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Research Article

Low-Complexity Transmit Antenna Selection and Beamforming for Large-Scale MIMO Communications

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Transmit antenna selection plays an important role in large-scale multiple-input multiple-output (MIMO) communications, but optimal large-scale MIMO antenna selection is a technical challenge. Exhaustive search is often employed in antenna selection, but it cannot be efficiently implemented in large-scale MIMO communication systems due to its prohibitive high computation complexity. This paper proposes a low-complexity interactive multiple-parameter optimization method for joint transmit antenna selection and beamforming in large-scale MIMO communication systems. The objective is to jointly maximize the channel outrage capacity and signal-to-noise (SNR) performance and minimize the mean square error in transmit antenna selection and minimum variance distortionless response (MVDR) beamforming without exhaustive search. The effectiveness of all the proposed methods is verified by extensive simulation results. It is shown that the required antenna selection processing time of the proposed method does not increase along with the increase of selected antennas, but the computation complexity of conventional exhaustive search method will significantly increase when large-scale antennas are employed in the system. This is particularly useful in antenna selection for large-scale MIMO communication systems.

1. Introduction

Large-scale multiple-input multiple-output (MIMO) with a very large number of antennas has been an active research topic in wireless communication and navigation systems [1–5]. The research focus is placed on multiuser MIMO communications [6–9] and communications on the uplink as well as the downlink [10–12] in such large systems. The main motivation of large-scale MIMO is the potential to realize theoretically predicted MIMO benefits in terms of very high spectral efficiencies, increased reliability, and power efficiency [6]. This is because more antennas mean more degrees-of-freedom (DOFs) that the propagation channel can provide. Certainly, the number of antennas cannot be arbitrarily large in a practical system due to physical space constraints [13]. It is recommend in [1] that the systems should have at least 100 antennas at the base station, but probably fewer than 1000. Large-scale MIMO systems also have a potential to reduce the operational power at the transmitter and enable the use of low-complexity schemes for suppressing multiuser interferences [12]. Large-scale MIMO communications are thus envisaged for next-generation wireless systems.

However, the price to pay for large-scale MIMO is increased radio frequency (RF) hardware complexities. Antenna selection is an elegant solution to such problems [14] (see [15–20] and the references therein). In particular, a fast MIMO antenna subset based on the QR decomposition of channel matrix is proposed in [21]. In [22], a fast and efficient transmit antenna selection algorithm is developed based on maximum-volume submatrix searching. But these methods are usually impractical for large-scale MIMO communications, as they require complex search algorithms and consequently the excessive number of antennas in large-scale MIMO hinders the efficient antenna selection. A random antenna selection is proposed in [23], but a perfect random antenna selection is difficult to implement for actual large-scale MIMO systems.

Large-scale MIMO brings also signal processing complexities. Transmitter-based processing techniques are commonly employed to transfer the processing complexity from the mobile units to the base station, thus facilitating cheap and energy efficient mobile units. To reduce signal processing complexity, beamforming is necessary for large-scale MIMO systems [13]. Although transmit-receive beamforming is widely employed in general MIMO systems [24–26], much less is known about beamforming for large-scale MIMO communications [27–33]. Even so, the literature focuses on receive beamforming, not transmit beamforming. Moreover, antenna selection is often ignored in the transmit beamforming literature. It is thus necessary to develop joint transmit antenna selection and beamforming algorithms for large-scale MIMO communication systems.

This paper considers low-complexity and joint transmit antenna selection and beamforming for large-scale MIMO communication systems. Joint antenna selection and beamforming have not only great theoretical interest, but also good practical useness [34–37]. In particular, a joint transmit beamforming and antenna selection for cognitive radio networks is proposed in [37]. The objective is to maximize the achievable rates of the secondary users to the interference constraints on the primary users exploiting transmit beamforming at secondary user transmitter while reducing the costs associated with RF chains at the radio front end. A joint multicast beamforming and antenna selection is proposed in [34]. The objective is to select sparse beamforming vectors such that the transmit power is minimized, subject to the signal-to-noise ratio (SNR) constraints at all subscribers. We concentrate on convex optimization-based joint transmit antenna selection and beamforming. Although convex optimization has been widely employed in antenna selection and beamforming [34, 38, 39], they often require an exhaustive search. In [37, 40], the original nonconvex optimization problem is approximated by using an iterative approach to solve a series of smaller convex problems, but they concentrate on the receive antenna selection.

To avoid exhaustive search in antenna selection, we present a low-complexity interactive multiple-parameter optimization approach for joint transmit antenna selection and beamforming for large-scale MIMO communication systems. Our objective is to jointly maximize the channel outrage capacity and SNR performance and minimize the mean square error in transmit antenna selection and minimum variance distortionless response (MVDR) beamforming without exhaustive search. The proposed method first selects an initial transmit antenna subset and estimates the weight vector using the MVDR beamformer. Next, the transmit antenna subset is updated by the optimization algorithm. The final antenna subset and weight vector are determined after several repeated optimization steps.

The remaining sections of this paper are organized as follows. Section 2 formalizes the background and motivation of this work. Section 3 describes the system model and Section 4 proposes the low-complexity and joint transmit antenna selection and beamforming for large-scale MIMO systems. Next, simulation results that validate all the proposed methods are provided in Section 5. Finally, this paper is concluded in Section 6 with a short discussion of future work.

2. Large-Scale MIMO Communication System Model

In this paper, we consider a large-scale MIMO communication system model, as shown in Figure 1. It comprises a single base station (BS) transmitter with M_t antennas and a M_r-antenna receiver, $M_t \gg M_r$. Antenna selection is implemented at the receiver, and the selected antenna subset is fed back to the transmitter. At the transmitter, we selected M_s transmit antennas from M_t candidates according to the antenna selection criterion and connected them to the M_s RF chains. Also, we do not take into account channel estimation errors, errors in the feedback paths, and time-delays in the feedback paths.

The MIMO channel between the mth and nth antenna at the transmitter and receiver, respectively, is assumed to be quasistatic and flat Rayleigh fading channel $h_{n,m}$, which is modeled as zero mean, stationary complex Gaussian processes, and independent from different paths. Correspondingly, the channel matrix can be denoted by $\mathbf{H} = [\mathbf{h}_1 \ \mathbf{h}_2 \ \cdots \ \mathbf{h}_{M_t}]$, where the $M_r \times 1$ vector $\mathbf{h}_m$ is the channel vector that corresponds to the mth transmit antenna. The channel matrix $\mathbf{H}$ is assumed to be known perfectly at the receiver.

