Antenna Selections Strategies for Massive MIMO Systems With Limited-Resolution ADCs/DACs

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***Abstract*— In millimeter wave (mmWave) communication systems with massive multiple-input multiple-output (MIMO) architecture, selecting the antennas contributing most from the candidate array to transmit/receive signals is one of the effective solutions to reduce hardware cost and power consumption while maintaining high spectral efficiency. In this paper, for the communication systems where the base station (BS) equipped with massive MIMO antenna array communicates with multiple single-antenna users, the impact of limited-resolution analog-to-digital converters (ADCs) and digital-to-analog converters (DACs) on system capacity is investigated, and two antenna selection (AS) algorithms, namely quantization-aware greedy with square maximum-volume (QAG-SMV) and group-selection (GS) schemes, are proposed to enhance system capacity for the uplink and downlink transmission, respectively. Specifically, after the quantization noise caused by limited-resolution ADCs/DACs is converted to independent additive noise, the problem of maximizing system capacity is formulated. Then, two novel AS schemes are proposed to improve system capacity. Simulation results show that the proposed AS algorithms can obtain higher average system capacity, and the computational complexity is reduced as well.**

***Index Terms*— Limited-resolution ADCs/DACs, average achievable capacity, massive MIMO, antenna selection.**

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I. Introduction

IN wireless communications, to cater the increasing demands in system capacity and real-time services, some effective techniques on the network layer have been proposed in the past decade [1], [2], [3], [4]. Nevertheless, extending communication frequency into millimeter-wave (mmWave) band still seems the essential solution to the current gridlock in spectrum resource requirements. Hence, mmWave is promising to be exploited in the fifth/sixth generation (5G/6G) mobile communication systems [5], [6], [7]. For the wireless communication with mmWave band, in order to enhance signal gain for reliable decoding via reducing the effect of severe path-loss in signal propagation, massive multiple-input multiple-output (MIMO) architecture is commonly adopted [8], [9]. Consequently, massive MIMO antenna array is becoming the mainstream architecture in the future mmWave communication systems, and it is one of the current hot spots in both academy and industry [10], [11].

For mmWave massive MIMO systems, there are dozens or even hundreds of antennas. For such wireless communication systems, it is hard to provide a dedicated radio-frequency (RF) chain and other supporting circuits for each antenna. Hence, the technique of hybrid precoding emerges as one of the most effective solutions to decrease the number of RF chains, the corresponding hardware cost and power consumption, while maintaining high spectral efficiency [12]. Accordingly, some novel hybrid precoding schemes have been proposed in the past several years [13], [14], [15], [16]. In fact, among the antennas being densely deployed in a small space, some antennas are correlated one another and their contributions in enhancing system capacity are usually unequal [17]. Therefore, if only the antennas that contribute most are exploited to transmit or receive signals, not only hardware cost and energy consumption can be saved, but also the computational complexity to implement hybrid precoding can be further reduced [18], [19]. Consequently, antenna selection (AS) in massive MIMO systems will play a significant role to realize the vision of broadband green communication in the future.

In the past decade, many AS schemes have been proposed to enhance the system capacity for MIMO architecture.

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Based on the concept of constructive interference, a joint optimization scheme of transmit-antenna-selection (TAS) and hybrid precoding was proposed via the mixed-integer programming approach in [20]. For the continuous and gusty communication scenarios with different data request probabilities, an efficient AS scheme using genetic algorithms was developed in [21]. The conjunct design of secure beamforming and receive-antenna-selection (RAS) scheme was investigated for both complete and incomplete channel state information (CSI) scenarios in [22], and then a branch and bounded (BAB) algorithm to obtain the optimal antenna subset was proposed. In [23], based on the successive convex approximation technique to deal with max-min fairness, a joint scheme of AS and multicast beamforming was proposed for a single multicast group in massive MIMO systems. A novel AS algorithm was presented to maximize the system capacity based on the rectangular maximum-volume (RMV) technique in [24]. For single-input multiple-output (SIMO) multi-antenna systems with discrete inputs, a RAS scheme was proposed in [25]. Two low-complexity AS algorithms were proposed for the downlink multi-user massive MIMO systems using the matched filter precoding technique in [26], where vector multiplications were avoided successfully during the iterative selection procedure. Based on global searching, two iterative-swapping AS schemes were proposed in [27]. A local-swapping (LS) AS algorithm was proposed in [28], and the global swapping strategy was proposed to reduce its complexity. In [29], Gorokhov proposed a decremental AS strategy, which can almost find the optimal antennas in maximizing system capacity, and its low-complexity version was proposed in [30] rendering just a little degradation in system capacity. In [31], based on the Monte Carlo type search approach, an intelligent AS strategy was proposed to enhance system capacity in a simple manner. To decrease the required number of RF chains and power consumption, several TAS schemes were proposed to minimize the mean square reception error and reduce the transmit power with the matching pursuit techniques in [32]. Furthermore, AS schemes were investigated to combat wiretap for massive MIMO systems in [33] and [34].

All the aforementioned AS algorithms can achieve good performance in enhancing system capacity. Nevertheless, most of them supposed that the analog-to-digital converters/digital-to-analog converters (ADCs/DACs) are infinite-resolution, which is infeasible for practical massive MIMO systems owing to the huge hardware cost and power consumption [35], [36]. In fact, the resolution of ADCs/DACs affects system capacity and it should be considered when AS schemes are designed. For instance, the achievable rates in the uplink and downlink of full-duplex (FD) massive MIMO systems with low-resolution ADC/DACs were investigated in [37], and it was shown that the approximate achievable rate becomes constant only when the number of quantization bits tends to infinity. However, the number of quantization bits is usually 2 or 3 in practice.

Consequently, when AS schemes are leveraged for enhancing system capacity, the quantization errors caused by the limited-resolution ADCs/DACs should be considered. However, most prior works omitted this issue. To the best of our knowledge, only a few existing works mentioned this. For the massive multi-user MIMO systems equipped with low-resolution DACs, a joint AS and user scheduling scheme was proposed to maximize the system total rate based on the cross-entropy optimization concept in [38]. To maximize the energy efficiency and spectral efficiency at the same time, an AS framework to jointly allocate the best active RF chains was proposed in [39], which not only can implement the selection between the DACs of random resolution optimally, but also can determine the optimal number of RF chains to be activated. However, these two methods operate either in an iterative manner or sorting operation was required, and so their computational complexity is considerably high. In this paper, for the massive MIMO systems with limited-resolution ADCs/DACs at the BS, when the quantization errors are considered, two low-complexity AS algorithms, namely quantization-aware greedy with the square maximum-volume (QAG-SMV) AS and group-selection (GS) AS, are proposed to improve the average achievable capacity in the uplink and downlink transmission, respectively. The main contributions of this paper are summarized as follows.

- Based on the additive quantization noise model (AQNM), the impact of limited-resolution ADCs/DACs is converted to independent additive noise, and then the expressions of the achievable capacity in closed form are derived for the uplink and downlink transmission, respectively, through which valuable insights into the joint effect of the quantization bits of ADCs/DACs and antenna selection algorithms on the system capacity can be obtained.
- For the uplink transmission, a novel QAG-SMV AS scheme is proposed, through which both the global optimization and implementation complexity are considered, and the antennas contributing most are selected to maximize system capacity in a low-complexity manner.
- A GS scheme is proposed for the downlink transmission, through which the antennas contributing most for each user are obtained, and the same number of antennas are selected finally. Not only the maximal system capacity is promising to achieve, but also the fairness among users is considered.
- For the proposed AS schemes, the performance in average achievable capacity and complexity is evaluated. Simulation results are presented to validate the superior performance over the existing algorithms in both average achievable capacity and implementation complexity.

The remainder of this paper is organized as follows. In Section II, the system model considered in this paper is presented and the problem of signal transmission with limited-resolution ADCs/DACs is formulated. The QAG-SMV AS scheme is proposed for the uplink transmission in Section III, and a novel AS strategy is proposed for the downlink transmission based on the GS concept as well. In Section VI, simulation results are presented to evaluate the performance of the proposed AS schemes for both the uplink and downlink transmission. The computational complexity of the proposed schemes is analyzed in Section VI-C. Some ideas on extending the proposed schemes to multi-antenna user scenarios are

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presented in Section V. Finally, the paper is concluded and our future interested research point is presented in Section VII.

