i,$$

(9)

$$R_i = \sigma_e^2 h_i h_i^H + \sigma_s^2 I_{N_{Rx}}.$$  

(10)

Notice that $R_i$ is positive definite, we apply Cholesky decomposition as $R_i = L_i L_i^H$ where $L_i$ is one $N_{Rx} \times N_{Rx}$ lower-triangular matrix. The expression of MSE can then be written as

$$\text{MSE} = \sigma_e^2 - h_{s,i}^H L_i L_i^{-1} \tilde{h}_i - \tilde{h}_i L_i^{-H} L_i^H h_{s,i} + h_{s,i}^H L_i L_i^H h_{s,i},$$

(11)

$$= \sigma_e^2 - h_{s,i}^H \sigma_e^2 L_i^{-1} \tilde{h}_i + \|L_i^H h_{s,i} - L_i^{-1} \tilde{h}_i\|^2_2.$$  

(12)

The only component in (12) related to the antenna selection vector $h_{s,i}$ and can be further processed, is the last $L_2$ norm (denoted by $\| \cdot \|_2$). Such procedure can be efficiently proceeded with low complexity by using sparse approximation algorithms, which is also well described in the literature, e.g., [12]. Since the vector $h_{s,i}$ reflects the receiver antenna selection process, the only non-zero entries of $h_{s,i}$ correspond to the selected receiver antenna (i.e., $h_{s,i}$ becomes a sparsely structured vector). Hence, the acquisition of this channel gain vector $h_{s,i}$ transforms to a sparse approximation problem. We formulate this sparse approximation problem by generating a link between the sparse approximation and the MSE optimisation: the objective can be the minimisation of the $L_2$ norm, and the measurement dictionary and the target vector are $L_i^H$ and $L_i^{-1} \tilde{h}_i$, respectively. Here we consider a widely applied sparse approximation algorithm, referred as orthogonal matching pursuit (OMP) [17], to solve the minimisation problem. OMP consists of an iterative calculation process to locate one column vector in the measurement dictionary that is the most correlated vector to the residual vector (which is generally initialised to be the target vector), at each iteration. One locally optimum solution is measured by solving a least-squared problem to update the residual vector. Details for theOMP can be found in, e.g., [17]. Here, for the sake of simplicity, we highlight the parameters in the algorithm relating to this work. The inputs of the OMP process are the measurement dictionary $L_i^H$ and the target vector $L_i^{-1} \tilde{h}_i$, as well as a stopping criterion. Here the stopping criterion is selected as the desired number of iterations for the OMP algorithm, named $K_s$. We denote the proposed OMP algorithm as

$$h_{s,i} = \arg \min_{h_{s,i,\text{OMP}}} \|L_i^H h_{s,i} - L_i^{-1} \tilde{h}_i\|^2_2,$$

s.t. $\|h_{s,i}\|_0 = K_s,$

(13)

where s.t. stands for “subject to”, $\| \cdot \|_0$ represents the $L_0$ norm, also informally the number of non-zero entries in a vector, and $h_{s,i,\text{OMP}}$ refers to the value of $h_{s,i}$ calculated by OMP algorithm. Notice that at the end of each iteration, the optimum solution is obtained, corresponding to one selection process of the sparsely structured channel gain vector $h_{s,i}$. Therefore, the stopping criterion $K_s$ also indicates the desired number of selected receiver antennas, and multiple antenna selection can be realised by using the sparsely structured channel gain vector generated by the (13).

IV. SPATIAL CORRELATED CHANNEL WITH IMPERFECT CHANNEL ESTIMATION

In this section, we extend the OMP operation based antenna selection scheme taking into account spatial correlation among the antennas and imperfect channel estimation. Recalling (2), in the case of single antenna UT uplink transmission with large scale antenna BS, the spatial correlation at the receiver can be focused on, and the transmitter side correlation matrix $\Phi_{T_x}$ becomes an identity matrix. Such assumption is valid for MU-MIMO systems, since user terminals are autonomous [2]. Considering the $N_{Rx} \times 1$-dimensional uncorrelated channel vector $h_i$, the spatially correlated channel vector can be given as

$$h = \Phi_{R_x}^{1/2} h_i.$$

(14)