The signal received at the receive side can be expressed as [37]

$$\mathbf{y} = \mathbf{H}\mathbf{w} \odot \mathbf{x} + \mathbf{n}, \tag{1}$$

where $\mathbf{x} = [x_1, x_2, \ldots, x_{M_t}]^T$ with T being the transpose is the transmitted signal, $\odot$ is the Hadamard product, x_i is the transmit symbol from the ith transmit antenna, such as a complex QAM symbol, and $\mathbf{n}$ is the zero-mean additive noise vector ($n \sim CN(0, \mathbf{I}_{\mathrm{Mr}})$). Let $E\{|\mathbf{x}|^2\} = P_s$, subjected to

$$E\left\{\mathbf{w}\mathbf{w}^H|\mathbf{x}|^2\right\} \triangleq \mathbf{w}^H\mathbf{w}P_s \le P_{\max}, \tag{2}$$

where H, P_s, and $P_{\max}$ denote the Hermitian transpose operator, signal power, and maximum transmit power, respectively. The weighting vector $\mathbf{w} \in \mathbb{C}^{M_t \times 1}$ is formed by the beamformer applied to M_t transmit antennas, which should fulfill the transmit power constraint $\|\mathbf{w}\|^2 < 1$.

Without regard to coding and modulation, the MIMO system capacity using all antennas is given by [41]

$$C_{\text{full}}(\mathbf{H}) = \log_2\left[\det\left(\mathbf{I}_{M_r} + \mathbf{H}\mathbf{R}_{ss}\mathbf{H}^H\mathbf{R}_{i+n}^{-1}\right)\right], \tag{3}$$

where $\mathbf{I}_{M_r}$ denotes an $M_r \times M_r$ identity matrix and $\det[\cdot]$ is the matrix determinant. The transmitted signal covariance $\mathbf{R}_{ss}$ and noise-plus-interference covariance $\mathbf{R}_{i+n}$ are determined, respectively, by [37]

$$\begin{aligned} \mathbf{R}_{ss} &= E\left\{\mathbf{w}\mathbf{w}^H|\mathbf{x}|^2\right\} \\ \mathbf{R}_{i+n} &= E\left\{\mathbf{n}\mathbf{n}^H\right\}. \end{aligned} \tag{4}$$

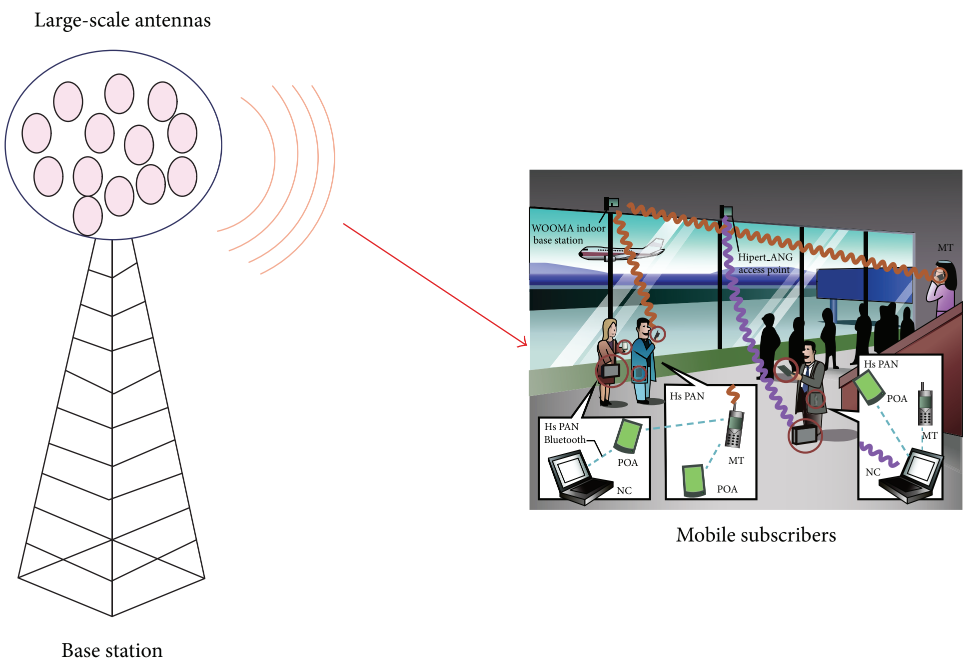

FIGURE 1: Large-scale MIMO communication system model.

Antenna selection is usually implemented at the receiver, and the selected antenna index is fed back to the transmitter. If M_s antennas are selected from the M_t transmit antennas, the system capacity after antenna selection can be expressed as

$$C_{\text{sel}}\left(\mathbf{H}_s, \mathbf{w}\right) = \log_2\left[\det\left(\mathbf{I}_{M_r} + \mathbf{H}_s\mathbf{R}_{ss}\mathbf{H}_s^H\mathbf{R}_{i+n}^{-1}\right)\right], \quad (5)$$

where $\mathbf{H}_s$ is the channel matrix after antenna selection.

Similar to the method used in [40], define a diagonal matrix $\mathbf{S} \in \mathbb{R}^{M_t \times M_t}$ such that

$$(\mathbf{S})_{mm} = \begin{cases} 1, & m\text{th transmit antenna selected} \\ 0, & \text{otherwise.} \end{cases} \quad (6)$$

Now, the chosen channel submatrix can be expressed as

$$\mathbf{H}_s = \mathbf{H}\mathbf{S}. \quad (7)$$

Correspondingly, the data model (1) can be rewritten as

$$\mathbf{y} = \mathbf{H}\mathbf{S}\mathbf{w} \odot \mathbf{x} + \mathbf{n}. \quad (8)$$

The problem of joint transmit antenna selection and beamforming for capacity maximization is approximated by the following optimization problem [37]:

$$\begin{aligned} \max \quad & \log_2 \det\left(\mathbf{I}_{M_r} + P_s\mathbf{H}\widehat{\mathbf{R}}_{i+n}^{-1/2}\mathbf{S}\mathbf{w}\mathbf{w}^H\mathbf{S}^H\widehat{\mathbf{R}}_{i+n}^{-1/2}\mathbf{H}^H\right) \\ \text{s.t.} \quad & (\mathbf{S})_{mm} \in \{0, 1\}, \quad m = 1, 2, \ldots, M_t \\ & \operatorname{trace}(\mathbf{S}) = M_s \\ & \mathbf{w}^H\mathbf{w}E\left\{|\mathbf{x}|^2\right\} \triangleq P_s \le P_{\max} \\ & \|\mathbf{w}\| \le 1 \\ & \text{variables} \quad \mathbf{w}, \mathbf{S}, P_s. \end{aligned} \quad (9)$$

For calculating $\widehat{\mathbf{R}}_{i+n}$, we consider that new noise and interference covariance matrix $\mathbf{R}_{\text{reduced}} \in \mathbb{R}^{M_s \times M_s}$. So, with adding all-zero rows and columns corresponding to the transmit antennas not selected at transmit side, $\mathbf{U}_{\text{reduced}}$ is expanded to result in a matrix $\widehat{\mathbf{R}}_{i+n} \in \mathbb{R}^{M_t \times M_t}$.