Notation: The following notations are used throughout this paper. Lowercase letters, bold lowercase letters and bold uppercase letters represent scalars, vectors and matrices, respectively. $\mathbf{H}^H$ and $\mathbf{H}^T$ denote the Hermitian and transpose of $\mathbf{H}$, respectively. $\mathbf{I}_N \in \mathbb{C}^{N\times N}$ denotes the identity matrix with dimension $N \times N$. $||\mathbf{x}||$ is the Euclidean norm of $\mathbf{x}$. $|\mathbf{x}|$ means obtaining the absolute value for each element of vector $\mathbf{x}$. $|x|$ is the absolute value of scalar x. $\det(\mathbf{X})$ means applying the determinant operator of matrix $\mathbf{X}$. $\mathbf{A}\backslash\mathbf{B}$ means removing element $\mathbf{B}$ from set $\mathbf{A}$.

II. System Model and Problem Formulation

In this section, the system model with massive MIMO architecture is described, and the quantization noise caused by limited-resolution DACs/ADCs is formulated.

A. Massive MIMO Systems With Limited-Resolution ADCs/DACs

In this paper, a single-cell massive MIMO system with multiple users is considered, where the BS equipped with N_b antennas transmits signals to N_u users who are equipped with single antenna simultaneously. As the number of antennas at user terminals is usually very small, it is assumed that the user terminals are capable of presenting infinite-resolution ADCs/DACs. On the contrary, there are usually hundreds or even thousands of antennas at the BS, and if so many ADCs/DACs are infinite-resolution, the BS can hardly provide such huge hardware cost and power consumption. Consequently, it is assumed that the ADCs/DACs at the BS are limited-resolution, but the ones at the users are infinite-resolution.

Both the uplink and downlink transmissions are investigated in this paper. It is assumed that N_u users send their signals to the BS with same transmit power in the uplink transmission phase[1], and the BS transmits signals to the N_u users after encoding being operated in the downlink phase. It is supposed that the channels are in slow block fading, which means that the channel coefficients keep invariant during a coherence time.

To reduce hardware cost and power consumption, only the candidate antennas contributing most are selected to transmit/receive signals at the BS. In this section, we investigate AS schemes when the impact of limited-resolution ADCs/DACs is considered for both the uplink and downlink transmissions.

B. The Uplink Transmission With Limited-Resolution ADCs

In the phase of the uplink transmission, when signals are transmitted from the users, the BS receives them via a large-scale array and tries to decode them after sampling with limited-resolution ADCs. Let $\mathbf{H} = [\mathbf{h}_1, \mathbf{h}_2, \cdots, \mathbf{h}_{N_b}]^T \in \mathbb{C}^{N_b\times N_u}$ be the channel from the N_u users to the BS, and it is assumed that each element of $\mathbf{H}$ is independent and identically distributed (i.i.d) with the parameter of $\mathcal{CN}(0,\sigma^2)$, where $\mathbf{h}_i$, $i \in \{1, 2, \cdots, N_b\}$, represents the i^{th} row of matrix $\mathbf{H}$ and corresponds to the N_b links from the N_u users to the i^{th} antenna. When the signals $\mathbf{x}_u = [x_1, x_2, \cdots, x_{N_u}]^T \in \mathbb{C}^{\mathrm{N}_u\times 1}$ are transmitted from the users, the received signals at the BS can be expressed as

$$\hat{\mathbf{y}}_u = \sqrt{P_u}\mathbf{H}\mathbf{x}_u + \mathbf{n}_u, \tag{1}$$

where P_u is the average transmit power of each user, $\mathbf{n}_u = [n_{u,1}, n_{u,2}, \cdots, n_{u,N_b}]^T \in \mathbb{C}^{N_b\times 1}$ is the vector of the i.i.d. additive white Gaussian noise (AWGN) at the BS with the parameter of $\mathcal{CN}(0, \mathrm{I}_{N_b})$.

Due to the limited-resolution of the ADCs at the BS, quantization error occurs inevitably when sampling is operated. Unfortunately, such error is hard to obtain accurately even if the nonlinearity of the quantization function is known. Therefore, an AQNM is usually adopted to measure the quantization error of the low-resolution ADCs/DACs. Consequently, (1) can be rephrased as

$$\begin{aligned}\mathbf{y}_u &= \mathcal{Q}_u(R_e(\hat{\mathbf{y}}_u)) + j\mathcal{Q}_u(I_m(\hat{\mathbf{y}}_u))\\ &= \alpha_u\sqrt{P_u}\mathbf{H}\mathbf{x}_u + \alpha_u\mathbf{n}_u + \mathbf{q}_u,\end{aligned} \tag{2}$$

where $\mathcal{Q}_u(\cdot)$ is the scalar quantization function of the limited-resolution ADCs, α_u represents the quantization gain, which is commonly expressed by $\alpha_u \approx 1 - \frac{\pi\sqrt{3}}{2}2^{-2b_u}$ when $b_u \leq 5$ holds [38], [40], where b_u denotes the number of bits that the DACs can provide for quantification and $1-\alpha_u$ represents the quantitative distortion factor. $\mathbf{q}_u = [q_{u,1}, q_{u,2}, \cdots, q_{u,N_b}]^T$ is the additive Gaussian quantization noise. Generally, the distribution of the quantization noise also depends on the nonlinearity nature of the quantizer. Nevertheless, as our focus is to select the optimal antennas under the consideration of limited-resolution of ADCs/DACs, it is assumed that high-quality quantizers are used and the nonlinearity has been processed with the existing scheme in [41]. Hence, it is supposed that the quantization noise is i.i.d. with the parameter of $\mathcal{CN}(0, \mathbf{R}_u)$, and it is determined by the limited-resolution ADCs and is uncorrelated to $\hat{\mathbf{y}}_u$. $\mathbf{R}_u$ is the covariance matrix of the quantization noise $\mathbf{q}_u$, which can be expressed as[2]

$$\mathbf{R}_u = \alpha_u(1-\alpha_u)\mathrm{diag}(P_u\mathbf{H}\mathbf{H}^H + \mathbf{I}_{N_b}). \tag{3}$$

From (2), it can be seen that the noise at the BS involves two terms, which are quantization noise and AWGN, respectively. The covariance matrix of the total noise can be defined as

$$\mathbf{R}_t = \alpha_u(1-\alpha_u)\mathrm{diag}(P_u\mathbf{H}\mathbf{H}^H + \mathbf{I}_{N_b}) + {\alpha_u}^2\mathbf{I}_{N_b}. \tag{4}$$

It can be seen that when AS schemes are investigated for enhancing system capacity, the total noise imposed on the received signals should be considered.

[1]For practical systems, the distances from users to the BS are usually different, and the users should scale their transmit power to ensure the received signal power at the BS be almost the same. Nevertheless, from the perspective of the BS, when antenna selection schemes are designed to maximize the achievable system capacity, considering large-scale fading and ensuring the same received signal gain at the BS is equivalent to transmitting signals with same transmit power at the users while omitting the large-scale fading.

[2]The derivation process is similar to (5) in [40], and it is omitted here for the sake of simplicity.

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TABLE I
THE QUANTIZATION GAIN $\alpha_u(\alpha_d)$ WHEN $b_u(b_d) \leq 5$

$b_u(b_d)$	1	2	3	4	5
$\alpha_u(\alpha_d)$	0.6366	0.8825	0.96546	0.990503	0.997501

C. The Downlink Transmission With Limited-Resolution DACs

In the downlink transmission, it is assumed that N_u data streams, denoted as vector $\mathbf{s} \in \mathbb{C}^{N_u \times 1}$, are transmitted in parallel from the BS to the N_u users simultaneously. Before being transmitted, it is assumed that the data is precoded by the maximum ratio transmission (MRT) precoding matrix $\mathbf{W} = \overline{\mathrm{H}}^H \in \mathbb{C}^{N_b \times N_u}$, where $\overline{\mathbf{H}} = \mathbf{H}^T \in \mathbb{C}^{N_u \times N_b}$ represents the channel from the BS to the N_u users[3]. Hence, the transmitted signals from the BS are presented as $\overline{\mathbf{x}} = \mathrm{W}\mathbf{P}^{1/2}\mathbf{s}$, where $\mathbf{P} = \text{diag}\{p_1, p_2, \cdots, p_{N_u}\} \in \mathbb{C}^{N_u \times N_u}$ is the transmit power of the signal vector $\mathbf{s}$. Let P_t be the total transmit power, and it is assumed that the transmit power is allocated equally among the N_u users, and so the transmit power on each data stream is $P_u = P_\text{t}/N_u$. Accordingly, the final transmitted signals can be rephrased as $\overline{\mathbf{x}} = \sqrt{P_u}\mathbf{W}\mathbf{s}$.

