An opportunistic scheduling algorithm using aged CSI in massive MIMO systems

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ABSTRACT

In time-division duplex (TDD) massive multiple-input multiple-output (MIMO) systems, the spatial multiplexing gain cannot be fully achieved since available pilot resources at each channel coherence time interval are limited. In this paper, we propose an Opportunistic user Scheduling algorithm, termed OpSAC, that uses Aged Channel state information (CSI) to increase spatial multiplexing gain without incurring additional pilot overhead. Assuming the base station (BS) employs two popular precoders of maximum ratio transmission (MRT) and zero-forcing (ZF), we first derive their closed-form lower bounds on the achievable sum-rate under channel aging. According to the analysis results, we develop a heuristic solution that estimates the amount of channel variation for each user by using correlation of CSI samples, and exploits channel conditions to opportunistically schedule more users by using aged CSI, thereby enhancing spectral efficiency. Through numerical analysis and simulation we confirm that the proposed lower bounds are very tight, and show the impact of channel aging on the performance of massive MIMO systems. In addition, it is shown that OpSAC achieves near-optimal performance and considerably outperforms the conventional user scheduling algorithm that uses current CSI only.

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1. Introduction

Recently, massive multiple-input multiple-output (MIMO) has been considered as a key technology in wireless communications due to its many advantages. First, it achieves higher multiplexing gain by simply increasing the number of base station (BS) antennas [2]. Second, it improves energy efficiency significantly by reducing uplink and downlink transmit power [3]. Moreover, it has been shown that two simple linear precoders of maximum ratio transmission (MRT) and zero-forcing (ZF) can achieve optimal performance when a very large number of BS antennas serve a small number of users [4].

To exploit these features, it is necessary for a BS to acquire channel state information (CSI) between itself and users before transmission. In frequency-division duplex (FDD) operation, the BS estimates the CSI via downlink pilots and the training overhead is proportional to the number of BS antennas. However, in massive MIMO systems, the number of BS antennas is very large, thereby the training burden becomes challenging. In contrast, in time-division duplex (TDD) operation, the BS can obtain the CSI using uplink pilots via leveraging the channel reciprocity. Then, the training overhead scales linearly with the number of scheduled users and is independent of the number of BS antennas. From the reason, many previous works have adopted TDD operation combined with uplink pilots in massive MIMO systems [5-9].

The TDD operation is repeatedly performed at each channel coherence time interval, which is divided into uplink channel training period and downlink data transmission period. In the uplink training period, the BS first assigns orthogonal pilot sequences to the users who will be served next. Then, the users with pilot assignment simultaneously transmit uplink pilots to the BS, which provides the BS with current CSI. According to the obtained CSI, the BS designs a precoder for each user and transmits data signals in the following downlink transmission period.

Since the number of required uplink pilot sequences is directly proportional to the number of scheduled users in downlink transmission, the BS needs a substantial amount of time-frequency resources for uplink pilots in achieving high spatial multiplexing gain. Although the multiplexing gain can be further enhanced by assigning more time-frequency resources for uplink pilots, this results in reduced downlink transmission resources, i.e., lowered spectral efficiency. Similarly, if the BS assigns uplink pilots in a conservative manner to secure downlink transmission time, the multiplexing gain in massive MIMO systems can not be fully

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achieved although the degree of freedom in BS antennas is large enough.

Motivated by this, in this paper, we propose an Opportunistic user Scheduling algorithm, termed OpSAC, that exploits Aged CSI to increase spatial multiplexing gain without incurring additional pilot overhead. To this end, we first mathematically derive the lower bounds on the downlink achievable sum-rates of the two well-known linear precoders, i.e., MRT and ZF under channel aging\(^1\). Based on the analytical results, we provide a heuristic user scheduling solution that consists of the following parts: (i) estimation of channel variation coefficients, which helps the BS predict the amount of each user's channel variation according to the time elapsed from the last CSI training; and (ii) selection of valid users, which exploits obtained channel conditions to opportunistically schedule more users by using aged but valid CSI in improving performance further.

The contributions of this paper are summarized as follows:

- We derive closed-form lower bounds on the achievable downlink rate of MRT and ZF in a single-cell massive MIMO system considering channel aging effects, which are valid for a finite number of BS antennas and different user mobility, thereby reflecting a practical scenario. Through numerical analysis and simulation, we show that our proposed analytical lower bounds match well with simulation results.
- We propose an opportunistic user scheduling algorithm which estimates the amount of channel variation of each user according to aged CSI samples, and schedules more users without resort to extra CSI estimation. Therefore, the proposed algorithm improves spectral efficiency by exploiting higher multiplexing gain while maintaining the same amount of pilot overhead. While previous works have focused only on the physical (PHY) layer performance under channel aging, our algorithm, to the best of our knowledge, is the first medium access control (MAC) layer user scheduling algorithm that uses aged CSI in massive MIMO systems.
- Through extensive simulation, we show that our algorithm achieves near-optimal performance in polynomial time, and outperforms the conventional scheduling algorithm that uses current CSI only. Also, the simulation results reveal the impacts of various factors such as user mobility, number of BS antennas, number of pilot sequences and beamforming methods on the performance gain.

The rest of this paper is organized as follows. We introduce the related work in Section 2, and present our system model in Section 3. Section 4 analyzes the lower bounds on the achievable sum-rates of MRT and ZF using aged CSI. In Section 5, we introduce the components of our proposed OpSAC, and evaluate its performance in Section 6. Finally, we conclude this paper in Section 7.

Notations: We use upper/lower boldface letters to represent matrices/vectors. \(\mathbf{tr}(\mathbf{A})\) denotes the trace of matrix \(\mathbf{A}\). \(\text{Var}(\mathbf{R})\) denotes the variance of random variable \(\mathbf{R}\), and \(\mathbf{I}_N\) is the \(N \times N\) identity matrix. We denote \([\mathbf{A}]_{m,n}\) as the \((m, n)\)th element of \(\mathbf{A}\). The superscripts \(T\), \(^*\), and \(H\) stand for the transpose, conjugate, and conjugate-transpose, respectively. We use \(\mathbf{C} \mathbf{A} \mathbf{V}(\mathbf{m}, \mathbf{R})\) to denote the circular symmetric complex Gaussian distribution with mean \(\mathbf{m}\) and covariance matrix \(\mathbf{R}\). Lastly, the expectation operator and the Euclidean norm are denoted by \(\mathbb{E}[\cdot]\) and \(|| \cdot ||\), respectively.