Exhaustive search is widely used in current antenna selection literature. However, to select the transmit antennas in the optimal way, we have to be computed for $\binom{M_t}{M_s}$ possible combinations of them. This is not practicable for large-scale MIMO communication systems. A wise suggestion is to use optimization methods, but (9) is a nonconvex problem.

3. Joint Transmit Antenna Selection and Beamforming

When the variables $(\mathbf{S})_{mm}$ are binary valued (0 or 1) integer variables, (9) will be a NP-hard problem. To overcome this disadvantage, we relax the $\mathbf{S}$ to be values in the interval 0 and 1 [38]. In this case, the optimization problem of (9) should be rewritten as [37]

$$\begin{aligned} \max \quad & \log_2 \det\left(\mathbf{I}_{M_r} + P_s\mathbf{H}\mathbf{S}\mathbf{w}\mathbf{w}^H\mathbf{S}^H\mathbf{H}^H\right) \\ \text{s.t.} \quad & 0 \le (\mathbf{S})_{mm} \le 1, \quad m = 1, 2, \ldots, M_t \\ & \operatorname{trace}(\mathbf{S}) = M_s \\ & \mathbf{w}^H\mathbf{w}E\left\{|\mathbf{x}|^2\right\} \triangleq P_s \le P_{\max} \\ & \|\mathbf{w}\| \le 1 \\ & \text{variables} \quad \mathbf{w}, \mathbf{S}, P_s. \end{aligned} \quad (10)$$

This problem is still nonconvex due to nonconcavity of the objective function. As the cost function is concave when two of the three variables are known, [37] proposes a convex optimization solution with iterative processing step: first, the convex optimization problem is solved with an initial value for P_s and $\mathbf{w}$. Next, using the optimum $\mathbf{S}$ and the initial value for P_s, optimum $\mathbf{w}$ is obtained by the convex optimization. Ultimately, the optimum value for transmit power P_s is calculated by solving the resultant convex optimization problem with the optimum $\mathbf{S}$ and $\mathbf{w}$. However, the method may suffer from low convergence rate, since a reduced complexity method has been proposed for an originally nonconvex problem. To overcome this disadvantage, we propose a multiobject optimization problem with iterative processing steps for joint transmit antenna selection and beamforming for large-scale MIMO communication systems.

The first optimization object of our method is to minimize the least squares (LS) estimation error. This LS-based formulation necessitates a pilot-aided transmission protocol and thus provides better performance than the method of [37], which also does not need auxiliary information. Suppose $\mathbf{x}$ is the training symbol transmitted for all M_t transmit antennas and the signal received by the M_r receive antennas is $\mathbf{y}$. The signal model for LS estimation can be formulated as

$$\begin{aligned} \text{P1:}\ \min\quad & \left\| \mathbf{y} - \mathbf{HSw} \odot \mathbf{x} \right\|_2 \\ \text{s.t.}\quad & \mathbf{w}^H \mathbf{w} \le \frac{P_{\max}}{P_s} \\ & \text{variables}\quad \mathbf{w}, \mathbf{S}, \end{aligned} \tag{11}$$

where $P_s = E\{|\mathbf{x}|^2\}$. If the variable $\mathbf{S}$ is known, the cost function will be convex in the other variable $\mathbf{w}$. Consider

$$\begin{aligned} \text{P1:}\ \min\quad & \left\| \mathbf{y} - \mathbf{HSw} \odot \mathbf{x} \right\|_2 \\ \text{s.t.}\quad & \operatorname{trace}(\mathbf{S}) = M_s \\ & 0 \le (\mathbf{S})_{mm} \le 1, \quad m = 1, 2, \ldots, M_t \\ & \text{variables}\quad \mathbf{S}. \end{aligned} \tag{12}$$

In this case, the optimization problem of (12) can then be cast as a semidefinite programming (SDP) problem.

The second optimization object of our method is to maximize the output SNR. Let the equivalent $M_t \times 1$ beamforming vector after the antenna selection matrix $\mathbf{S}$ combing $\mathbf{w}$ denoted by

$$\widetilde{\mathbf{w}} = \mathbf{Sw}. \tag{13}$$

Then, the joint optimization problem of the transmit antenna selection and beamforming for maximum output SNR can be formulated as follows:

$$\text{P2:}\ \max \|\mathbf{H}\widetilde{\mathbf{w}}\|_2^2. \tag{14}$$

Although the weight vector also can be chosen by maximizing the achievable rate, we choose the weight vector by maximizing the SNR to avoid the nonconvex optimization problem as [37]. Using the fact that $\|\mathbf{H}\widetilde{\mathbf{w}}\|_2 \ge t$ if and only if $(\mathbf{H}\widetilde{\mathbf{w}})^T(\mathbf{H}\widetilde{\mathbf{w}}) \ge t^2\mathbf{I}$ (and $t \ge 0$), we can express the problem in the following form:

$$\begin{aligned} \text{P2:}\ \max\quad & t \\ \text{s.t.}\quad & (\mathbf{H}\widetilde{\mathbf{w}})^T (\mathbf{H}\widetilde{\mathbf{w}}) \ge t\mathbf{I} \\ & \text{variables}\quad \widetilde{\mathbf{w}}. \end{aligned} \tag{15}$$