When the AQNM is exploited to measure the quantization error of the limited-resolution DACs at the BS, the transmitted signals after digital-to-analog conversion can be expressed as

$$\begin{aligned} \mathbf{x}_d &= \mathcal{Q}_d(\overline{\mathbf{x}}) \\ &= \alpha_d \overline{\mathbf{x}} + \mathbf{q}_d = \alpha_d \sqrt{P_u}\mathrm{W}\mathrm{s} + \mathbf{q}_d, \end{aligned} \tag{5}$$

where the operation $\mathcal{Q}_d(\cdot)$ is similar to that of $\mathcal{Q}_u(\cdot)$, representing the quantization function due to the limited-resolution DACs, and α_d denotes the quantization gain, which can be expressed as $\alpha_d \approx 1 - \frac{\pi\sqrt{3}}{2}2^{-2b_d}$ in case of $b_d \leq 5$, wherein b_d denotes the number of bits that the DACs can provide for quantification. The approximation of the quantization gain α_u/α_d is given in *Table I*. $\mathbf{q}_d = [q_{d,1}, q_{d,2}, \ldots, q_{d,N_u}]^T$ is the quantization noise vector with the i.i.d. nature and the parameter of $\mathcal{CN}(0, \mathbf{R}_d)$, where $\mathbf{R}_d$ is the covariance matrix and it can be obtained by

$$\mathbf{R}_d = \alpha_d(1 - \alpha_d)\mathrm{P}_d \text{diag}(\mathrm{W}\mathrm{W}^H). \tag{6}$$

Accordingly, the received signals at the users can be given by

$$\mathbf{y}_d = \overline{\mathbf{H}}\overline{\mathbf{x}} = \alpha_d \sqrt{\mathrm{P}_d}\overline{\mathbf{H}}\mathrm{W}\mathbf{s} + \overline{\mathbf{H}}\mathbf{q}_d + \mathbf{n}_d, \tag{7}$$

where $\mathbf{n}_d = [n_{d,1}, n_{d,2}, \cdots, n_{d,N_u}]^T$ is the AWGN vector with the i.i.d. nature and the parameter $\mathcal{CN}(0, \mathrm{I}_{N_u})$.

Due to the fact that quantization noise occurs during the sampling operation at the BS, when the transmitted signals are received at the N_u users, the noise is composed of two parts, namely quantization noise and AWGN. As a result, the total noise is shown as

$$\mathbf{R}_d = \alpha_d(1 - \alpha_d)\mathrm{P}_d \overline{\mathrm{H}} \text{diag}(\mathrm{W}\mathrm{W}^H)\overline{\mathrm{H}}^H + \mathrm{I}_{N_u}. \tag{8}$$

[3]For massive MIMO systems, hybrid precoding is usually implemented at the transmitter. As the focus of this paper is AS schemes, fully digital precoding is used here for the sake of notational brevity.

Accordingly, both the quantization errors introduced by the limited-resolution ADCs and DACs are modeled as additive noises imposed on the received/transmitted signals, based on which AS schemes are designed in the following sections.

III. QAG-SMV AS SCHEME FOR UPLINK TRANSMISSION

For the considered massive MIMO system, among the N_b candidate antennas at the BS, N_r antennas are selected to receive signals and the same number of RF chains are utilized to process the received signals from the antennas. In this section, the impact of quantization error on system capacity is investigated first, and then a QAG-SMV RAS algorithm is proposed with the objective of enhancing system capacity.

A. Analysis on the Achievable Capacity in the Uplink Phase

To maximize the achievable rate in the uplink transmission, the N_r antennas contributing most at the BS should be selected from the N_b candidate antennas based on the CSI from the users to the BS. Denote the selected antenna set as Ω and the corresponding channel as $\mathbf{H}_u$. Then, the achievable capacity in the uplink phase can be shown as

$$C_u = \log_2 \det(\mathbf{I} + \mathrm{P}_u {\alpha_u}^2 {\mathbf{R}_u}^{-1}\mathbf{H}_u\mathbf{H}_u^H), \tag{9}$$

from which it can be seen that the covariance matrix $\mathbf{R}_u$ of the noise emerges as a penalty term in the expression of the system capacity, and it is caused by the limited-resolution ADCs at the BS[4].

To maximize the total capacity of the uplink transmission, the AS problem can be formulated as

$$\begin{aligned} &\arg\max\ C_u \\ &\text{s. t.} \sum_{i=1}^{N_b} \Delta_{i,i} = N_r, \end{aligned} \tag{10}$$

where $\Delta_{i,i} \in \{0, 1\}$ is the i^{th} diagonal entry of the matrix $\Delta \in \mathbb{C}^{N_b \times N_b}$, which is a diagonal matrix used to denote the selected antennas. This implies that after the optimal antennas having been selected, the corresponding channel matrix can be shown as $\mathbf{H}_u = \mathbf{H}\Delta$.

B. QAG-SMV RAS Strategy

To solve the optimization problem in (10), a QAG-SMV RAS algorithm is proposed, which consists of two consecutive processing stages. In the first stage, a SMV-based algorithm is used to select N_o antennas without considering the impact of finite resolution globally, and then a QAG algorithm is employed to select the remaining $N_r - N_o$ antennas, where $N_o < N_r$ is set.

Specifically, in the first pre-processing stage, the SMV algorithm is carried out with an empty set of selected RAS and then a certain number of antennas are selected from the

[4]When the blockage of the network is considered, the achievable system capacity should be discounted through multiplying a coefficient to the corresponding channel gains. In this case, the channel matrix will be rewritten as $\mathbf{H} = [\beta_1\mathbf{h}_1, \beta_2\mathbf{h}_2, \cdots, \beta_{N_b}\mathbf{h}_{N_b}]^T$, where β_i, $i \in \{1, 2, \cdots, N_b\}$ represents the strength of blockage, the value of which is located in the range of $(0, 1)$.

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perspective of global optimization while ignoring quantization error. Let ϕ be the selected antenna set and $\mathbf{H}_{u,\phi}$ be the corresponding channel matrix, and then the system capacity of the uplink transmission ignoring quantization error can be given by

$$\begin{aligned}\widehat{C_u} &= \log_2 \det(\mathbf{I} + P_u \mathbf{H}_{u,\phi}^H \mathbf{H}_{u,\phi}) \\ &= \sum_{i=1}^{N_o} \log_2(1 + P_u {\sigma_\mathrm{i}}^2),\end{aligned} \tag{11}$$

where σ_i, $i = 1, 2, 3, \cdots, N_o$, is the nonzero singular value of the channel matrix $\mathbf{H}_{u,\phi}$ with the dimension of $N_u \times N_o$. When the scenarios with moderate high SNR are considered, $P_u {\sigma_\mathrm{i}}^2 \gg 1$ holds. Accordingly, (11) can be further approximated as

$$\begin{aligned}\widehat{C_u} &\approx \sum_{i=1}^{N_o} \log_2(P_u {\sigma_\mathrm{i}}^2) \\ &= N_o \log_2(P_u) + \sum_{i=1}^{N_o} \log_2({\sigma_i}^2) \\ &= N_o \log_2(P_u) + \log_2 \det(\mathbf{H}_{u,\phi}^H \mathbf{H}_{u,\phi}).\end{aligned} \tag{12}$$

From (17), we can observe that to maximize the system capacity with the selected antenna set ϕ is to obtain the optimal matrix $\mathbf{H}_{u,\phi}$, which is denoted as $\mathbf{H}_{\phi,opt} \in \mathbb{C}^{N_u \times N_o}$. Hence, the optimal N_o antennas are selected when $\det(\mathbf{H}_{u,\phi}^H \mathbf{H}_{u,\phi}) = |\det(\mathbf{H}_{u,\phi})|^2$ is maximal.

To obtain the optimal antennas, let the first N_o rows of $\mathbf{H}$ be $\mathbf{H}_{u,\phi}$, and hence the total $\mathbf{H}$ with all antennas can be rewritten as

$$\mathbf{H} = \begin{bmatrix} \mathbf{H}_{u,\phi} \\ \mathbf{H}_r \end{bmatrix}, \tag{13}$$

where $\mathbf{H}_r$ is the remaining matrix after the first N_o rows are deleted from $\mathbf{H}$. Letting $\mathrm{Q} = \mathbf{H}\mathbf{H}_{u,\phi}^{-1}$, we can see that the dimension of Q is $N_b \times N_b$. Then, for the matrix Q, it is to find the element with maximum modulus, which is denoted as $\mathrm{Q}_{\mathrm{i,j}}$, $i \in \{N_o + 1, N_o + 2, \cdots, N_r\}$, $j \in \{1, 2, \cdots, N_o\}$. If $|\mathrm{Q}_{\mathrm{i,j}}| > 1$ holds, exchange the i^{th} row with the j^{th} row in $\mathbf{H}$ until $|\mathrm{Q}_{\mathrm{i,j}}| \leq 1$ holds. In this way, the first N_o rows of matrix $\mathbf{H}$ are updated constantly, and finally the optimal antenna set $\mathbf{H}_{\phi,opt}$ is obtained. In this stage, the SMV algorithm is not only beneficial to reduce the number of candidate antennas for the subsequent second stage, but also greatly improves the system capacity of the uplink transmission due to its global optimization.