1 In massive MIMO systems, due to the large number of BS antennas, the signal processing at the BS should be simple. In this work, we have focused on the MRT and ZF because they are widely accepted linear precoders in the literature [5,6,8,10–12].

2. Related work

Channel aging: There is a significant channel imperfection known as channel aging which refers to channel mismatch between estimated and current CSI at the BS due to channel variation in time and processing delays at the BS. Due to its importance, channel aging effects in massive MIMO systems have attracted a lot of attention from academia [10,13–16]. In [10], considering the channel aging effects, deterministic equivalents on uplink and downlink were derived when maximum ratio combining (MRC) detector and MRT precoder are available at the BS, respectively. In [13], the authors obtained complex deterministic equivalents for minimum mean-square error (MMSE) detector and regularized ZF. Also, an optimal linear receiver in cellular systems has been derived, which exploits correlation between channel estimates and interference from other cells [14].

However, these deterministic equivalent approaches assumed infinite BS antennas and users in number for mathematical derivation. Moreover, these expressions with respect to impact of channel aging on the performance are too complicated to understand. For these reasons, the authors in [15] and [16] considered a finite number of BS antennas, and derived a lower bound of the sum-rate of a system that employs MRC and ZF for uplink and MRT for downlink at the BS. However, they assumed that all associated users have the same velocity, and have not investigated downlink scenarios that employ ZF.

Different from the aforementioned works that have focused only on PHY layer, in this work, we also consider MAC layer, e.g., user scheduling. To the best of our knowledge, our work is the first user scheduling algorithm using aged CSI in massive MIMO systems. Through numerical results, we confirm that aged CSI has potential to improve performance in massive MIMO systems. Additionally, we consider the cases of a finite number of BS antennas and users with different speeds to reflect practical scenarios, thus finding closed form lower bounds on the downlink achievable rate for MRT and ZF becomes more tractable.

User selection: In TDD massive MIMO systems, user selection in each coherence interval consists of selection procedures for pilot users and then for users to be scheduled. The former selects users to be assigned to pilot sequences for uplink channel training, and the latter chooses a subset of users to be served at current scheduling according to the obtained CSI at the BS. To reduce the pilot overhead (or sounding overhead) for uplink channel training, there have been many works to find an optimal number of pilot sequences [17–19]. Also, the authors in [20] and [21] tackled the problem of reusing pilot sequences to efficiently utilize limited resources. In addition, antenna grouping and user grouping are also considered in user selection to increase spectral efficiency [22–24]. However, these works focused on reducing the pilot overhead or user selection complexity, assuming that the same set of pilot users is served in the downlink period.

In contrast, our algorithm helps the BS serve additional users with aged CSI, thereby achieving higher multiplexing gain. Since OpSAC decouples pilot user selection from scheduling user selection, it can further improve performance when combined with an existing pilot overhead reducing algorithm. Although the concept of decoupling pilot user selection from scheduling user selection has been previously proposed in [25], the pilot user selection in [25] requires accumulated channel statistics (i.e., a large number of CSI samples) to accurately estimate the channel variation of each associated user. Meanwhile, our algorithm reliably estimates the channel variation of each user by utilizing only two CSI samples according to Eq. (29) since each sample has a large number (i.e., \(M\)) of CSI elements. Furthermore, in [25], the authors did not specify the scheduling user selection procedures. In contrast, we proposed a scheduling user selection algorithm with
low complexity, thereby making it applicable in massive MIMO systems.

3. System model

As shown in Fig. 1, we consider downlink transmission in a single-cell multi-user MIMO system that comprises an M-antenna BS and $K_u (K_s < M)$ single-antenna users. In this paper, we focus on the single-cell scenario because it provides more engineering insights compared to the multi-cell scenario as reported in [15,16,21]. To illustrate channel variation, we assume a quasi-static block fading channel model where channel coefficients between the BS and users stay constant within a slot duration of $T$ symbols, but vary from slot to slot depending on each user’s velocity. As illustrated in Fig. 2, we consider a system with TDD operation which has the uplink pilot training period ($\tau_u$ symbols) and the downlink transmission period ($T - \tau_u$ symbols).

3.1. Uplink training

To estimate the channel matrix between the BS and users at current time slot $n$, the BS first assigns orthogonal pilot sequences (with the length of $\tau_u$ symbols) to a user set $\mathbb{K}_u[n]$ ($|\mathbb{K}_u[n]| = K_u$) selected from the associated user set $\mathbb{K}_a[n] = \{1, 2, \ldots, K_s\}$. Then, the users with pilot assignment transmit uplink pilots to the BS, from which the BS obtains the $M \times K_p$ observation matrix $\mathbf{Y}_t[n]$ [6] as

$$\mathbf{Y}_t[n] = \sqrt{\tau_u \rho_u} \mathbf{G}_p[n] + \mathbf{V}[n], \quad (1)$$

where $\rho_u$ is the average transmit power at each user, $\mathbf{G}_p[n]$ represents the $M \times K_p$ channel matrix between the BS and the pilot users, and $\mathbf{V}[n]$ is the $M \times K_p$ post-processed noise matrix at the BS whose elements are independent and identically distributed (i.i.d.) with zero-mean and unit-variance.

The $M \times 1$ channel vector for each user $k$ is given by

$$\mathbf{g}_k[n] = \mathbf{h}_k[n] \sqrt{\beta_k}, \quad (2)$$

where $\mathbf{h}_k[n] \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_M)$ is the Rayleigh fast fading channel vector from the BS to user $k$, and $\beta_k$ is the large-scale fading coefficient that counts path-loss and log-normal shadow fading, which is assumed to be constant over many coherence intervals and known a priori.

The minimum mean squared error (MMSE) estimate [26] of $\mathbf{g}_k[n]$ for user $k \in \mathbb{K}_p[n]$ becomes

$$\hat{\mathbf{g}}_k[n] = \frac{\sqrt{\tau_u \rho_u} \mathbf{y}_{uk}[n]}{1 + \tau_u \rho_u \beta_k}, \quad (3)$$

where $\mathbf{y}_{uk}[n]$ is the column vector for user $k$ in $\mathbf{Y}_u[n]$.