The above optimization problem can be solved by SVD decomposition as follows:

$$\begin{aligned} \widetilde{\mathbf{w}}_{\text{opt}} &= \arg\max_{\|\widetilde{\mathbf{w}}\|=1} E\left\{ \left| \mathbf{H}^H \widetilde{\mathbf{w}} \right|^2 \right\} = \arg\max_{\|\widetilde{\mathbf{w}}\|=1} \widetilde{\mathbf{w}}^H R \widetilde{\mathbf{w}} \\ &= (\text{principal eigenvector}) \text{ of } R, \end{aligned} \tag{16}$$

where $R = E\{\mathbf{H}^H\mathbf{H}\}$ is the correlation matrix of $\mathbf{H}$ and the principal eigenvector is the eigenvector corresponding to the largest eigenvalue of $\mathbf{R}$. Once the optimum $\widetilde{\mathbf{w}}$ is obtained and $\mathbf{S}$ is known from (12), the weighting vector $\mathbf{w}$ can be expressed as

$$\mathbf{w} = \frac{\widetilde{\mathbf{w}}}{\mathbf{S}}. \tag{17}$$

Using the optimum $\mathbf{w}$ and $\mathbf{S}$ obtained by (12) and (17), respectively, the third optimization object of our method is to maximize the channel capacity. Consider

$$\begin{aligned} \text{P3:}\ \max\quad & \log_2 \det\left(\mathbf{I}_{M_r} + P_s \mathbf{H}\widetilde{\mathbf{w}}\widetilde{\mathbf{w}}^H \mathbf{H}^H \right) \\ \text{s.t.}\quad & \operatorname{trace}\left(\mathbf{w}\mathbf{w}^{\mathbf{H}} \mathbf{P}_{\mathbf{s}} \right) \le P_{\max} \\ & \text{variables}\quad P_s. \end{aligned} \tag{18}$$

P3 can be reformulated as follows:

$$\begin{aligned} C &= \max \log_2 \det\left(\mathbf{I}_{M_r} + P_s \mathbf{H}\widetilde{\mathbf{w}}\widetilde{\mathbf{w}}^H \mathbf{H}^H \right) \\ &= \max \prod_{i=1}^{k} \left(1 + P_s \sigma_i^2 \right) \\ &\approx \max \left(k \log_2 (P_s) + \sum_{i=1}^{k} \log_2 \sigma_i^2 \right), \end{aligned} \tag{19}$$

where σ_i^2, $i = 1, 2, \ldots, k$ are the nonzero singular values of the channel matrix $\mathbf{H}$, $k \le \min(M_t, M_r)$. So, when $P_s = P_{\max}/\operatorname{trace}(\mathbf{w}\mathbf{w}^{\mathbf{H}})$, P3 can be optimized.

Therefore, the joint transmit antenna selection and beamforming can be processed in the following procedure: at first, we solve the P1 optimization problem with an initial value for $\mathbf{w}$, and then using the optimum $\mathbf{S}$, optimum $\mathbf{w}$ is obtained by solving the P2 optimization problem and ultimately, by having $\mathbf{S}$ and $\mathbf{w}$ at hand, optimum value for the transmit power P_s is calculated by solving the P3 convex optimization problem. Since the elements of $\mathbf{S}$ are nonbinary, the index of chosen antennas are the M_s-largest diagonal elements of $\mathbf{S}$. The detailed processing procedure is illustrated in Algorithm 1.

Input: M_t, M_r and M_s
Output: $\mathbf{w}$, $\mathbf{S}$ and P_s
(1) **function** Estimating $\mathbf{S}$ by LS
(2) $\mathbf{w} \leftarrow$ select an initial value for $\mathbf{w}$
(3) $P_s \leftarrow$ select an initial value for P_s
(4) $\mathbf{S} \leftarrow$ solve the optimization problem of P1 (12) and find the solution $\mathbf{S}$.
(5) **return** $\mathbf{S}$
(6) **end function**
(7)
(8) **function** Estimating $\mathbf{w}$ by maximizing the output SNR
(9) $\mathbf{S} \leftarrow$ the optimum $\mathbf{S}$ of P1.
(10) $P_s \leftarrow$ the initial value of P_s.
(11) $\mathbf{w} \leftarrow$ solve the optimization problem of P2 (15) and find the solution $\mathbf{w}$.
(12) **return** $\mathbf{w}$
(13) **end function**
(14)
(15) **function** Estimating P_s by maximizing the channel capacity
(16) $\mathbf{S} \leftarrow$ the optimum $\mathbf{S}$ of P1.
(17) $\mathbf{w} \leftarrow$ the optimum $\mathbf{w}$ of P2.
(18) $P_s \leftarrow$ solve the optimization problem of P3 (18) and find the solution P_s.
(19) **return** P_s
(20) **end function**
(21)
(22) **Iteration:** Rerun the steps 1 to 20 for some appropriate number of iterations and the achievable performance will be the average of results at that specific SNR.
(23) **return** $\mathbf{w}$, $\mathbf{S}$ and P_s
(24) Finally, the antennas are chosen corresponding to the M_s-largest diagonal elements of $\mathbf{S}$.

Algorithm 1: Processing procedure of the proposed low-complexity and joint transmit antenna selection and beamforming for large-scale MIMO communications.

4. Performance Analysis

The cumulative distribution function (CDF) and pairwise error probability (PEP) are analyzed in this section.

4.1. Cumulative Distribution Function. Even for the exhaustive search method, it is noted in [40] that a general performance analysis of the MIMO system with antenna selection is highly complex, and thus, a specific CDF of the SNR with single link selection is derived in the literature. As it is difficult to derive a general CDF analysis for the large-scale MIMO communication system with joint transmit antenna selection and beamforming, we also derive the CDF with single-link and evaluate the general large-scale MIMO CDF performance through Monte Carlo simulations in Section 5.

The SNR of one transmit-receive link can be represented by

$$Y = \max_{n,m} P_s \left|h_{nm}\right|^2. \tag{20}$$

The CDF of Y is as

$$\begin{aligned}\mathbb{F}_Y(y) &= \mathbb{P}\left(\max_{n,m} P_s \left|h_{nm}\right|^2 \le y\right) \\ &= \mathbb{E}\left\{\mathbb{P}\left(\left|h_{nm}\right|^2 \le \frac{y}{P_s}\right)\right\} \\ &= \left[\sum_{n=0}^{M_r} C_{M_r}^{n}(-1)^n \mathbb{E}\left\{\exp\left(-\frac{n}{P_s}y\right)\right\}\right]^{M_t}.\end{aligned} \tag{21}$$