It is suggested that the exponential correlation model is a widely adopted approximation for the structure of the correlation matrix [13], which can suitably evaluate the level of spatial correlation among antennas, as given by,

$$\Phi_{ij} = \begin{cases} \phi^{j-i}, & i \leq j, \\ (\phi^{j-i})^*, & i > j, \end{cases}$$

(15)

where $\Phi_{ij}$ is the entry of the receiver side correlation matrix $\Phi_{R_x}$ and corresponds to the correlation between $i^{th}$ and $j^{th}$ receiver antenna. A single coefficient $\phi$ is also introduced, with $|\phi| \leq 1$, where, here and in (15), $| \cdot |$ and $(\cdot)^*$ denote the absolute value and complex conjugate operation, respectively. Notice that, similar to the imperfect channel estimation and estimation variance parameter $\tau$, the effect of the antenna correlation can be investigated by adjusting the correlation
positive semi/definite matrix, it is easy to prove the conjugate transpose operation. Due to the property of the conjugate transpose zero complex vector cannot be achieved. Therefore, there exists no such one non-case is a symmetric real matrix, then required. which indicates that \( R \) is a symmetric real positive semidefinite matrix [14], so it is necessary to verify the positive definiteness of \( R \) for its availability of Cholesky decomposition. To do so, we introduce the following lemma, and further define the \( \Phi_{Rz} \) as a symmetric real positive semidefinite matrix (i.e., \( \phi \in [0, 1] \)).

**Lemma 1.** Let \( \Phi_{Rz} \) be a symmetric real positive semidefinite matrix, and \( R_h = h_h h_h^H \) be a positive definite Hermitian matrix. Then \( \Phi_{Rz}^{1/2} R_h \Phi_{Rz}^{H/2} \) is positive definite.

**Proof:** Since \( \Phi_{Rz} \) is positive semidefinite, then its square root \( \Phi_{Rz}^{1/2} \) is positive semidefinite as well. In addition, \( \Phi_{Rz} \) is a symmetric real matrix, then \( \Phi_{Rz}^{-1} \) is equal to its own conjugate transpose \( \Phi_{Rz}^{H} \), where \( (\cdot)^H \) represents conjugate transpose operation. Due to the property of the positive semi/definite matrix, it is easy to prove \( \Phi_{Rz}^{1/2} R_h \Phi_{Rz}^{H/2} \) is positive semidefinite, equivalently to

\[
z^H \Phi_{Rz}^{-1/2} R_h \Phi_{Rz}^{H/2} z \geq 0, \forall z \in \{ z \in \mathbb{C}^{N_{Rz}} | z \neq 0 \}. \tag{18}
\]

Then assuming in this case, \( \exists z_c \in \{ z \in \mathbb{C}^{N_{Rz}} | z \neq 0 \} \), let

\[
z_c^H \Phi_{Rz}^{-1/2} R_h \Phi_{Rz}^{H/2} z_c = 0,
\]

so

\[
(\Phi_{Rz}^{-1/2} z_c)^H R_h (\Phi_{Rz}^{H/2} z_c) = 0. \tag{19}
\]

Since \( R_h \) is positive definite, to ensure the above equality, the \( \Phi_{Rz}^{-1/2} z_c \) has to be equal to zero vector 0. Consider a specific case \( \phi = 0 \) and \( \Phi_{Rz}^{1/2} \) is an identity matrix, in order to ensure \( \Phi_{Rz}^{-1/2} z_c = 0 \), \( \Phi_{Rz}^{H/2} \) has to be a zero matrix as well, which cannot be achieved. Therefore, there exists no such one non-zero complex vector \( z_c \), so

\[
z^H \Phi_{Rz}^{-1/2} R_h \Phi_{Rz}^{H/2} z > 0, \forall z \in \{ z \in \mathbb{C}^{N_{Rz}} | z \neq 0 \}, \tag{20}
\]

which indicates that \( \Phi_{Rz}^{1/2} R_h \Phi_{Rz}^{H/2} \) is positive definite, as required.