Using the orthogonality property of MMSE estimation, we can decompose $\mathbf{g}_k[n]$ into

$$\mathbf{g}_k[n] = \hat{\mathbf{g}}_k[n] + \tilde{\mathbf{g}}_k[n], \quad (4)$$

where $\tilde{\mathbf{g}}_k[n]$ is the uncorrelated estimation error vector, which is also statistically independent of $\hat{\mathbf{g}}_k[n]$ because the two vectors are jointly Gaussian. From (3) and (4), each element of $\tilde{\mathbf{g}}_k[n]$ is i.i.d. with zero-mean and variance $\frac{\tau_u \rho_u \beta_k}{1 + \tau_u \rho_u \beta_k}$.  

3.2. Downlink transmission

After the uplink training period, the BS transmits data signals to the users in the scheduling user set $\mathbb{K}_u[n]$ ($K_u \leq |\mathbb{K}_u[n]| = K_s \ll M$) during the data transmission period of remaining $T - \tau_u$ symbols. The $K_s \times 1$ downlink received signal vector is given by

$$\mathbf{y}_d[n] = \sqrt{\tau_d \rho_d} \mathbf{G}_f[n] \mathbf{s}[n] + \mathbf{z}[n], \quad (5)$$

where $\rho_d$ is the transmit power at the BS, $\mathbf{G}_f[n]$ represents the $M \times K_s$ channel matrix between the BS and the scheduled users, $\mathbf{z}[n] \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_K)$ is the additive noise vector, and $\mathbf{s}[n]$ is the $M \times 1$ transmit signal vector at the BS. The transmit signal vector $\mathbf{s}[n]$ is given as

$$\mathbf{s}[n] = \mathbf{W}[n] \mathbf{x}[n], \quad (6)$$

where $\mathbf{x}[n]$ is the $K_s \times 1$ data signal vector transmitted to the users, whose elements are uncorrelated with each other and have unit-variance, and $\mathbf{W}[n]$ denotes the $M \times K_s$ precoding matrix. Due to the power constraint at the BS, $\mathbf{W}[n]$ is chosen to satisfy that $\mathbb{E}[\|\mathbf{s}[n]\|^2] = 1$. Thus, we obtain

$$\mathbb{E}[\|\mathbf{W}[n] \mathbf{W}[n]^H\|] = 1. \quad (7)$$

3.3. Channel aging

When the BS tries acquired CSI, channel variation inevitably occurs to the users who are in the valid user set but not in the pilot user set due to the time difference between channel estimation and actual channel use for precoding. To illustrate channel aging effects, we adopt the first-order Gauss-Markov fading model [10,15,16,27,28] where the channel vector of user $k$ is modeled as

$$\mathbf{g}_k[n] = \alpha_k \mathbf{g}_k[n - 1] + \mathbf{e}_k[n], \quad (8)$$

where $\alpha_k$ is the temporal correlation coefficient and $\mathbf{e}_k[n]$ is the $M \times 1$ uncorrelated channel error vector due to the channel aging

Note that OpSAC schedules more users than those in the pilot user set ($|\mathbb{K}_a[n]| < |\mathbb{K}_u[n]|$), which is different from conventional user scheduling algorithms where the scheduling user set is the same as the pilot user set ($|\mathbb{K}_a[n]| = |\mathbb{K}_u[n]|$).
with each element's variance $\beta_k(1 - \alpha_k^2)$. The $\alpha_k$ can be expressed by the Jakes model [29] as

$$\alpha_k = J_0(2\pi f_{D,k} T_i),$$

where $J_0(\cdot)$ is the zeroth-order Bessel function of the first kind, $T_i$ is the duration of a time slot, and $f_{D,k}$ is the maximum Doppler shift. Then the maximum Doppler shift $f_{D,k}$ is given by

$$f_{D,k} = \frac{v_k f_c}{c}$$

where $v_k$ is the velocity of user $k$, $f_c$ is the carrier frequency, and $c$ is the speed of light. According to the property of Bessel function, if the user velocity increases, $|\alpha_k|$ decreases from 1 to 0, i.e., channel aging becomes severe.

Assume $k$ is the last time slot when the CSI of user $k$ is obtained, and the BS uses it at current time $n$. To measure the amount of channel variation between the two instances, we define the channel variation coefficient $\delta_k[n]$, which is given from (8), as

$$\delta_k[n] = (\alpha_k)^{n-k}.$$  

From (4), (8) and (11), the current CSI $g_k[n]$ can be decomposed into

$$g_k[n] = \delta_k[n]g_k[l_k] + e_k[n]$$

$$= \delta_k[n]g_k[l_k] + \sum_{n \in K_k, n \neq k} \tilde{g}_k[n]\tilde{g}_k[l_k] + e_k[n]$$

where $\tilde{e}_k[n]$ is the error vector accounting for combined effects of estimation error and channel aging which is mutually independent of $g_k[l_k]$. Hence, each element of $\tilde{e}_k[n]$ is i.i.d. with zero-mean and variance $\beta_k - \delta_k^2[n]$. Then, the received signal at user $k$ is given as

$$y_{d,k}[n] = \sqrt{P_k}\tilde{g}_k[n][W][n][x][n] + z_k[n]$$

$$= \sqrt{P_k}\tilde{g}_k[n][W][n][x][n] + \sqrt{P_k}\tilde{e}_k[n][W][n][x][n] + z_k[n]$$

$$= \sqrt{P_k}\tilde{g}_k[n][W][n][x][n] + \sqrt{P_k}\sum_{n \in K_k, n \neq k} \tilde{g}_k[n][W][n][x][n]$$

$$+ \sqrt{P_k}\tilde{e}_k[n][W][n][x][n] + z_k[n],$$

where $x_k[n]$ and $z_k[n]$ are user $k$'s element of $x[n]$ and that of $z[n]$, respectively.