Let

$$Z = \max_{n}\left|h_{nm}\right|^2. \tag{22}$$

Its CDF and probability distribution function (PDF) are represented, respectively, by

$$\mathbb{F}_Z(z) = \mathbb{P}\left(\left|h_{nm}\right|^2 \le z\right) = \prod_{n=1}^{M_r}\left(1 - e^{-\lambda_n z}\right) \tag{23}$$

$$f_Z(z) = \sum_{n=1}^{M_r} \lambda_n e^{-\lambda_n z} \prod_{n=1}^{M_r}\left(1 - e^{-\lambda_n z}\right), \tag{24}$$

where we assume the $\left|h_{nm}\right|^2$ are exponentially distributed with means $1/\lambda_n$. Equations (21) to (24) are derived from [40]. The expectation in (21) can then be derived as

$$\begin{aligned}\mathbb{E}\left\{\exp\left(-\frac{n}{P_s}y\right)\right\} &= \int_0^\infty \exp\left(-\frac{n}{P_s}y\right) f_Z(z)\,\mathrm{d}z \\ &= \exp\left(-\frac{n}{P_s}y\right)\mathbb{F}_Z(\infty) \\ &\cong \exp\left(-\frac{n}{P_s}y\right).\end{aligned} \tag{25}$$

Substituting (25) to (21), we then have

$$\mathbb{F}_Y(y) = \left[\sum_{n=0}^{M_r} C_{M_r}^n (-1)^n \exp\left(-\frac{n}{P_s}y\right)\right]^{M_t}. \tag{26}$$

This is a closed-form CDF for the optimal one-link selection capacity with the optimized power constraints, but it is suitable only for one-link configuration; that is, the selected system should be single-input single-output (SISO) system. In Section 5, we will further simulate the general CDF performance for large-scale MIMO communication with joint transmit antenna selection and beamforming.

4.2. Conditional Pair Error Probability. Consider the signal model (1); the maximum likelihood (ML) detection of the transmitted signal vector is [42]

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{y} - \mathbf{H}_{sw}\mathbf{x}\|^2, \tag{27}$$

where

$$\mathbf{H}_{sw} = \mathbf{HSw} \tag{28}$$

is the equivalent channel matrix after joint transmit antenna selection and beamforming. Since it is difficult to derive the exact error probability with a closed form, the union bound on error probability is often calculated alternatively by using the conditional PEP [43]. It can be represented by [44, 45]

$$\begin{aligned}&\mathbb{P}(\mathbf{x} \longrightarrow \hat{\mathbf{x}} \mid \mathbf{H}_{sw}) \\ &\quad = \mathbb{P}\left(\|\mathbf{y} - \mathbf{H}_{sw}\hat{\mathbf{x}}\|^2 < \|\mathbf{y} - \mathbf{H}_{sw}\mathbf{x}\|^2\right) \\ &\quad = \mathbb{P}\left(\|\mathbf{H}_{sw}[\mathbf{x} - \hat{\mathbf{x}}]\|^2 + \|\mathbf{v}\|^2 \right. \\ &\qquad \left. + 2\Re\left\{\operatorname{tr}\left(\mathbf{H}_{sw}[\mathbf{x} - \hat{\mathbf{x}}]^H\right)\right\} < \|\mathbf{v}\|^2\right),\end{aligned} \tag{29}$$

where $\Re(\cdot)$ and $\operatorname{tr}(\cdot)$ are the real part of a complex signal and trace of a matrix, respectively.

Since $2\Re\{\operatorname{tr}(\mathbf{H}_{sw}[\mathbf{x} - \hat{\mathbf{x}}]^H)\}$ is a real Gaussian random variable with zero mean and variance $2\sigma_n^2\|\mathbf{H}_{sw}[\mathbf{x} - \hat{\mathbf{x}}]\|^2$, the conditional PEP is then derived as

$$\begin{aligned}&\mathbb{P}(\mathbf{x} \longrightarrow \hat{\mathbf{x}} \mid \mathbf{H}_{sw}) \\ &\quad = \mathbb{Q}\left(\sqrt{\frac{1}{2\sigma_n^2}\|\mathbf{H}_{sw}[\mathbf{x} - \hat{\mathbf{x}}]\|^2}\right) \\ &\quad = \frac{1}{\pi}\int_0^{\pi/2} \exp\left(-\frac{\|\mathbf{H}_{sw}[\mathbf{x} - \hat{\mathbf{x}}]\|^2}{4\sigma_n^2\sin^2\theta}\right)\mathrm{d}\theta,\end{aligned} \tag{30}$$

where

$$\begin{aligned}\mathbb{Q}(x) &= \frac{1}{\sqrt{2\pi}}\int_x^\infty \exp\left(-\frac{y^2}{2}\right)\mathrm{d}y \\ &= \frac{1}{\pi}\int_0^{\pi/2} \exp\left(-\frac{x^2}{2\sin^2\theta}\right)\mathrm{d}\theta\end{aligned} \tag{31}$$

is used in deriving the second equation [46]. In doing so, the average PEP can be derived as [47]

$$\begin{aligned}&\mathbb{E}\{\mathbb{P}(\mathbf{x} \longrightarrow \hat{\mathbf{x}})\} \\ &\quad = \mathbb{Q}\left(\sqrt{\frac{1}{2\sigma_n^2}\|\mathbf{H}_{sw}[\mathbf{x} - \hat{\mathbf{x}}]\|^2}\right) \\ &\quad = \frac{1}{\pi}\int_0^{\pi/2} \mathbb{E}\left\{\exp\left(-\frac{\|\mathbf{H}_{sw}[\mathbf{x} - \hat{\mathbf{x}}]\|^2}{4\sigma_n^2\sin^2\theta}\right)\right\}\mathrm{d}\theta \\ &\quad = \frac{1}{\pi}\int_0^{\pi/2} \left(\mathbb{E}\left\{\exp\left(-\frac{\|[\mathbf{H}_{sw}]_i[\mathbf{x} - \hat{\mathbf{x}}]\|^2}{4\sigma_n^2\sin^2\theta}\right)\right\}\right)^{M_r}\mathrm{d}\theta \\ &\quad = \frac{1}{\pi}\int_0^{\pi/2} \left|\mathbf{I} + \frac{1}{4\sigma_n^2\sin^2\theta}\mathbb{E}\left\{[\mathbf{H}_s]_i^H[\mathbf{H}_{sw}]_i\right\}\right. \\ &\qquad \left. \cdot (\mathbf{x} - \hat{\mathbf{x}})(\mathbf{x} - \hat{\mathbf{x}})^H\right|^{-M_r}\mathrm{d}\theta,\end{aligned} \tag{32}$$

where $[\mathbf{H}_{sw}]_i$ is the ith row of $\mathbf{H}_{sw}$.