Since the diagonal elements of $\mathbf{R}_u$ contain the aggregate gain, which corresponds to the selected antennas, QAG RAS algorithms in the post-processing stage can be exploited to measure the influence of channel gain and quantization error, through which the optimal antennas can be selected.

In the second stage, the remaining $N_r - N_o$ antennas are selected from the remaining channel matrix $\mathbf{H}_r$ based on the QAG RAS algorithm. To select the optimal $N_r - N_o$ antennas, it is assumed that all the candidate antennas are selected at the beginning, and then the antennas that contribute the least are eliminated one by one until there are only $N_r - N_o$ candidate antennas.

While letting ω be the set of the remaining candidate antennas, the system capacity with all the $N_r - N_o$ antennas can be given as

$$\begin{aligned}C_r &= \log_2 \det(\mathbf{I} + P_u \alpha_u^2 \mathbf{R}_{u,\omega}^{-1} \mathbf{H}_{u,\omega} \mathbf{H}_{u,\omega}^H) \\ &= \log_2 \det(\mathbf{I} + P_u \alpha_u \mathbf{D}_{u,\omega}^{-1} \mathbf{H}_{u,\omega} \mathbf{H}_{u,\omega}^H),\end{aligned} \tag{14}$$

where $\mathbf{D}_{u,\omega} = \mathbf{R}_{u,\omega} / \alpha_u$ is a diagonal matrix and its diagonal element d_j is $1 + (1 - \alpha_u) P_u \|\mathbf{h}_{r,\mathrm{j}}\|$, $j \in \{1, 2, \ldots, N_r - N_o\}$, and $\mathbf{h}_{r,\mathrm{j}}$ denotes the j^{th} row vector of $\mathbf{H}_r$. According to (20), when $(n+1)(n < N_b - N_r + N_o)$ antennas have been deleted based on the QAG algorithm, the achievable capacity with such candidate antennas can be expressed as

$$\begin{aligned}C_{r,n+1} &= \log_2 \det(\mathbf{I} + \alpha_u P_u \mathbf{D}_{n+1}^{-1} \mathbf{H}_{r,n+1} \mathbf{H}_{r,n+1}^H) \\ &= \log_2 \det(\mathbf{I} + \alpha_u P_u \mathbf{H}_{r,n+1}^H \mathbf{D}_{n+1}^{-1} \mathbf{H}_{r,n+1}),\end{aligned} \tag{15}$$

where

$$\mathbf{H}_{r,n+1}^H \mathbf{D}_{n+1}^{-1} \mathbf{H}_{r,n+1} = \mathbf{H}_{r,n}^H \mathbf{D}_n^{-1} \mathbf{H}_{r,n} - \frac{1}{d_{n+1}} \mathbf{h}_{r,n+1}^H \mathbf{h}_{r,n+1}. \tag{16}$$

According to the lemma of matrix determinant $|\mathrm{A} + \mathrm{u}\mathrm{v}^H| = |\mathrm{A}|(1 + \mathrm{v}^H \mathrm{A}^{-1} \mathrm{u})$, (21) can be rephrased as

$$\begin{aligned}C_{r,n+1} &= \log_2 \det[\mathbf{I} + P_u \alpha_u (\mathbf{H}_{r,n}^H \mathbf{D}_n^{-1} \mathbf{H}_{r,n} - \frac{\mathbf{h}_{r,n+1} \mathbf{h}_{r,n+1}^H}{\mathrm{d}_{n+1}})] \\ &= C_{r,n} - \log_2 |1 + \alpha_u P_u \frac{\beta_{n+1}}{d_{n+1}}|,\end{aligned} \tag{17}$$

where $\beta_{n+1} = \mathbf{h}_{r,n+1} (\mathbf{I} + P_u \alpha_u \mathbf{H}_{r,n}^H \mathbf{D}_n^{-1} \mathbf{H}_{r,n})^{-1} \mathbf{h}_{n+1}^H$. For the notational simplicity, we define $\mathbf{B}_n = (\mathbf{I} + P_u \alpha_u \mathbf{H}_{r,n}^H \mathbf{D}_n^{-1} \mathbf{H}_{r,n})^{-1}$. From (23), we can see that maximizing $C_{r,n}(\mathbf{H}_{r,n})$ is equivalent to minimizing $\log_2 |1 + \alpha_u P_u \frac{\beta_{n+1}}{d_{n+1}}|$. Consequently, the optimization problem can be rewritten as

$$\arg\min \ \log_2 |1 + \alpha_u P_u \frac{\beta_{n+1}}{d_{n+1}}|. \tag{18}$$

The expression (18) represents the system capacity loss caused by removing the $(n+1)^{th}$ candidate antenna, and d_{n+1} refers to the effect of the quantization error. It can be concluded that maximizing $C_{r,n+1}$ after one antenna being deleted can be converted to deleting the antenna with the minimal β_{n+1}/d_{n+1}.

In this way, the antenna with the least contribution in enhancing the system capacity is deleted one by one until there are only $(N_r - N_o)$ antennas left. It can be seen that both the channel gain and quantization error are considered in the proposed QAG-AS algorithm, and enhanced system capacity can be obtained for practical massive MIMO systems. The detail procedure to select the optimal antennas for the uplink transmission is summarized in *Algorithm 1*.

IV. TAS for Downlink Transmission Based on GS

In this section, the selection of transmit antennas in the downlink phase is investigated under the consideration of limited-resolution ADCs/DACs. It is assumed that the BS is equipped with N_t RF chains, N_b candidate antennas

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Algorithm 1 AS for the Uplink Transmission at the BS Based on QAG-SMV Scheme

1: Initialization: let $\mathbf{H}_{u,\phi} = \mathbf{H}(1 : N_o, :)$ and $\mathbf{H}_r = \mathbf{H}(N_o + 1 : N_b, :)$.
2: Compute $\mathrm{Q} = \mathbf{H}\mathbf{H}_{u,\phi}^{-1}$, and search the element $\mathrm{Q}_{i,j}$, $i \in \{N_o+1, N_o+2, \cdots, N_r\}$, $j \in \{1, 2, \cdots, N_o\}$, with the maximal modulus.
3: if $|\mathrm{Q}_{i,j}| > 1$, exchange the i^{th} row with the j^{th} row by $T = \mathbf{H}(i, :)$, $\mathbf{H}(i, :) = \mathbf{H}(j, :)$ and $\mathbf{H}(j, :) = T$.
4: Return to step 2 until $|\mathrm{Q}_{i,j}| \leq 1$.
5: Obtain the first N_o antennas by $\mathbf{H}_{u,\phi} = \mathbf{H}(1 : N_o, :)$.
6: Initialize $\mathbf{B} = (\mathrm{I} + \alpha_u P_u \mathbf{H}_r^H \mathbf{D}_{u,\omega}^{-1} \mathbf{H}_r)^{-1}$ and the candidate set $\omega = \{1, 2, \cdots, N_b - N_o\}$.
7: Compute all the channel gain of each antenna $\beta_k = \|\mathbf{H}_r(k, :)\|^2$ and quantization error $d_k = 1 + (1 - \alpha_u) P_u \|\mathbf{H}_r(k, :)\|^2$, where $k \in \omega$.
8: Obtain the index $\mathrm{k}^*$of the candidate antenna contributing the least by $\mathrm{k}^* = \arg\min \beta_k / d_k$.
9: Delete the k^* antenna from the set ω and remove the k^* row from $\mathbf{H}_r$.
10: Compute $\mathrm{a} = \frac{B\mathbf{H}_r(k^*, :)}{\sqrt{\frac{\mathrm{d}_{k^*}}{\alpha_u P_u} - \beta_{k^*}}}$, update $\mathbf{B} = \mathbf{B} + \mathrm{a}\mathrm{a}^H$.
11: Update β_k by $\beta_k = \beta_k + |\mathbf{H}_r(k^*, :)\mathrm{a}|^2$.
12: Return to step 7 and repeat until only $(N_b - N_r)$ antennas are left.
13: Output the selected antennas by $\mathbf{H}_s = \begin{bmatrix} \mathrm{H}_{u,\phi} \\ \mathrm{H}_r \end{bmatrix}$.

and limited-resolution ADCs/DACs, while the N_u users are equipped with single antenna and infinite resolution ADCs/DACs. To reduce power consumption, it is supposed that N_t of N_b antennas are used to transmit signals. It is known that the computational complexity of the optimal TAS is considerably high due to the exhaustive search. Therefore, a GS AS algorithm is proposed to reduce the resultant complexity.