Applying the methods widely used in the literature [3,4,6,10], we decompose the received signal for each user into the average effective channel gain times the transmitted signal, plus the effective noise as follows.

$$y_{d,k}[n] = \sqrt{P_k}\tilde{g}_k[n][W][n][x][n] + \sigma_k[n],$$

where $\sigma_k[n]$ represents the effective noise, which is given as

$$\sigma_k[n] = \sqrt{P_k}\tilde{g}_k[n][W][n][x][n] - \mathbb{E}\{\tilde{g}_k[n][W][n][x][n]\}$$

$$+ \sum_{n \in K_k, n \neq k} \tilde{g}_k[n][W][n][x][n] + z_k[n] + \sqrt{P_k}\tilde{e}_k[n][W][n][x][n] + z_k[n].$$

4. Achievable sum-rate under channel aging

To investigate the impact of channel aging on the performance, we now derive lower bounds on the achievable downlink sum-rate when aged CSI is used for scheduling. For mathematical derivation, we temporarily assume that the scheduling set $(K_k[n])$ and available CSI information $(\delta_k[n], \tilde{g}_k[l_k])$ are given a priori. From (12), the BS obtains the MMSE estimate of the current CSI $\hat{g}_k[n]$ depending on the last CSI $\tilde{g}_k[l_k]$ as

$$\hat{g}_k[n] = \delta_k[n]\tilde{g}_k[l_k].$$

Then, the received signal at user $k$ is given as

$$y_{d,k}[n] = \sqrt{P_k}\tilde{g}_k[n][W][n][x][n] + z_k[n]$$

$$= \sqrt{P_k}\tilde{g}_k[n][W][n][x][n] + \sqrt{P_k}\tilde{e}_k[n][W][n][x][n] + z_k[n]$$

$$= \sqrt{P_k}\tilde{g}_k[n][W][n][x][n] + \sqrt{P_k}\sum_{n \in K_k, n \neq k} \tilde{g}_k[n][W][n][x][n]$$

$$+ \sqrt{P_k}\tilde{e}_k[n][W][n][x][n] + z_k[n].$$

The effective noise is non-Gaussian and its entropy is upper-bounded by the entropy of Gaussian noise having the same variance. By treating the effective noise as the worst-case uncorrelated Gaussian noise, we next derive the lower bounds on the sum-rate for the two popular linear precoders, i.e., MRT and ZF.

4.1. Maximum ratio transmission

For MRT, the precoding matrix $W[n]$ is given by

$$W[n] = \sqrt{\lambda_{\text{mrt}}} \tilde{C}_k[n].$$

where $\lambda_{\text{mrt}}$ is the normalization constant chosen to meet the transmit power constraint (7). Therefore,

$$\lambda_{\text{mrt}} = \left( \mathbb{E}\{\mathbf{tr}(\tilde{C}_k[n]\tilde{C}_k[n])\} \right)^{-1} = \left( \sum_{i \in K_k[n]} \delta_i^2[n] \phi_i \right)^{-1},$$

where $\phi_i$ denotes $\frac{\tau_{\text{mrt}}}{\tau_{\text{mrt}}^2} + \rho_{\text{mrt}}$ for notational simplicity.

From (15) and (17), the received signal at user $k$ with MRT is given by

$$y_{r,mrt}[n] = \sqrt{\rho_{\text{mrt}}} \lambda_{\text{mrt}} \sum_{i \in K_k[n]} \tilde{g}_k[n][W][n][x][n]$$

$$+ \sqrt{\rho_{\text{mrt}}} \lambda_{\text{mrt}} \sum_{i \in K_k[n]} \tilde{g}_k[n][W][n][x][n]$$

$$+ \sqrt{\rho_{\text{mrt}}} \lambda_{\text{mrt}} \sum_{i \in K_k[n]} \tilde{g}_k[n][W][n][x][n]$$

4.2. Zero-forcing

For ZF, the precoding matrix $W[n]$ is given by

$$W[n] = \sqrt{\lambda_{\text{zf}}} \tilde{C}_k[n]\tilde{C}_k[n]^{-1},$$

where $\lambda_{\text{zf}}$ is the normalization constant chosen to satisfy the transmit power constraint (7). Therefore,

$$\lambda_{\text{zf}} = \left( \mathbb{E}\{\mathbf{tr}(\tilde{C}_k[n]\tilde{C}_k[n])\} \right)^{-1}.$$  

Recalling that the variance of each element of $\tilde{g}_k[n]$ is $\delta_k^2[n] \phi_k$, we decompose the estimated channel propagation matrix $\tilde{C}_k[n]$ into

$$\tilde{C}_k[n] = A[n]D[n].$$

where $A[n]$ is the $M \times K_k$ matrix with column vector $\tilde{g}_k[n]$, (i.e., $\tilde{g}_k[n]$, $\sqrt{\delta_k^2[n] \phi_k}$), and $D[n]$ is the $K_k \times K_k$ deterministic diagonal matrix with $D[n][ii] = \sqrt{\delta_k^2[n] \phi_k}$. Then,

$$\mathbf{tr}(\tilde{C}_k[n]\tilde{C}_k[n])^{-1} = \mathbf{tr}(\mathbf{D}[n]\mathbf{D}[n]^{-1}(A[n]A[n])^{-1})$$

5 Detailed procedures to obtain the information are described in Section 5.
Since \( A^T[n]A[n] \) is a central complex Wishart matrix \([30]\) and \((D^T[n]D^*[n])^{-1}\) is \( \frac{1}{\delta^2[n]p_k} \), from \((22)\) and \((24)\), we obtain

\[
\lambda_{ZF} = \left( \sum_{k \in \mathcal{K}[n]} \frac{1}{\delta^2[n]p_k} \right)^{-1} \left( \sum_{k \in \mathcal{K}[n]} \frac{1}{\delta^2[n]p_k} \right)^{-1}.
\]

\[
\hat{\lambda}_{ZF} = \frac{\sum_{k \in \mathcal{K}[n]} \frac{1}{\delta^2[n]p_k} \left[ \left( A^T[n]A[n] \right)^{-1} \right]_{ii} }{M - K}.
\]

From \((15)\) and \((21)\), the received signal at user \( k \) with ZF is given by

\[
y_{d,k}^Z[n] = \sqrt{\rho_d \lambda_{ZF} x_k[n]} + \sqrt{\rho_d \lambda_{ZF} \bar{e}^T_k[n] \bar{C}_k[n] \bar{C}_k[n]} x[n] + z_k[n].
\]

Note that the terms of beamforming uncertainty (2nd term) and inter-user interference (3rd term) in \((19)\) disappeared thanks to the characteristics of ZF \([6]\).