The lower bound is [48]

$$\begin{aligned}&\mathbb{E}\{\mathbb{P}(\mathbf{x} \longrightarrow \hat{\mathbf{x}})\} \\ &\quad \geq \frac{1}{\pi}\int_0^{\pi/2}\left[\frac{1}{1 + \left(|x_1 - \hat{x}_1|^2/4\sigma_n^2\sin^2\theta\right)}\right]^{M_r(M_t - M_s + 1)}\mathrm{d}\theta,\end{aligned} \tag{33}$$

where x_1 and $\hat{x}_1$ denote one element of the $\mathbf{x}$ and $\hat{\mathbf{x}}$, respectively. Obviously, the lower bound is improved when more antennas are employed in the system. This validates the advantage of large-scale MIMO in achieving better lower estimation bound in signal detection.

5. Simulation Results

In this section, we provide extensive simulations to evaluate our proposed method. To compare the different approaches, we use the measures of CDF versus the achievable rates, channel capability, SNR improvement, and optimization processing time. Unless stated otherwise, the CDF curves and each point on the simulation graphs are determined by averaging over the results obtained from 500 i.i.d. channel realizations.

First, we simulate the advantages of large-scale antennas in MIMO communications. Figure 2 demonstrates that 20×2 antenna selection from larger ($80 \times 2 > 25 \times 2$) systems can enhance the CDF of capability to reach and go beyond the

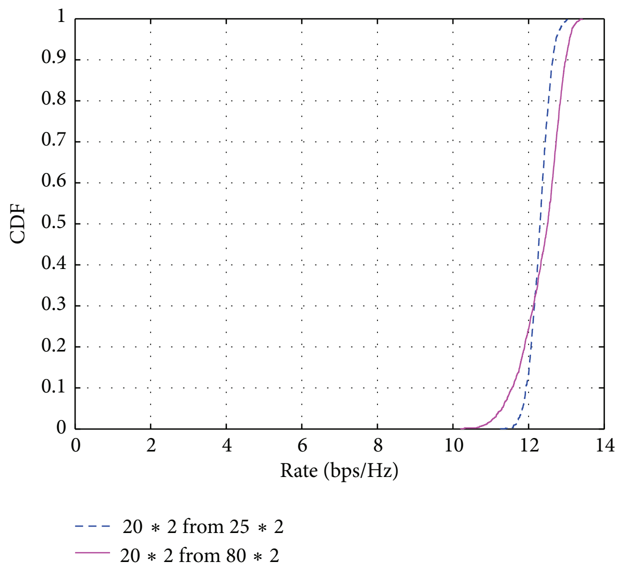

Figure 2: Impact of MIMO system size on CDF.

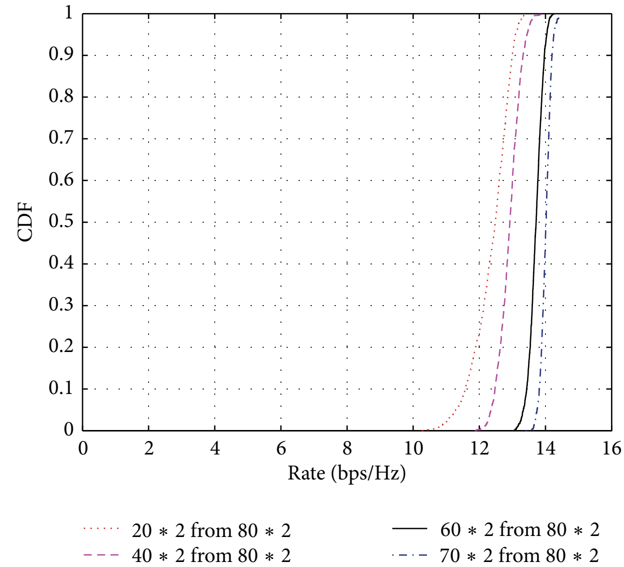

Figure 4: CDFs of rates for various M_s for a MIMO with a fixed M_t.

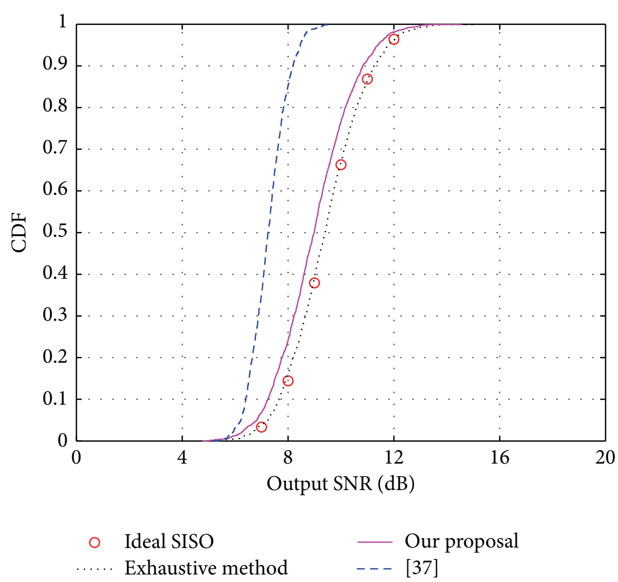

Figure 3: Comparison of simulated and theoretical CDFs.

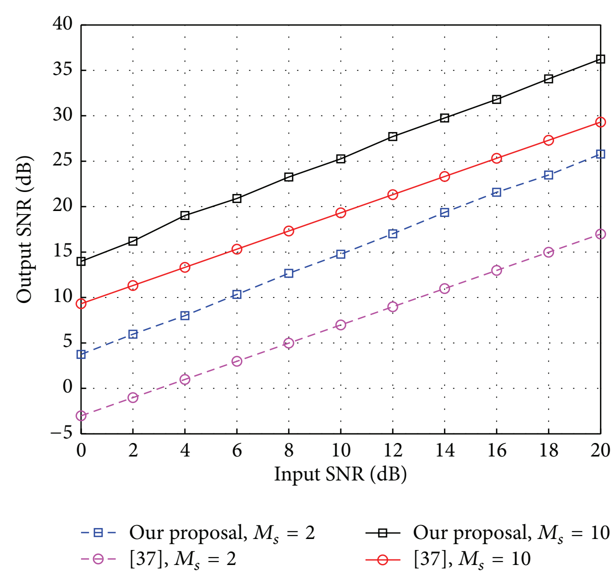

Figure 5: Output SNR versus input SNR.

benchmark performance of a 20×2 system. To investigate the feasibility of our interactive optimization algorithm in transmit antenna selection, Figure 3 compares the simulated and theoretical CDFs for SISO selected link, including [37] as mentioned above (10), where the theoretical results are derived from (24). It can be observed that satisfactory performance is achieved, which validates the effectiveness of our method.