Based on Lemma 1 it can be proved that \( R \) in (12) is positive definite, and the multiple antenna selection with the receiver side spatially correlated channel can be realised, by measuring revised sparse channel gain vector \( h_{s,e} \), instead of \( h_{s,i} \) in (13), and the relative components in the OMP algorithm. More specifically, we have the generalised \( h \) in (16) and \( R \) in (17), and \( L \) is the \( N_{Rz} \times N_{Rz} \) lower-triangular matrix from Cholesky decomposed \( R \). Correspondingly, the measurement dictionary and the target vector become \( L^H \) and \( L^{-1} \hat{h} \) respectively. We rewrite the structure of \( h_{s,e} \) as

\[
h_{s,e} = \arg\min_{h_{s,e}} \| L^H h_{s,e} - L^{-1} \hat{h} \|_2,
\]

\[
\text{s.t.} \| h_{s,e} \|_0 = K_s, \tag{21}
\]

by considering the same stopping criterion in the OMP operation as [13], i.e., the number of selected antennas.

Recall the Equation (4) and (5), we now consider the case with imperfect channel estimation. Under the same assumption of a single antenna UT uplink transmission, we have channel estimate vectors \( \hat{h}, h_i \), estimation error vectors \( e \) and \( e_i \), correspondingly. Generalise the \( \hat{h} \) and \( R \) to \( h_e \) and \( R_e \), respectively, which can be given as

\[
h_e = \sigma_z^2 (\hat{h} + e) = \sqrt{1 - \tau} \sigma_z^2 \Phi_{Rz}^{1/2} h_i + \sqrt{\tau} \sigma_z^2 \Phi_{Rz}^{1/2} e_i, \tag{22}
\]

\[
R_e = \sigma_z^2 (\hat{h} + e)(\hat{h} + e)^H + \sigma_z^2 I_{N_{Rz}} = (1 - \tau) \sigma_z^2 \Phi_{Rz}^{1/2} (h_i h_i^H + e_i e_i^H) \Phi_{Rz}^{H/2} + \sigma_z^2 I_{N_{Rz}}. \tag{23}
\]

In a similar way, it is evident that the positive definiteness of \( R_e \) and the its availability of Cholesky decomposition can be satisfied, due to the expected identical distribution of \( h_i \) and \( e_i \), as well as the proof of Lemma 1. We can allocate the parameters for the OMP algorithm with imperfect channel estimation as

\[
h_{s,e} = \arg\min_{h_{s,e}} \| L^H h_{s,e} - L^{-1} \hat{h} \|_2,
\]

\[
\text{s.t.} \| h_{s,e} \|_0 = K_s, \tag{24}
\]

where the \( h_{s,e} \) is the updated version of \( h_{s,e} \) in (21) with consideration of channel estimation error, and \( L_e \) is the \( N_{Rz} \times N_{Rz} \) lower-triangular matrix generated by the Cholesky decomposition of \( R_e \). Again, the stopping criterion is the desired number of selected antennas.

V. SIMULATION RESULTS

In this section, we compare a series of bit error rate (BER) performances of our proposed scheme with MRC scheme, for the massive MIMO uplink transmission. A single cell scenario is considered, consisting of one single-antenna UT and one BS with a large number of antennas. More specifically, we assume \( N_{Tx} = 1 \), \( N_{Rx} = 16, 64 \) or 128. BPSK modulation is applied in our simulations. The effect of sparsity of the channel gain vector, antenna spatial correlation and imperfect channel estimation can be taken into account by adjusting the value of the parameter \( K_s, \phi \) and \( \tau \) in our programme.

Fig. 11 demonstrates the BER performance of the both schemes with different SNR per bit levels. The total number of BS antennas \( N_{Tx} \) is set to 64, and correspondingly, we select the half number, i.e., \( K_s \) equals to 32 out of 64, and more than half number of the BS antennas, i.e., \( K_s \) is equal to 50 out of 64. Also, we examine several combinations of \( \phi \) and \( \tau \). It is not surprising to observe that the both schemes are considerably impacted by the high level of \( K_s \), \( \phi \) and \( \tau \). However, due to the effective antenna selection process in our algorithms that can minimise the effect of highly correlated channels as well as the channel estimation error during the transmission, our proposed scheme with larger number of selected antennas (i.e., \( K_s = 50 \)) has nearly same performance as MRC, and the gap between the results of MRC and our method with only half antennas selected is fairly negligible. Notice that we show
Fig. 1. BER versus SNR comparison between our proposed scheme and MRC scheme for Massive MIMO uplinks \((N_{Rx} = 64)\), with different levels of \(K_s\), \(\tau\) and \(\phi\), and BPSK modulation.

Fig. 2. BER versus \(\phi\) performance comparison for our scheme and MRC with \((N_{Rx} = 64)\) and high estimation error (i.e., \(\tau = 0.8\)), and different levels of \(K_s\), in the low SNR regime (SNR = 2dB). BPSK applied.