A. The Formulation of AS to Maximizing Downlink Capacity

For the N_t selected antennas, while denoting the corresponding channel as $\mathbf{H}_d$, the downlink capacity can be shown as

$$C_d = \log_2 \det(\mathbf{I} + \alpha_d^2 P_d \mathbf{R}_d^{-1} \mathbf{H}_d \mathbf{W}_d \mathbf{W}_d^H \mathbf{H}_d^H), \tag{19}$$

where $\mathbf{W}_d$ is a precoding matrix to encode the data before being transmitted.

Accordingly, selecting the optimal N_t antennas to maximize the system capacity can be formulated as

$$\begin{aligned} &\arg\max\, C_d \\ &\text{s. t.} \sum_{i=1}^{N_b} \mathrm{V}_{i,i} = N_t, \end{aligned} \tag{20}$$

where $\mathrm{V}_{i,i} \in \{0, 1\}$ is the i^{th} diagonal entry of the matrix $\mathrm{V} \in \mathbb{C}^{N_b \times N_b}$. V is a diagonal matrix, denoting the selected antennas. Consequently, when AS has been applied, the channel matrix can be shown as $\mathbf{H}_d = \overline{\mathbf{H}}\mathrm{V}$.

B. AS Algorithm Based on the GS Concept

As antennas contribute unequally in enhancing system capacity for real propagation channels [17], selecting the antennas that contribute the most by the GS technology can effectively improve system capacity and can reduce power consumption as well.

When all red the transmit antennas are considered, the downlink channel can be denoted as $\overline{\mathbf{H}} = [\mathrm{h}_1, \mathrm{h}_2, \cdots, \mathrm{h}_{N_b}]$, which consists of N_b column vectors. For the channel matrix $\overline{\mathbf{H}}$, each column represents a transmit antenna. While letting $\mathrm{h}_i = [\mathrm{h}_{i,1}, \mathrm{h}_{i,2}, \cdots, \mathrm{h}_{i,\mathrm{N}_u}]^T$, $i \in \{1, 2, \cdots, N_b\}$, $\mathrm{h}_{i,j}$, $j \in \{1, 2, \cdots, N_u\}$ represent the channel coefficient from the i^{th} transmit antenna at the BS to the j^{th} user. According to the channel $\overline{\mathbf{H}}$, the corresponding gain can be obtained, which is shown as

$$\mathrm{G} = \begin{pmatrix} |\mathrm{h}_{1,1}|^2 & |\mathrm{h}_{1,2}|^2 & \ldots & |\mathrm{h}_{1,N_b}|^2 \\ |\mathrm{h}_{2,1}|^2 & |\mathrm{h}_{2,2}|^2 & \ldots & |\mathrm{h}_{2,N_b}|^2 \\ \vdots & \vdots & \ldots & \vdots \\ |\mathrm{h}_{N_u,1}|^2 & |\mathrm{h}_{N_u,2}|^2 & \ldots & |\mathrm{h}_{N_u,N_b}|^2 \end{pmatrix}. \tag{21}$$

To obtain the system capacity as large as possible, the N_b antennas are classified into N_u groups equally depending on their contribution to the users. Specifically, for antenna i, compare $|\mathrm{h}_{1,i}|^2$, $|\mathrm{h}_{2,i}|^2$, $\cdots$, $|\mathrm{h}_{N_u,i}|^2$, if the value of $|\mathrm{h}_{k,i}|^2$, $k \in \{1, 2, \cdots, N_u\}$ is the largest, antenna i should be assigned to user k. Meanwhile, if there are already N_b/N_u antennas for user k, the user with the second largest gain is considered, and so on until every user has N_b/N_u antennas.

Then, for each group of the antennas, the users measure the contribution in enhancing system capacity that each antenna can provide for the assigned user independently based on (22).

$$C_{i,j} = \log_2 \left| 1 + \alpha_d^2 P_u \mathbf{R}_{i,j}^{-1} \overline{\mathbf{H}}_{i,j} \mathbf{W}_{i,j} \mathbf{W}_{i,j}^H \overline{\mathbf{H}}_{i,j}^H \right|, \tag{22}$$

where $\overline{\mathbf{H}}_{i,j}$ represents the channel from the antenna i in group j to user j, $\mathbf{W}_{i,j}$ is a precoding vector, and $\mathbf{R}_{i,j}^{-1}$ is the noise covariance, which can be given by

$$\mathbf{R}_{i,j} = 1 + \alpha_d (1 - \alpha_d) P_u \overline{\mathbf{H}}_{i,j} \overline{\mathrm{W}}_j \overline{\mathbf{H}}_{i,j}^H, \tag{23}$$

where $\overline{\mathrm{W}}_j$ is the j^{th} diagonal entry of matrix $(\mathbf{W}\mathbf{W}^H)$. For each group of antennas, the N_t/N_u antennas contributing most are selected.

In this way, the N_t antennas contributing most are selected. The detail procedure to select the optimal antennas for the downlink transmission is summarized in *Algorithm 2*.

V. Extension to the Scenarios With Multi-Antenna Users

When the scenarios with multi-antenna served users are considered, without loss of generality, it is assumed that each user has the same number of antennas, and it is denoted as m. Then, the channel matrix $\mathbf{H}$ from the N_u users to the BS can be rewritten as $\mathbf{H} = [\mathbf{H}_1, \mathbf{H}_2, \cdots, \mathbf{H}_{N_b}]^T \in \mathbb{C}^{N_b \times m N_u}$, where $\mathbf{H}_i \in \mathbb{C}^{N_b \times m}$, $i \in \{1, 2, \cdots, N_u\}$. It is also assumed that each element of $\mathbf{H}$ is i.i.d with the parameter of

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Algorithm 2 AS Algorithm Base on Grouping

1: Input N_b, N_u, N_t and $\overline{\mathbf{H}}$.
2: Initiate the N_u antenna groups by $G_i = \emptyset$, $i \in \{1, 2, \cdots, N_u\}$ and the selected antenna set by $\Omega = \emptyset$.
3: for $i = 1 : N_b$ do
4: $\quad\Omega = [\ ]$.
5: $\quad$for $j = 1 : N_u$ do
6: $\quad\quad\Omega = \left[\Omega \ \ |h_{j,i}|^2\right]$.
7: $\quad$end
8: $\quad[va, in\ ] = \max(\Omega)$.
9: $\quad$if (length$(G_{in}) < N_b/N_u$)
10: $\quad\quad G_{in} = [G_{in}\ i]$.
11: else
12: $\Omega(va, in) = -inf$, goto step 8.
13: $\quad$end
14: end
15: Based on (22), select N_t/N_u antennas with the most contribution from each antenna group, and obtain the total N_t antennas.
16: Output the selected antennas.

$\mathcal{CN}(0, \sigma^2)$. As our task is to select the optimal antennas of the BS to transmit or receive signals for maximizing system capacity, the considered issue is the CSI from the antennas of the BS to the antennas of the users whether the served users are equipped with single antenna or multiple antennas. Hence, the AS schemes proposed for single-antenna users are still available. The only difference is that the dimension of the channel matrix increases, and hence the computational complexity increases accordingly.

To reduce the computational complexity of the proposed AS schemes under the consideration of multi-antenna users, aggregating the channel gains of each user may be available. For the i^{th} user, the channel matrix $\mathbf{H}_i \in \mathbb{C}^{m \times N_b}$ can be rewritten as $\mathbf{H}_i = [\mathbf{H}_{i,1}, \mathbf{H}_{i,2}, \cdots, \mathbf{H}_{i,N_b}]^T$. Hence, $\mathbf{h}_i = |\mathbf{H}_{i,1}| + |\mathbf{H}_{i,2}| + \cdots + |\mathbf{H}_{i,N_b}|$ can be used for the proposed AS schemes to represent the channel from user i to the BS. In this way, the dimension of the channel matrix is the same with that of the single-antenna user scenarios, and the proposed AS schemes can be applied directly.

VI. Simulation Results and Complexity Analysis

In order to show the superior performance of the proposed AS schemes in both enhancing system capacity and reducing computational complexity, simulation results with different settings and complexity analysis are presented in this section. For the two near-optimal AS schemes, decremental AS in the uplink transmission [29] and the LS in the downlink transmission [27], their achievable system capacities are also presented for the sake of comparison. Meanwhile, the random AS and QAG schemes are also presented to highlight the enhanced performance in system capacity when optimization strategies are adopted.