Next, we consider a large-scale MIMO system with 80 antennas in the transmitter and 2 antennas in the receiver. Suppose the input SNR is 20 dB and use the proposed Algorithm 1 to optimally design the joint transmit antenna selection and beamforming. Figure 4 compares the CDF of capability for various number of selected transmit antennas. Three iterations are used in the optimization algorithm for all the simulations. Obviously, the CDF of capability is increased when more transmit antennas are selected in the system. Figure 5 shows the output SNR as a function of input SNR. Antenna number is also configured to 80×2, and input SNR 20 dB is selected. It can be noticed that the output SNR performance is improved when more antennas are selected. This validates again the advantage of large-scale MIMO in improving wireless communication system capability.

Furthermore, we compare our method with the conventional exhaustive search and [37] in antenna selection. Without loss of generality, to avoid the problem of "out of memory" in the PC- (personal computer-) based MATLAB numerical simulations, a relative small number of transmit

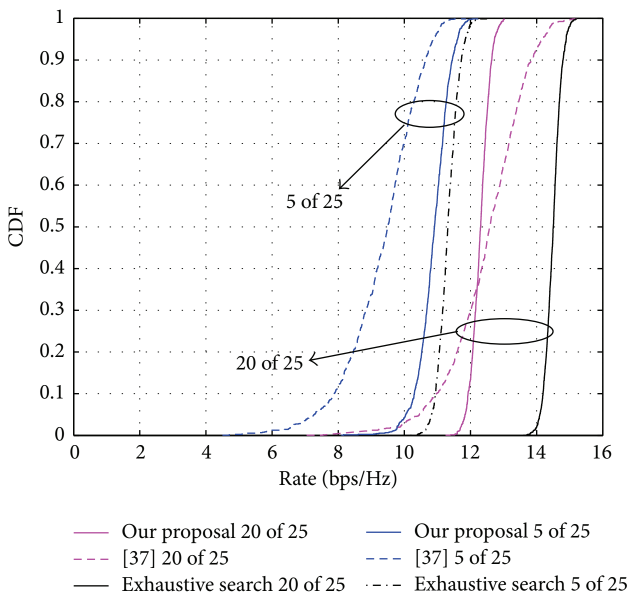

FIGURE 6: Comparison of CDF versus achievable rates of our proposal with exhaustive search method and [37].

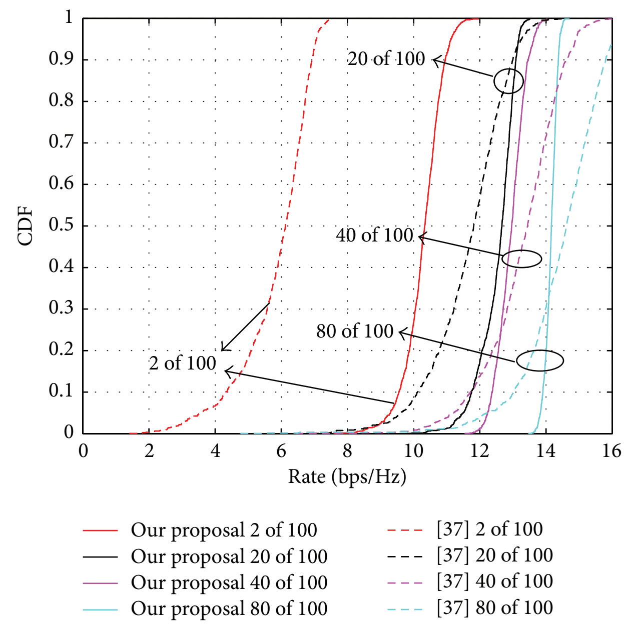

FIGURE 8: Comparison of CDF versus achievable rates of our proposal with [37] when M_t = 100.

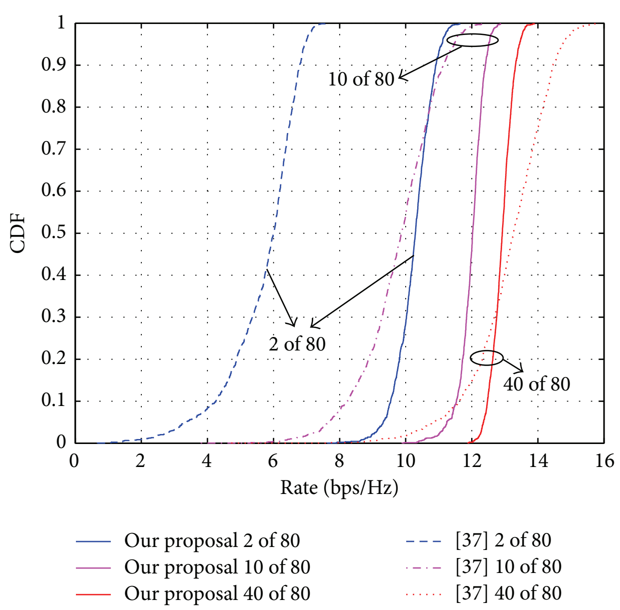

FIGURE 7: Comparison of CDF versus achievable rates of our proposal with [37] when M_t = 80.