**Theorem 2.** For ZF with aged CSI, the lower bound on the achievable rate \([\text{bps/Hz}]\) of user \( k \in \mathcal{K}_a[n] \) is given as

\[
R_k^{ZF}(\mathcal{K}_a[n]) = \log_2 \left( 1 + \frac{\rho_d(M - K)}{(1 + \rho_d(\beta_k - \delta^2_k p_k))} \sum_{k \in \mathcal{K}_a[n]} \frac{1}{\beta_k p_k} \right).
\]

**Proof.** See Appendix B. \( \square \)

According to the analytical results, we now define the cell spectral efficiency \([\text{bps/Hz}]\) of the system using aged CSI as

\[
S^{PC}(\mathcal{K}_a[n]) = \left( 1 - \frac{T_u}{T} \right) \sum_{k \in \mathcal{K}_a[n]} R_k^{PC}(\mathcal{K}_a[n])
\]

where \( 'PC' \in \{ \text{mrt, zf} \} \) corresponds to either one of the precoders MRT and ZF. According to \((20), (27)\) and \((28)\), the spectral efficiency is dependent on the combination of users in the scheduling user set \( \mathcal{K}_a[n] \) and the channel variation coefficient of each user, i.e., \( \delta_k[n] \). In the following, we describe how efficiently OpSAC uses aged CSI in performing user selection procedures according to the analytical results.

**5. OpSAC design**

To guarantee that CSI is up-to-date before downlink transmission, the BS estimates the CSI by using uplink pilots from all the users to be served next \([3,5,8,9]\). This process provides the BS with accurate or updated CSI, but at the same time, time-frequency resource consumption increases proportionally to the number of scheduled users \([6]\). Thus, as we assign more and more time-frequency resources for uplink pilots to increase multiplexing gain, the amount of available resources for downlink transmission is reduced instead. Due to this trade-off, the multiplexing gain in massive MIMO systems can be exploited in a limited manner although the degree of freedom in BS antennas is sufficiently large. Moreover, if channel states for some users do not change frequently, i.e., slow or static users, resources may be unnecessarily wasted for updating the CSI which has not been changed since the last training period.

To alleviate the problem, we propose an opportunistic user scheduling algorithm that schedules more users by exploiting aged CSI. The key idea in OpSAC design is to use aged CSI as well as current CSI for user scheduling. That is, our algorithm targets to achieve both higher multiplexing gain and spectral efficiency without losing downlink transmission time. As shown in Fig. 3, our algorithm consists of the following two parts: estimation of channel variation coefficients which helps the BS estimate the amount of channel variation for each user according to the time elapsed from the last CSI training, and valid user selection which allows users to be scheduled opportunistically with aged but valid CSI to increase the spatial multiplexing gain, thereby enhancing spectral efficiency.

**5.1. Estimation of channel variation coefficients**

Different from conventional systems where the BS schedules users which set is the same as the pilot user set \( \mathcal{K}_a[n] \), OpSAC enables more users to be scheduled with aged CSI. To determine whether user scheduling using aged CSI is helpful in enhancing spectral efficiency or not, the BS faces challenges of precise estimation on channel variation of each associated user from the last training. To achieve this, we first propose a novel mechanism that uses collected CSI samples in estimating the temporal correlation coefficient \( (\hat{\delta}_k) \) of each user \( k \). Then, this provides the BS with the expected channel variation of user \( k \), denoted as \( \delta_k[n] \), from the last training to the current time \( n \).

During each uplink channel training period, the BS first selects the pilot user set, \( \mathcal{K}_{\delta}[n] \), according to the given pilot scheduling policy or objective function\(^6\) for (instance, spectral efficiency or fairness). Then, whenever the BS updates the CSI of each user \( k \in \mathcal{K}_{\delta}[n] \), it maintains the information of \( (\hat{l}_k, \hat{\delta}_k[l_k], \hat{\lambda}_k) \). According to this information, newly obtained CSI \( \hat{\delta}_k[l_k] \) from the training, and correlation between CSI samples \( \hat{\delta}_k[l_k] \) and \( \hat{\delta}_k[l_k] \), the BS estimates \( \hat{\delta}_k \) as

\[
\hat{\delta}_k = \sqrt{\frac{\hat{\delta}_k[l_k] \hat{\delta}_k[l_k]}{M \hat{\delta}_k}}.
\]

From \((13)\), we have

\[
\hat{\delta}_k[l_k] \hat{\delta}_k[l_k] = \delta_k[n] \cdot \left\{ \hat{\delta}_k[l_k] \hat{\delta}_k[l_k] \right\}
\]

---

\(^6\) Note that OpSAC operates independently of the pilot scheduler. In this paper, we assume the BS selects \( \mathcal{K}_{\delta}[n] \) in a simple round-robin manner.
\( \delta_k[n] = \delta_k[n] \cdot \sum_{m=1}^{M} |\hat{g}_{k,m}[l_k]|^2 \)

(a) \( \delta_k[n] \cdot M \phi_k \),

where \( \hat{g}_{k,m}[l_k] \) is the \( m \)th \((m = 1, 2, \ldots, M)\) element of \( \hat{g}_k[l_k] \) and (a) comes from the law of large numbers.

From (11) and (29), the BS obtains \( \delta_k[n] \) as follows:

\[
\delta_k[n] = \begin{cases} 
1, & \text{if } k \in \mathbb{X}_p[n] \\
(\hat{\alpha}_k)^{n-l_k}, & \text{if } k \notin \mathbb{X}_p[n]
\end{cases}
\]

(30)

In this way, the BS keeps updating \( \delta_k[n] \) of each associated user at each time slot. Although our algorithm uses only two CSI samples, it provides reliable estimation of the channel variation for each user (as shown in Section 6.3) because each CSI sample has a large number (i.e., \( M \)) of CSI elements. Note that this is why our algorithm is effective in massive MIMO systems and uses much smaller CSI samples than other training algorithms [25] which require accumulated channel statistics. The estimation procedures for channel variation coefficients are shown in Algorithm 1.