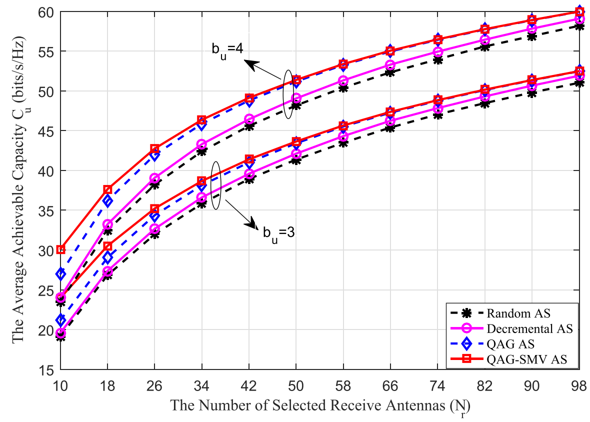

Fig. 1. The average achievable capacity of uplink versus the increasing number of selected antennas when $N_b = 130$, $N_u = 10$ and $P_u = 3$ dB are set.

A. The Evaluation of the Proposed RAS Scheme in Uplink Phase

In the uplink transmission, as the capacity of each user is usually unequal, the total average achievable capacity is used to show the performance of the proposed scheme in enhancing system capacity. In the simulations, Nakagami-m channel model is considered. As the distances from the candidate antennas to all the users are the same, the coefficient of path-loss fading is set as $f = 1$. The total number of candidate antennas is set as $N_b = 130$, and the number of users is set as $N_u = 10$. Without loss of generality, it is supposed that the transmit power of all the users are equal, and $P_u = 3$ dB is set.

To highlight the performance of our proposed QAG-SMV RAS scheme under the consideration of limited-resolution of ADCs/DACs, the near-optimal decremental AS scheme, the QAG-AS strategy without SMV and the random AS scheme without optimization consideration, are also simulated. The average achievable capacities with the increasing number of receive antennas are shown in Fig. 1, from which we can see the following results. Firstly, the average achievable capacities increase monotonously with the number of receive antennas for all the RAS algorithms, but the increasing rates decrease gradually when the number of selected antennas become more and more. Hence, increasing receive antennas is beneficial to enhance system capacity, but these antennas contribute to enhancing system capacity unequally. Therefore, for massive MIMO systems, selecting the antennas with the most contribution is an effective way to maintain high capacity with less hardware cost and power consumption. Secondly, the proposed QAG-SMV RAS algorithm is superior to all the other algorithms except for the QAG-AS scheme with $N_r > 58$[5]. The reason is that both quantization error and channel gains are considered in the QAG-SMV RAS algorithm. Consequently, it can be concluded that the SMV method can be used to improve average achievable capacity when QAG RAS scheme is employed.

[5]In fact, its average achievable capacity is still a bit greater than that of QAG-AS, which can be seen more clearly when Fig. 1 is enlarged.

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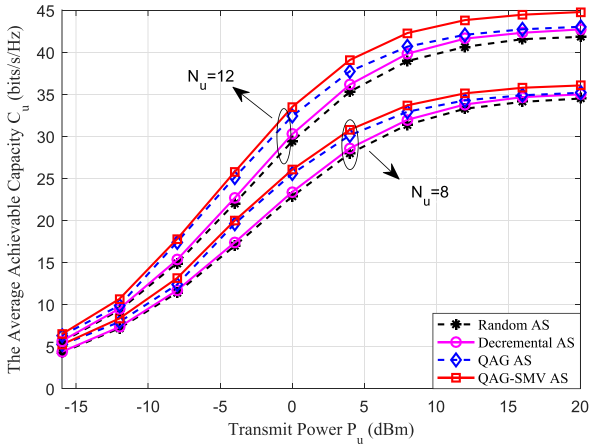

Fig. 2. The average achievable capacity of uplink versus the transmit power when $N_b = 128$, $N_r = 24$, $N_u = 10$, $b_u = 3$ bit is set.

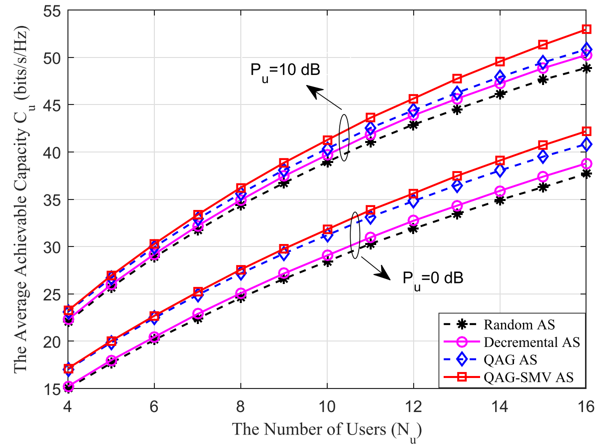

Fig. 3. The average achievable capacity of uplink versus the number of users when $N_b = 128$, $N_r = 28$, $b_u = 3$ bit, $P_u = 10$ dB.

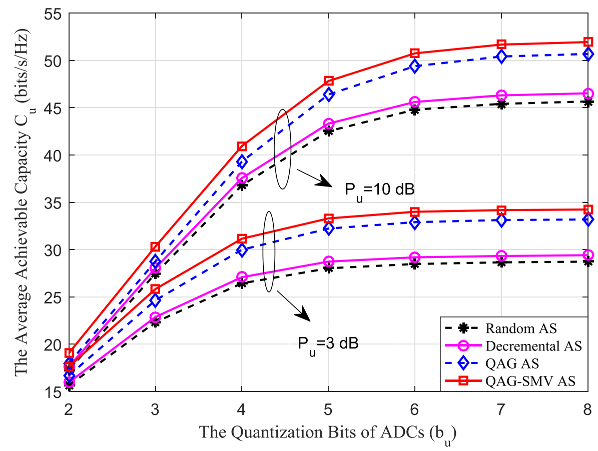

Fig. 4. The average achievable capacity of uplink versus the number of quantization bits of ADCs when $N_b = 128$, $N_r = 20$, $N_u = 10$, $P_u = 10$ dB.

To show the performance in enhancing system capacity with different transmit power, the relationship between average achievable capacity and transmit power is simulated, which is shown in Fig. 2. From the simulation results, it can be observed that the average achievable capacities of all the RAS algorithms increase monotonously with the increasing of transmit power, but the growth rates slow down gradually when transmit power becomes more and more. Accordingly, there may be an optimal value of the transmit power when energy efficiency is considered. It may be one of our research points in the future, and hence it is omitted here. Meanwhile, it also can be seen that the average achievable capacity with the proposed RAS scheme is always the highest one, especially in the case with high transmit power.

The average achievable capacities with the increasing number of the served users are presented in Fig. 3, from which we can see that, for all of the RAS schemes, their average achievable capacities always increase with the number of users, while the performance of the proposed RAS strategy QAG-SMV is always better compared to other algorithms, especially under the scenarios with many users. As the impact of the low-resolution ADCs/DACs is considered during AS in the proposed RAS scheme, the most appropriate antennas beneficial to obtain high system capacity are selected out via jointly considering both the channel gains and the interference among users. Hence, the served users is more, the superiority in enhancing average achievable capacity is more obvious.

To insight the impact of the resolution ratio of ADCs on the system capacity in the unlink transmission, the simulation results of average achievable capacities with the increasing number of quantization bits of ADCs are presented, which are shown in Fig. 4. It can be seen that increasing the resolution of ADCs is beneficial to enhance average achievable capacity. When the number of quantization bits varies from 2 bits to 5 bits, the achievable capacity increases rapidly. Nevertheless, the increasing ratios slow down with the incrementing trend of b_u from 5 bits to 7 bits, and the achievable capacities almost keep constant after 7 bits. There is a pronounced increase in the average achievable capacities with the increasing b_u when b_u is less than or equal to 7 for all AS algorithms, while the average secrecy capacities no longer increase when b_u exceeds 8. Therefore, it is reasonable and advantageous to adopt low-resolution ADCs in the practical deployment of massive MIMO systems since the use of high-resolution ADCs will cause excessive power consumption and hardware complexity.

B. Simulation With the Proposed TAS Scheme in the Downlink Phase

In the downlink transmission, the BS selects the N_t antennas contributing most from the candidates based on the obtained CSI, and the performance in average achievable capacity of each user with varying parameters are evaluated. Meanwhile, the similar existing algorithms on GS TAS selection are also simulated for the sake of comparison.