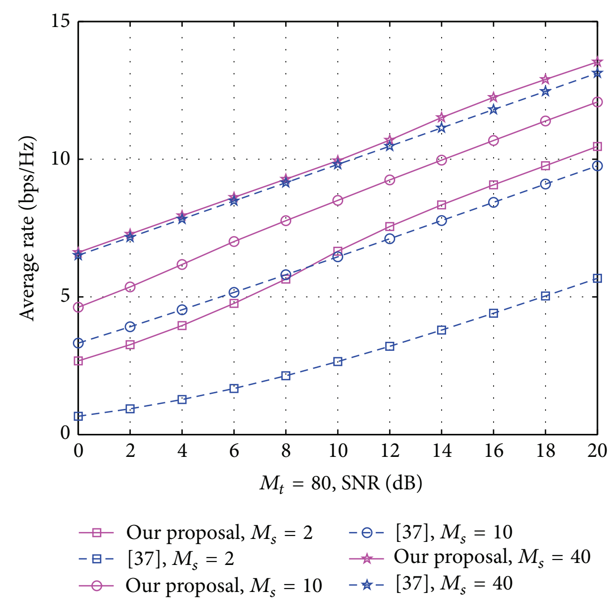

FIGURE 9: M_t = 80, comparison of system capability versus SNR.

antennas, namely, $M_t = 25$, is used and fixed in this simulation. Figure 6 compares the CDF of the achievable rates of our method with the conventional exhaustive search method for various number of selected transmit antennas. When it comes to large number of antennas, transmit antenna number 80 is considered. In this case, exhaustive search cannot be realized successfully, so we just compare our proposal with [37] in Figure 7. Transmit antenna number 100 is considered in Figure 8; we can see that the changing trend is almost similar to Figure 7, and its performance has a little improvement with the increase of transmit antenna number. From Figures 6–8, we notice that the CDF of our proposal goes beyond the performance of [37] when less antenna number (M_s) is selected from transmit side and is very close to the exhaustive search. Our performance is relatively low when more M_s is chosen, but our proposal is superior to [37] in the output SNR and the averaged conditional PEP. Figure 9 compares the system capability as a function of SNR. It is observed that our method outperforms [37].

Using the simulation computer is with the following configuration parameters: the computer processor is "Inter(R)

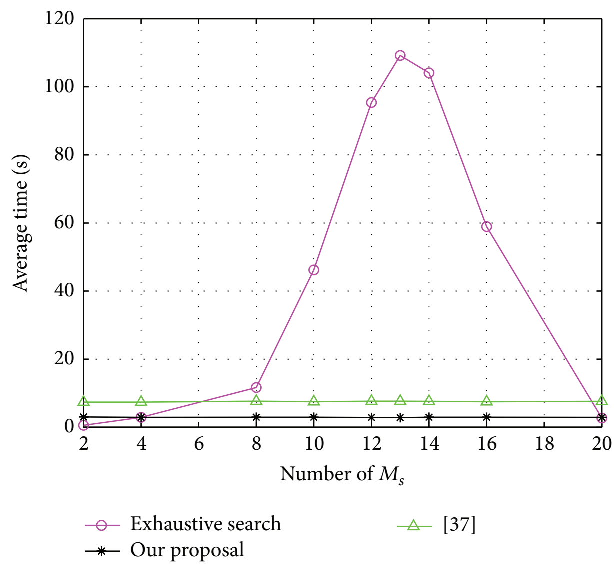

Figure 10: Comparison of optimization processing time of our method with exhaustive search method and [37].

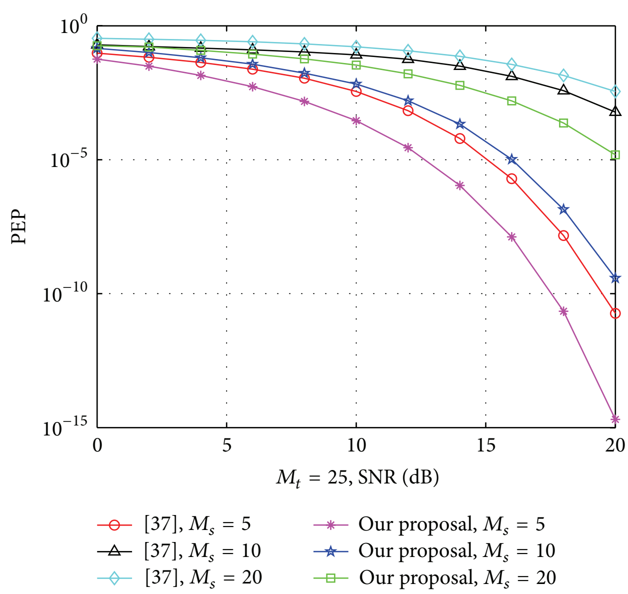

Figure 11: $M_t = 25$, conditional PEP versus SNR.

Core (TM) i7-2600 CPU @ 3.40 GHz" and its memory is 4 GHz; their processing time are compared in Figure 10. It is obvious that our method significantly outperforms the conventional exhaustive search method and is slightly over [37] in the required processing time. More importantly, the required processing time of our method does not increase along with the increased number of selected antennas, but for conventional exhaustive search method, the required time will significantly increase when large-scale antennas are employed in the system. In addition, since there are two convex optimization problems to be solved in each interaction for [37] whereas our proposal only has one, the processing time of [37] is double of ours. With the increase of M_t, this phenomenon is more obvious. Therefore, our method is particularly useful in antenna selection for large-scale MIMO communication systems. Note that since an equal time is required for selecting $M_s \times M_r$ and $(M_t - M_s) \times M_r$ antennas from an $M_t \times M_r$ MIMO system, the curve of the conventional exhaustive search method is not a linear function of the number of antennas.

Finally, we simulate the conditional PEP. Consider also a MIMO system with $M_t = 25$ transmit antennas and $M_r = 2$ receive antennas. After applying the proposed joint transmit antenna selection and beamforming, we use the maximum-likelihood detector to estimate the transmitted data. Figure 11 shows the averaged conditional PER as a function of SNR. It can be observed that satisfactory estimate performance can be obtained for the method and the estimate performance will be improved by selecting more antennas. Our proposal surpasses [37] again. This verifies the advantage of large-scale MIMO in achieving better signal detection and estimation performance.

6. Conclusion

Large-scale MIMO communication has received much attention in recent years, but antenna selection for large-scale MIMO communication system is a technical challenge because the conventional exhaustive search method cannot be efficiently implemented in large-scale MIMO systems. This paper proposes a low-complexity interactive multiple-parameter optimization for large-scale MIMO communication systems. The proposed method first selects the initial transmit antenna subset and estimates the weight vector using the MVDR beamformer. Next, the transmit antenna subset is updated by the joint optimization algorithm. The final antenna subset and weight vector are determined after several repeated optimization steps. Extensive simulation results are provided. It is shown that the proposed method significantly outperforms the conventional exhaustive search method in optimization processing time, without significant degradation of CDF versus the achieved rates, system capacity, and SNR improvement. Therefore, the proposed method is particularly useful in designing joint transmit antenna selection and beamforming for large-scale MIMO communication systems. In this paper, the performance of our proposal is compared with the classic exhaustive search method because it is the most optimal antenna selection method excluding computation complexity in existing methods. We plan to perform more performance comparisons with some other advanced tools in future work.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

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