Algorithm 1 Estimation of Channel Variation Coefficients.
1: Initialization
2: \( n = 0 \)
3: \( l_k = 0, \hat{\alpha}_k = 0, \delta_k[n] = 0 \) for \( \forall k \in \mathbb{X}_a[n] \)
4: while (1) do // At each time slot
5: \( n = n + 1 \)
6: Select \( \mathbb{X}_p[n] \) in a round-robin manner // Pilot user set
7: for user \( k \in \mathbb{X}_p[n] \) do
8: Estimate \( \hat{g}_k[n] \) using the uplink pilot
9: if \( l_k = 0 \) then // If this is the first uplink training
10: // Do nothing
11: else
12: // Update the temporal correlation coefficient
13: \( \hat{\alpha}_k = \frac{n-l_k}{n} \left( \sum_{m=1}^{M} |\hat{g}_{k,m}[l_k]|^2 \right) \)
14: end if
15: Update the last CSI \( \hat{g}_k[l_k] \) with \( \hat{g}_k[n] \)
16: \( l_k = n \)
17: \( \delta_k[n] = 1 \)
18: end for
19: for user \( k \notin \mathbb{X}_p[n] \) and \( \hat{\alpha}_k \neq 0 \) do
20: \( \delta_k[n] = (\hat{\alpha}_k)^{n-l_k} \)
21: end for
22: end while

5.2. Valid user selection

After estimating the channel variation coefficient for each user, the BS obtains the valid user set that contributes to increasing the multiplexing gain. To accomplish this, the BS needs precise selection of users who help to improve performance even when serving users with aged CSI. If the BS chooses valid users too aggressively, inaccurate calculation of the precoding matrix most likely leads to performance degradation due to increased inter-user interference or imperfect estimation of beamforming weights. Similarly, if the BS selects valid users conservatively to reflect uncertainty in current channel conditions, potential multiplexing gain can not be fully utilized. As a solution, we consider two valid user selection approaches: simple threshold-based approach and sub-optimal approach.

5.2.1. Simple threshold-based approach

Recall that \( \delta_k[n] \) indicates the amount of channel variation of user \( k \) from the last CSI \( \left( \hat{g}_k[l_k] \right) \) until the time user \( k \) is served. In this approach, to determine whether the available CSI is valid or not, the BS uses the valid user threshold \( \delta_{th} \), which denotes the amount of maximum channel variation allowed for valid user selection while avoiding severe performance loss due to the use of inaccurate aged CSI. When the pilot user set \( \mathbb{X}_p[n] \) is given, we define the rest of associated users as the valid user candidate set \( \mathbb{X}_c[n] = \mathbb{X}_a[n] \setminus \mathbb{X}_p[n] \). Then, the BS compares \( \delta_{th} \) with \( \delta_k[n] \) for each user \( k \in \mathbb{X}_c[n] \) in descending order of \( \delta_k[n] \). If \( \delta_k[n] \) is larger than the threshold \( \delta_{th} \), the BS considers user \( k \) as a valid user unless the total number of scheduled users reaches \( M \). These procedures are described in Algorithm 2.

Algorithm 2 Threshold-based Valid User Selection.
1: Initialization
2: \( n = 0 \)
3: \( l_k = 0, \hat{\alpha}_k = 0, \delta_k[n] = 0 \) for \( \forall k \in \mathbb{X}_a[n] \)
4: while (1) do // At each time slot
5: \( n = n + 1 \)
6: Select \( \mathbb{X}_p[n] \) in a round-robin manner // Pilot user set
7: \( \mathbb{X}_c[n] \leftarrow \mathbb{X}_p[n] // \) Scheduling user set
8: \( \mathbb{X}_c[n] \leftarrow \mathbb{X}_a[n] \setminus \mathbb{X}_p[n] // \) Valid user candidate set
9: Get \( \delta_k[n] \) from estimation of channel variation coefficients
10: for user \( k \in \mathbb{X}_c[n] \) do // In descending order of \( \delta_k[n] \)
11: if \( \delta_k[n] \geq \delta_{th} \) then
12: \( \mathbb{X}_a[n] \leftarrow \{k\} \cup \mathbb{X}_c[n] // \) Valid user selection
13: else
14: break
15: end if
16: if \( |\mathbb{X}_a[n]| = M \) then
17: break
18: end if
19: end for
20: Schedule \( \mathbb{X}_a[n] \) for downlink transmission
21: end while

Note that the multiplexing gain and performance loss due to the lack of accuracy in aged CSI depend on \( \delta_{th} \). For example, if we decrease \( \delta_{th} \), the multiplexing gain is likely to increase by having more valid users while the accuracy of CSI for the users decreases, and vice versa. Therefore, finding an optimal \( \delta_{th} \) is important for valid user selection. However, this is not straightforward since it needs to be determined by the combination of scheduled users and the amount of channel variation of each user at each time slot. In order to overcome the limitations of the simple threshold-based approach, we consider a sub-optimal approach next.

5.2.2. Sub-optimal approach

Since precoding is very sensitive to the accuracy of CSI (especially when the number of scheduled users is large), \( \text{OpSAC} \) maintains a balance between multiplexing gain and CSI accuracy. To determine whether to schedule a certain user by using aged CSI or not, \( \text{OpSAC} \) exploits our analysis results obtained in Section 4. More specifically, when the pilot user set \( \mathbb{X}_p[n] \) is selected, \( \text{OpSAC} \) targets to maximize the spectral efficiency \( \text{SEP}(\mathbb{X}_a[n]) \) in Eq. (28) at each transmission. To formulate the problem, we first introduce two scheduling indicator vectors: \( \mathbf{I}_p[n] = [I_{p,k}[n] : k \in \mathbb{X}_a[n]] \) for pilot user selection and \( \mathbf{I}_v[n] = [I_{v,k}[n] : k \in \mathbb{X}_a[n]] \) for valid user selection. Here the two indicator variables \( I_{p,k}[n] \) and \( I_{v,k}[n] \) are
defined as follows:

\[ I_{p,k}[n] = \begin{cases} 1, & \text{if user } k \text{ is selected as a pilot user,} \\ 0, & \text{otherwise.} \end{cases} \] (31)

\[ I_{v,k}[n] = \begin{cases} 1, & \text{if user } k \text{ is selected as a valid user,} \\ 0, & \text{otherwise.} \end{cases} \] (32)

Assuming \( \tau_u \) pilot sequences are available for uplink training, we have

\[ \sum_{k \in K_u[n]} I_{p,k}[n] \leq \tau_u. \] (33)

Also, \( I_{p,k}[n] \) and \( I_{v,k}[n] \) should satisfy the following degree of freedom constraint at the BS:

\[ \sum_{k \in K[n]} I_{p,k}[n] + I_{v,k}[n] \leq M. \] (34)

Since \( K_u[n] \) can be rewritten as a function of \( I_{p,k}[n] \) and \( I_{v,k}[n] \), we can formulate the problem that combines spectral efficiency maximization with user scheduling, as follows:\(^7\)

\[
\text{maximize } S^\text{up}(I_{p}[n], I_{v}[n]) \quad \text{subject to } \sum_{k \in K[n]} I_{p,k}[n] + I_{v,k}[n] \leq M. \] (35)

Finding an optimal scheduling user set in the above is a combinatorial problem with binary integer variables, thus exhaustive search is the only solution to this problem [31]. Despite its optimality, it is computationally intractable especially when the number of associated users \( K_u \) is large [32]. Hence, we propose a heuristic algorithm that performs incremental user selection with low complexity and obtains near-optimal performance [33].