The average achievable capacity versus the increasing number of the selected transmit antennas with the proposed TAS strategy is presented in Fig. 5, where the classic TAS schemes, such as the random TAS, the decremental TAS and the LS TAS, are also presented for the sake of contrast. From the simulation results, it can be seen that the average achievable capacities of all the TAS algorithms increase

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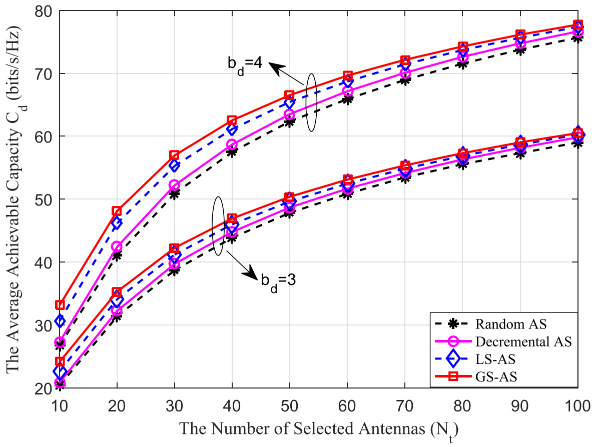

Fig. 5. The average achievable capacity of downlink versus the number of selected antennas when $N_b = 150$, $N_u = 10$, $P_d = 0$ dB are set.

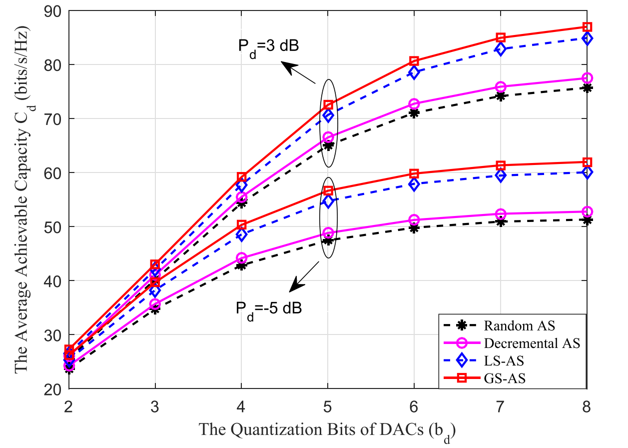

Fig. 7. The average achievable capacity of downlink versus the bits of quantization of DACs when $N_b = 150$, $N_t = 40$, $N_u = 10$, $P_d = -2$ dB are set.

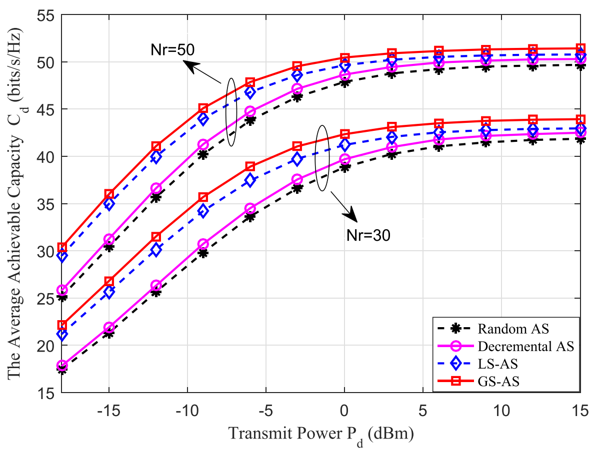

Fig. 6. The average achievable capacity of downlink versus the transmit power when $N_b = 160$, $N_t = 30$, $N_u = 10$, $b_d = 3$ bit are set.

monotonously with the number of the selected transmit antennas, while the proposed scheme outperforms all the existing strategies in average achievable capacity. Though the grouping method is also used in LS TAS scheme, its average achievable capacity is lower than that of GS TAS scheme. The reason is that the antenna contribution in enhancing system capacity is considered in the GS TAS scheme when grouping is carried out at the first stage, while the antennas are grouped randomly in the LS TAS scheme. The simulation results are consistent with the theoretical analysis.

The average achievable capacity with the increasing total transmit power at the BS is presented in Fig. 6, where $N_b = 160$, $N_t = 30$, $N_u = 10$ and $b_d = 3$ bits are set. From the simulation results, it can be seen that the average achievable capacity of all the TAS algorithms increases with the total transmit power at the BS, and the proposed GS AS scheme outperforms all other algorithms. The reason is that the resolution of ADCs/DACs is considered in transmit AS.

The average achievable capacity with the increasing bits of quantization in DACs is shown in Fig. 7. From the simulation results, it can be observed that increasing the quantization bit b_d will lead great enhancement in average achievable capacity firstly, and the growth rates slow down since the quantization bit is set as $b_d = 6$. Finally, this almost keeps constant after $b_d = 9$. This phenomenon is similar to the case in the uplink transmission, while the increasing rate in achievable capacity is smaller. The reason is that the quantization error is amplified and transmitted to the users, which probably leads to more additive noise. On the contrary, in the uplink transmission, the quantization error of the limited-resolution ADCs occurs at the receiver and the sampled signals are not transmitted anymore. Hence, the impact of quantization bits on average achievable capacity is greater in the downlink transmission compared to the uplink one. Compared to the existing counterpart strategies, the simulation results show that the proposed GS-RAS scheme can obtain larger average achievable capacity when the resolution of ADCs/DACs is considered.

C. Complexity Analysis

For the proposed AS schemes, to insight the performance in real time, the computational complexity and convergence are analyzed in this subsection. Among the three considered AS algorithms in the aforementioned section, for the QAG algorithm, as the noise covariance matrix is not diagonal, it is not applicable to the downlink transmission with limited-resolution DACs, and hence its complexity analysis is not presented here.

From *Algorithm* 1 it can be seen that, for the proposed QAG-SMV AS scheme, the main operation in the first stage is spent on computing $\mathbf{Q} = \mathbf{H}\mathbf{H}_{u,\phi}^{-1}$ when the selected antenna set $\mathbf{H}_{u,\phi}$ is being updated, and so its complexity is ${N_u}^4 + {N_u}^3 N_b$. For the worst case, $N_r \times N_o$ cycles are required to obtain the optimal first N_o antennas. In the second stage, $N_b - N_o$ cycles are needed and the most running time is spent on the inversion operation of the noise covariance matrix, which is usually time-consuming. Fortunately, its complexity has been decreased greatly due to the reduced number of candidate antennas after the SMV algorithm has been carried out in the first stage. As the number of cycles are dependent on the number of the candidate antennas, which is constant for a given massive MIMO system, *Algorithm 1* converges. For

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TABLE II
COMPLEXITY COMPARISON FOR AS ALGORITHMS

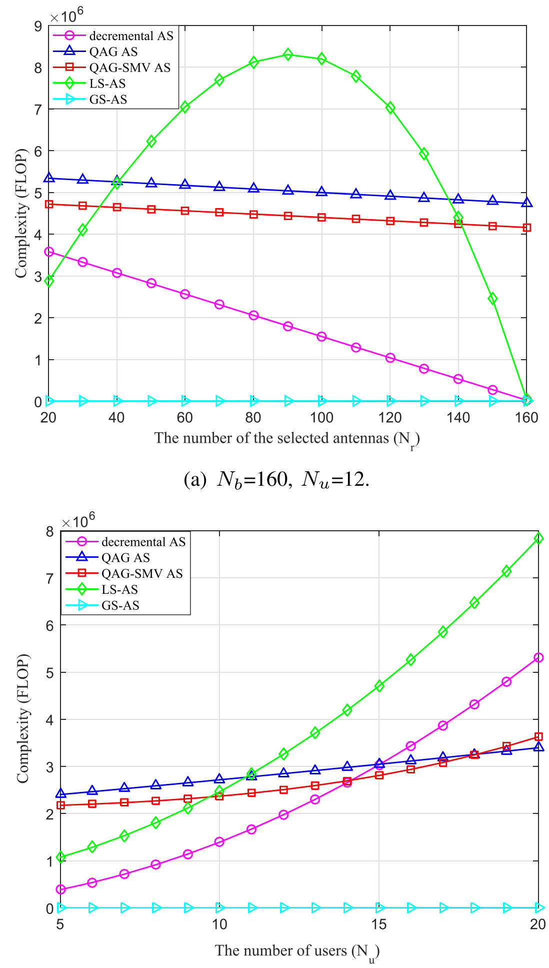
AS algorithm	Total operation times	Computational complexity
GS	$3N_bN_u + 3N_bN_r/N_u$	$\boldsymbol{O}(N_bN_u)$
QAG-SMV	$N_u{}^3 + 4N_bN_u{}^2 + N_u{}^4 + N_bN_u{}^3 + 2N_bN_u - 2N_u{}^2 +$ $2(N_b - N_u)^2N_u + (N_b - N_u)^3 + (N_b - N_r)(N_b - N_u + 2N_bN_u)$	$\boldsymbol{O}((N_b - N_u)^3)$
QAG	$N_bN_u(2N_b + N_u + 2) + N_b{}^3 + N_u{}^3 + (N_b - N_r)(N_b + 2N_u{}^2 + 2N_bN_u)$	$\boldsymbol{O}(N_b{}^3)$
LS	$N_bN_u + N_b{}^2/N_u + N_u{}^4 + N_u{}^2N_r +$ $T_s(N_b - N_r)(2N_u{}^2 + 2N_uN_r + N_u + N_u{}^2N_r + N_r + N_r{}^2)$	$\boldsymbol{O}(T_sN_u{}^2N_r(N_b - N_r))$
Decremental AS	$N_u{}^3 + N_bN_u{}^2 + (N_b - N_r)(N_bN_u{}^2 + N_bN_u + N_b + 2N_u{}^2)$	$\boldsymbol{O}(N_bN_u{}^2(N_b - N_r))$

the AS algorithm based on QAG without SMV, though its main operations are also spent on the inversion of the noise covariance matrix, the dimension of the matrix is $N_b \times N_b$, which is much larger than that of the proposed scheme. Consequently, the computational complexity of the QAG-SMV AS scheme is less compared to the QAG scheme without SMV.