Fig. 3. BER versus \(\phi\) performance comparison for our scheme and MRC with \((N_{Rx} = 16)\), and different levels of \(K_s\) and \(\tau\), in the low SNR regime (SNR = 2dB). BPSK applied.

the case with high levels of antenna correlation and channel estimation error (e.g., \(\phi\) and \(\tau\) equal to 0.6 or even 0.8). In fact, such highly correlated channels can be experienced in our system since the very large BS antenna equipped. In addition, the high level of channel estimation error can be certainly introduced, due to the realistic transmission conditions such as limited feedback and high mobility of UT.

After the general observation of the performance in Fig. 1, now we focus on the effect of different combinations of \(\tau\) and \(\phi\), and the required number of selected antennas, shown in Fig. 2 and Fig. 3 respectively. First, Fig. 2 illustrates the BER performance of the case, with \(N_{Rx} = 64\), \(K_s = 16\), 32 or 50, and \(\tau = 0.8\), by viewing a different aspect from Fig. 1 i.e., with different levels of \(\phi\) and in the low SNR regime (SNR = 2dB). It is shown that our scheme has very similar performance with MRC, especially in the high region of \(\phi\). In order to take a closer look of the performance with lower \(\tau\), in Fig. 3, we choose a lower number of \(N_{Rx}\), equals to 16, and select 8 or 10 antennas out of 16. The conclusion holds as well that the compared to the MRC, the performance of our proposed scheme is not degraded by combining only selected antennas, with high levels of \(\tau\) and \(\phi\) involving. Then, in the interest of high levels of antenna spatial correlation (\(\phi = 0.8\)) and imperfect channel estimation (\(\tau = 0.8\)), Fig. 4 shows the BER performance versus the number of selected antenna \(K_s\) of our scheme and MRC, for the massive MIMO uplinks with different levels of SNR. For the high SNR regime, the BER performance of our scheme is closely approached to that of MRC for \(N_{Rx} = 64\) is around 35. For the low SNR regime, approximately measuring, the required number of selected antenna \(K_s\) is equal to 60 for \(N_{Rx} = 128\), or only 30 for \(N_{Rx} = 64\). It is suggested that when the bad transmission condition introduced in our system, e.g., low SNR regime and high levels of \(\phi\) and \(\tau\), our proposed scheme has similar, even identical performance as the MRC scheme, with less than half antennas selected, due to the effective selection process designed for different transmission situations.

A. Complexity Analysis

The MRC algorithm requires a number of signal processing for entire diversity channels, which significantly increases the hardware complexity and cost due to the implementation of RF chains for all antennas in the massive MIMO system [9]. Instead, our proposed selection scheme allows the receiver to restore the signal to its original shape, only by weighting few (e.g., even less than the half number of antennas that shown
in Fig. 1 and 4 selected channels with the sparsely structured channel gain vector, and without degrading the system performance, which is a dramatic improvement in reducing the implementation overhead, e.g., the required number of RF chains, in practice. Consider the OMP algorithm presented in [13], [21] and [24], the input components are based on the channel estimation, which can be physically performed on each antenna with a less complex device rather than the full transceiver [9]. Then the antenna selection can be realised by using the output vector, i.e., the $N_{Rx} \times 1$-dimensional channel gain vector with only $K_s$ nonzero elements. In addition, the iteration times is equal to the stopping criterion $K_s$. Hence, the computational complexity of the OMP algorithms is $O(K_s^3 N_{Rx})$ [17].

VI. CONCLUSION

Throughout this work, we proposed a new antenna selection scheme for the massive MIMO uplink transmission by applying the sparsely structured channel gain vector, and then generalised our proposed scheme with the consideration of spatial correlation and imperfect channel estimation. Numerical simulation results show that when the severe transmission condition is experienced in our system, such as very low SNR regime, highly correlated channel and considerable estimation error, our proposed scheme has closely approached performance as the well-adopted MRC scheme, but requiring few selected antennas, due to the effective selection process by applying the sparsely structured channel gain vector, which can significantly reduce the implementation overhead.