After each uplink training, the BS calculates the expected spectral efficiency \( S_{\text{ex}} = S^\text{up}(K_u[n] = K^p[n]) \) as if only the pilot user set is scheduled. Then, among the users in the valid user candidate set \( K_u[n] = K_u[n] \setminus K^p[n] \), the BS selects the first user \( k_{\text{best}} \) that potentially achieves the best performance improvement when scheduled with the given \( K_u[n] \). If at least one user is selected, the BS adds that user to \( K_u[n] \) as a valid user, and updates \( S_{\text{ex}} \) with new \( K_u[n] \). In the same way, the BS continues choosing additional valid users until there is no valid user for performance improvement or the total number of scheduled users reaches \( M \). These procedures are shown in Algorithm 3.

6. Performance evaluation

In this section, we validate the analysis results obtained in Section 4, investigate the impact of channel aging on the performance, and evaluate OpSAC through simulation.

6.1. Simulation environments

We consider a single-cell with a radius of 500 m. We assume that users are uniformly distributed within the cell that has the guard range \( r_g \) of 100 m, which is defined as the minimum distance between a user and the BS. The large-scale fading is modeled as \( P_k = 1/(r_k/r_g)^\gamma \), where \( r_k \) is the distance between the BS and user

\[ k, \text{ and the pass loss exponent } \gamma \text{ equals 3.5. To observe channel aging effects clearly, we do not consider shadow fading.} \]

We use OFDM parameters similar to those of LTE standards [34]. Specifically, as in [3,5], we assumed that an OFDM symbol duration of \( T_{\text{sym}} = 71.4 \mu s \) is a useful symbol duration of \( T_u = 66.7 \mu s \), and a guard interval of \( T_g = T_{\text{sym}} - T_u = 4.7 \mu s \). We also set the duration of a time slot as \( T_s = 1 \) ms that comprises \( T = \frac{T_u}{T_{\text{sym}}} \frac{1}{T_g} = 14 \times 14 = 196 \) symbols, where \( \frac{T_u}{T_{\text{sym}}} = 14 \) is the number of OFDM symbols in a 1 ms subframe duration, and \( \frac{T_u}{T_g} = 14 \) corresponds to the “frequency smoothness interval” [5]. In all cases, we set the pilot sequence length \( \tau_u \) as \( K_p \), which is the minimum duration to train \( K_p \) users. Finally, we choose \( f_c = 2.1 \) GHz, \( \rho_d = 30 \) dB, and \( \rho_n = 20 \) dB.

6.2. Impact of channel aging in massive MIMO systems

Before evaluating OpSAC, we first validate our analysis results and verify channel aging effects on the performance of massive MIMO systems. To understand the effects clearly, we assume all the users are scheduled using aged CSI with a same channel variation coefficient, i.e., \( \delta_k[n] = \delta \) for all user \( k \in K[n] \).

Fig. 4 shows the spectral efficiencies according to \( \delta \) when \( M = 300 \) and \( K_0 = 42 \). The simulation results are generated via using Monte-Carlo simulations, and the analysis results are obtained by using (20) and (27). As we can easily observe, our analysis results are very close to the simulation results, which indicates the exactness of our analysis results. We also confirm that, as channel aging becomes severe (or \( \delta \) decreases), the performances of MRT and ZF are degraded rapidly due to the use of outdated CSI for calculating beamforming weights. In particular, ZF suffers more performance loss than MRT due to imperfect inter-user interference cancellation with aged CSI. Since MRT targets to maximize the desired received

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\(^7\) Although we only focus on maximizing spectral efficiency, we can also consider fairness by simply replacing the objective function with a network-wide aggregate utility function (for instance, log utility function for proportional fairness).
signal power, channel aging has a relatively smaller impact on MRT compared to ZF.

Next, we evaluate the channel aging effects according to the number of BS antennas $M$ when $K_a = 42$. Fig. 5 shows the normalized spectral efficiency when the BS uses aged CSI compared to the case of using current CSI. Interestingly, the normalized spectral efficiencies for both MRT and ZF increase with the number of deployed BS antennas, indicating that the impact of channel aging on spectral efficiency loss can be alleviated by using more antennas. This shows that aged CSI has a potential when it is used for a large number of BS antennas, especially in massive MIMO systems.

6.3. Accuracy of temporal correlation coefficient estimation

OpSAC aims to enhance multiplexing gain by scheduling more users with aged CSI. To avoid spectral efficiency loss due to inaccurate valid user selection, precise estimation of $\alpha_k$ has to be preceded to accurately estimate $\delta_k[n]$ through Eq. (30). As a measure to assess accuracy of $\alpha_k$ estimation in OpSAC, we define the normalized mean squared error of estimation accuracy as

$$\epsilon_k = \frac{\hat{\alpha}_k - \alpha_k}{\hat{\alpha}_k}. \quad (38)$$

We evaluate the estimation accuracy as follows. Whenever the BS updates $\hat{\alpha}_k$ after uplink training, it records the $\epsilon_k$, and takes average when the simulation is over. Fig. 6 depicts the cumulated distribution function (cdf) of averaged $\epsilon_k$ of all the associated users according to the mean user velocity $\bar{v}$ and the number of BS antennas when $K_a = 200$ and $K_f = 42$. In Fig. 6(a), we can see that estimation accuracy improves as the mean user velocity decreases since the estimation error due to channel aging is reduced. Also, it is shown in Fig. 6(b) that, as the number of BS antennas increases, the estimation accuracy improves because a larger number of channel coefficient samples are used for estimation. In both experiments, we can confirm that our $\alpha_k$ estimation only incurs negligible error, i.e., averaged $\epsilon_k$’s of all users are smaller than $10^{-3}$. This indicates that our estimation is reliable and applicable to massive MIMO systems.

6.4. Optimality

To show that the sub-optimal approach of OpSAC efficiently achieves near-optimal performance, we compare OpSAC with the
exhaustive search (ES) algorithm. Since the complexity of ES is very high, i.e., $O(2^K)$, we consider a feasible and tractable scenario of $M = 20$, $K_u = 10$, and $K_p = 2$. Fig. 7 shows spectral efficiencies obtained from ES and OpSAC for the both precoders, i.e., MRT and ZF. On average, the performance gap between ES and OpSAC is negligible, which means that OpSAC achieves near-optimal spectral efficiency. This is because our algorithm forces semi-orthogonality among users during the valid user selection procedures. Although ES achieves slightly better performance than OpSAC, its complexity becomes intractable as $K_u$ increases. On the other hand, OpSAC has the low complexity of $O(K_u^2)$. Therefore, we can conclude that OpSAC is a viable solution for practical cases.