For the proposed scheme GS-AS of the downlink transmission, the main computing operation is spent on the following two aspects: (a) classifying the N_b antennas into N_u groups depending on their contributions to the system capacity, (b) searching the N_t/N_u antennas with the largest contribution from each group when the resolution of ADCs/DACs is considered. The total operation times can be shown as $2N_bN_u + 3N_bN_r/N_u$. For the existing LS-AS algorithm, though the grouping method is also exploited to select the appropriate antennas, it is different from the proposed GS-AS scheme in two aspects: random method was used to group the antennas uniformly and the L-swapping method was exploited to select the N_r/N_u antennas from each group via the iterative swapping technique. Hence, the main complexity of the LS-AS algorithm depends on the inversion operation of the matrix in each iterative swapping phase, which can be presented as $T_sN_u{}^2N_r(N_b - N_r)$, where T_s is the number of iterations. On the other hand, for given N_t and N_u, N_t cycles are needed to classify the candidate antennas into N_t/N_u groups, and each user only needs N_t/N_u cycles to select the optimal N_b/N_u antennas. Consequently, *Algorithm 2* converges.

For the decremental AS algorithm, as its main operation is spent on removing $N_b - N_r$ antennas from the N_b candidate antennas according to their contributions in enhancing system capacity. In this algorithm, no inversion operations of matrix are involved, and so its complexity is lower compared to QAG-SMV. However, quantization error is not considered in such algorithms. The complexity of the decremental AS algorithm can be shown as $N_b(N_b - N_r)N_b{}^2$. To facilitate the comparison, the computational complexity of these AS algorithms is summarized in Table II.

To further validate the real-time performance of the proposed AS schemes, simulation results on computational complexity with varying N_r and N_b are presented. Without loss of generality, it is assumed that the addition between two real numbers is equivalent to 1 FLOP, and the multiplication of two real numbers is equivalent to 4 additions. Meanwhile, the comparison operation between two real numbers is equivalent to 1 addition, and solving the square root of a real number and division between two real numbers are both equivalent to 1 multiplication between two real numbers. The impact of the selected number of antennas N_r on the complexity is shown in Fig. 8 (a), from which it can be seen that the complexity of the GS-AS scheme does not vary with the increasing of N_r, while there is a slight decrease for QAG-SMV and the QAG without SMV algorithm. The reason is owing to the fact that their maximum complexity are proportional to $(N_b - N_u)^3$ and $N_b{}^3$, which depends on N_b instead of N_r. For the decremental



(a) N_b=160, N_u=12.

(b) N_b=128, N_r=32.

Fig. 8. Complexity versus the selected antenna number and the number of users, respectively.

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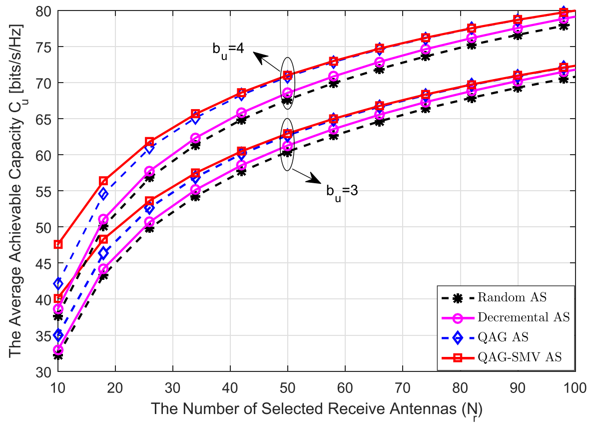

Fig. 9. The average achievable capacity of uplink versus the increasing number of selected antennas for multi-antenna served users when $N_b = 130$, $N_u = 10$, $P_u = 3$ dB and $m = 4$ are set.

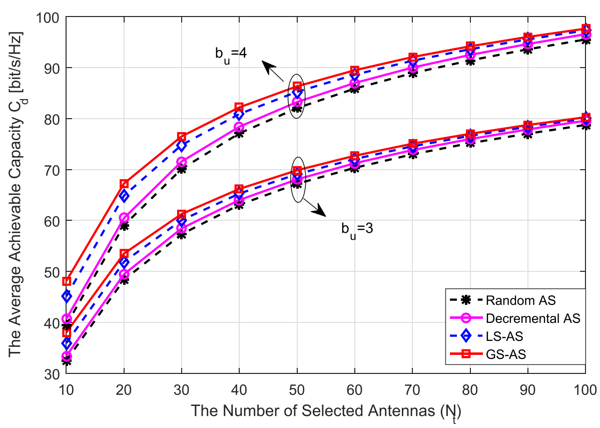

Fig. 10. The average achievable capacity of downlink versus the number of selected antennas for multi-antenna served users when $N_b = 150$, $N_u = 10$, $P_d = 0$ dB and $m = 4$ are set.

AS algorithm, the complexity decreases with the increasing number of the selected antennas due to the fact that the decremental algorithms eliminate antennas successively until only N_r antennas are remaining. Interestingly, the complexity of the LS algorithm is shown as a convex function of N_r, which increases with N_r when $N_r < 90$, and decreases with N_r when $N_r > 90$. Fig. 8 (b) depicts the complexity with the increasing number of users N_u. It is shown that the complexity increases with the increasing N_u for the LS algorithm and the decremental AS algorithm, and the growth rate of complexity in the LS algorithm is significantly greater compared to the decremental algorithms when N_u becomes increasingly larger. The complexity of the QAG-SMV scheme and the QAG algorithm without SMV slightly increases with N_u, and the complexity of QAG-SMV algorithm surpasses the QAG algorithm without SMV when $N_u > 18$, while the number of users is usually not too big in the considered system. All these results are consistent with the theoretical analysis on computational complexity.

D. Evaluation of the Scenarios With Multi-Antenna Users

To validate the availability of the proposed schemes for the scenarios with multi-antenna users, some simulation results are presented here. In the simulation, it is assumed that each user have four antennas, and the other settings are the same with single-antenna scenarios. The total achievable capacities in the uplink and the downlink transmission with the increasing number of the selected antennas are shown in Fig. 9 and Fig. 10, respectively.

From the simulation results, it can be seen that, similar to the scenarios with single-antenna served users, the proposed schemes outperform other existing strategies in the achievable system capacity in both the uplink and downlink phase when the resolution of ADCs/DACs are considered. Meanwhile, it also can be observed that the achievable system capacities are greater than that of the single-antenna served users while the total transmit power is the same.

VII. Conclusion

In this paper, we have investigated the effect of ADCs/DACs resolution on the average achievable capacity of massive MIMO systems when AS schemes are designed in Nakagami-m fading scenarios. Based on the AQMN model, the closed form expression of average achievable capacity has been derived, which is utilized to analyze the quantization noise caused by the limited-resolution ADCs/DACs. We have proposed two novel AS schemes for the uplink and downlink transmissions. Numerical simulation results have been presented to validate the performance of the proposed AS schemes. Compared to the existing strategies, such as random AS, decremental AS, QAD-AS and LS-AS, our proposed schemes QAG-SMV AS and GS-AS have larger achievable capacity in all the scenarios with the varying transmit power, the number of served users and the quantization bits of ADCs/DACs. Meanwhile, we also find that the impact of ADCs/DACs resolution is also dependent on the transmit power and channel fading. As the proposed AS schemes in this paper are aimed at enhancing system achievable capacity without considering the fairness among users, we will investigate this issue in our future research.

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