REFERENCES

[1] T. Marzetta, “Noncooperative Cellular Wireless with Unlimited Numbers of Base Station Antennas,” Wireless Communications, IEEE Transactions on, vol. 9, no. 11, pp. 3590–3600, November 2010.
[2] F. Rusek, D. Persson, B. K. Lau, E. Larsson, T. Marzetta, O. Edfors, and F. Tufvesson, “Scaling Up MIMO: Opportunities and Challenges with Very Large Arrays,” Signal Processing Magazine, IEEE, vol. 30, no. 1, pp. 40–60, Jan 2013.
[3] E. Larsson, O. Edfors, F. Tufvesson, and T. Marzetta, “Massive MIMO for next generation wireless systems,” Communications Magazine, IEEE, vol. 52, no. 2, pp. 186–195, February 2014.
[4] F. Boccardi, J. Heath, R.W., A. Lozano, T. Marzetta, and P. Popovski, “Five disruptive technology directions for 5G,” Communications Magazine, IEEE, vol. 52, no. 2, pp. 74–80, February 2014.
[5] S. Wagner, R. Couillet, M. Debbah, and D. T. M. Slock, “Large System Analysis of Linear Precoding in Correlated MISO Broadcast Channels Under Limited Feedback,” Information Theory, IEEE Transactions on, vol. 58, no. 7, pp. 4509–4537, 2012.
[6] J. Hoydis, S. ten Brink, and M. Debbah, “Massive MIMO in the UL/DL of Cellular Networks: How Many Antennas Do We Need?” Selected Areas in Communications, IEEE Journal on, vol. 31, no. 2, pp. 160–171, February 2013.
[7] H. Ngo, E. Larsson, and T. Marzetta, “The Multicell Multimuser MIMO Uplink with Very Large Antenna Arrays and a Finite-Dimensional Channel,” Communications, IEEE Transactions on, vol. 61, no. 6, pp. 2350–2361, June 2013.
[8] B. M. Lee, J. Choi, J. Bang, and B.-C. Kang, “An energy efficient antenna selection for large scale green MIMO systems,” in Circuits and Systems (ISCAS), 2013 IEEE International Symposium on, May 2013, pp. 950–953.
[9] X. Gao, O. Edfors, J. Liu, and F. Tufvesson, “Antenna selection in measured massive MIMO channels using convex optimization,” in IEEE GLOBECOM 2013 Workshop on Emerging Technologies for LTE-Advanced and Beyond-4G, 2013.
[10] A. Ghrayeb, “A Survey on Antenna Selection for MIMO Communication Systems,” in Information and Communication Technologies, 2006. ICTTA ’06. 2nd, vol. 2, 2006, pp. 2104–2109.
[11] W. Li and N. Baulieu, “Effects of channel-estimation errors on receiver selection-combining schemes for Alamouti MIMO systems with BPSK,” Communications, IEEE Transactions on, vol. 54, no. 1, pp. 169–178, Jan 2006.
[12] J. Lee and N. Al-Dhahir, “Exploiting Sparsity for Multiple Relay Selection with Relay Gain Control in Large AF Relay Networks,” Wireless Communications Letters, IEEE, vol. 2, no. 3, pp. 347–350, 2013.
[13] S. Chatzinotas, M. Imran, and R. Hoshny, “On the multicell processing capacity of the cellular MIMO uplink channel in correlated Rayleigh fading environment,” Wireless Communications, IEEE Transactions on, vol. 8, no. 7, pp. 3704–3715, 2009.
[14] J. Zhang, C.-K. Wen, S. Jin, X. Gao, and K.-K. Wong, “On Capacity of Large-Scale MIMO Multiple Access Channels with Distributed Sets of Correlated Antennas,” Selected Areas in Communications, IEEE Journal on, vol. 31, no. 2, pp. 133–148, February 2013.
[15] L. Mesbian and S. Aissa, “On the achievable sum-rate of correlated MIMO multiple access channel with imperfect channel estimation,” Wireless Communications, IEEE Transactions on, vol. 7, no. 7, pp. 2549–2559, July 2008.
[16] B. Nosrat-Makeouei, J. Andrews, and R. Heath, “MIMO Interference Alignment Over Correlated Channels With Imperfect CSI,” Signal Processing, IEEE Transactions on, vol. 59, no. 6, pp. 2783–2794, 2011.
[17] J. Tropp and A. Gilbert, “Signal Recovery From Random Measurements Via Orthogonal Matching Pursuit,” Information Theory, IEEE Transactions on, vol. 53, no. 12, pp. 4655–4666, 2007.