6.5. Performance evaluation

For performance evaluation, we compare the following algorithms:

- **OpSAC with Sub-optimal valid user selection (OpSAC-S):** This algorithm enables the BS to select more users from the valid user set according to the sub-optimal valid user selection. Therefore, the scheduling user set is the sum of the pilot user set and the valid user set, i.e., $K_u[n] = K_p[n] \cup K_v[n]$.

- **OpSAC with Threshold-based valid user selection (OpSAC-T):** In this algorithm, the BS selects more users from the valid user set according to the threshold-based valid user selection. Here, the scheduling user set is the sum of the pilot user set and the valid user set, i.e., $K_u[n] = K_p[n] \cup K_v[n]$.

- **Conventional Round-robin scheme (CR):** This algorithm only uses current CSI for user scheduling. Therefore, the scheduling user set is the same as the pilot user set, i.e., $K_u[n] = K_p[n]$.

We first investigate the impact of $\delta_{th}$ on the performance of OpSAC-T. Fig. 8 depicts spectral efficiencies of OpSAC-S, OpSAC-T, and CR according to $\delta_{th}$ when $M = 400$, $K_u = 200$, $K_p = 42$, and $\bar{v} = 40$ km/h. First of all, we can see that the performance of CR remains constant irrespective of $\delta_{th}$ since it only schedules users in the pilot user set without having additional valid user selection. It also shows that the performance of OpSAC-T is greatly affected by $\delta_{th}$. For example, as $\delta_{th}$ decreases, the performance with MRT is improved up to a certain $\delta_{th}$ first. After that point, the performance with MRT is saturated because the benefit of higher multiplexing gain is canceled out with the increase of inter-user interference.

Different from this, the performance with ZF is first improved by increasing multiplexing gain. However, as $\delta_{th}$ is decreased more, the performance sharply degrades due to overly reduced desired signal power and poor inter-user interference cancellation caused by aged CSI. This reveals that the performance of OpSAC-T is highly dependent on the $\delta_{th}$, thus choosing a proper $\delta_{th}$ is important to maximize performance. Meanwhile, OpSAC-S always achieves steady performance and outperforms the other schemes since it creates the sub-optimal user set, considering channel variation and scheduled user combination.

We now compare the additional multiplexing gain obtained from valid user selection procedures and the performance of each scheme according to the mean user velocity. Fig. 9 depicts the average number of scheduled valid users and the spectral efficiencies of each scheme when $M = 400$, $K_u = 200$, and $K_p = 42$. For OpSAC-T, we consider two threshold values, i.e., $\delta_{th} = 0.8$ and 0.6. As shown in Fig. 9(a), OpSAC-T for $\delta_{th} = 0.6$ always selects more number of valid users than that for 0.8 since the valid user set of both schemes are determined by the $\delta_{th}$ only. Specifically, the larger $\delta_{th}$ is used, the more valid users are selected. OpSAC-S, on the other hand, adaptively schedules proper number of valid users according to the given mean user velocity and the employed precoder. Fig. 9(b) and (c) show that, as the mean user velocity increases, the performance gain of OpSAC-S and OpSAC-T over CR decreases since the number of available valid users decreases or channel aging becomes severe. Interestingly, OpSAC-T with MRT for $\delta_{th} = 0.6$ shows better performance than that for 0.8, and vice versa with ZF. It means that achieving higher multiplexing gain even with inter-user interference is effective with MRT, and using aged CSI in a conservative manner is preferred for ZF. In contrast, OpSAC-S always achieves better performance than the other schemes by scheduling the valid users adaptively.

Fig. 10 shows the performance of each scheme as $\tau_u$ (the number of pilot sequences) increases from 14 to 182 when $M = 400$, $K_u = 200$, and $\bar{v} = 40$ km/h. From Fig. 10(b) and (c), we can observe the spectral efficiency of each scheme first increases owing to its use of more pilot sequences for uplink training. However, as $\tau_u$ increases more, the performance of each scheme rather decreases due to the reduced downlink transmission time. It indicates that maintaining the balance between multiplexing gain and downlink transmission time is important to maximize the performance. It is also shown that the optimal $\tau_u$’s for both OpSAC-S and OpSAC-T are smaller than that of CR. For example, when MRT is used at the BS, the optimal $\tau_u$’s for OpSAC-S and CR are 42 and 70, respectively. This is because both OpSAC-S and OpSAC-T can compensate reduced multiplexing gain by using aged CSI while they mainly allocate...
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Fig. 9. The number of average valid users and spectral efficiencies of each scheme according to the mean user velocity.

(a) Average valid users vs. Mean user velocity
(b) Spectral efficiency vs. Mean user velocity (MRT)
(c) Spectral efficiency vs. Mean user velocity (ZF)

Fig. 10. The number of average valid users and spectral efficiencies of each scheme according to the number of pilot sequences.

(a) Average valid users vs. Pilot Sequences
(b) Spectral efficiency vs. Pilot sequences (MRT)
(c) Spectral efficiency vs. Pilot sequences (ZF)

Fig. 11. Spectral efficiencies of each scheme according to the number of BS antennas.

(a) Spectral efficiency vs. BS antennas (MRT)
(b) Spectral efficiency vs. BS antennas (ZF)

(extra resources for downlink transmission, thereby enhancing spectral efficiency. Again, OpSAC-S outperforms the other schemes due to its adaptive scheduling of valid users as depicted in Fig. 10(a).

Lastly, we investigate how the number of BS antennas influences the performance of each scheme $K_b = 200$, $K_p = 42$, and $v = 40 \text{ km/h}$. Fig. 11 shows, as the number of BS antennas increases, the performance of each scheme is improved as expected. Also, the performance gains of OpSAC-S and OpSAC-T over CR increase since the performance degradation due to the use of aged CSI becomes less affected with the number of BS antennas. In addition, MRT attains relatively larger gain compared to ZF, indicating that ZF is more susceptible to aged CSI than MRT especially when the number of BS antennas is small. Nevertheless, we can confirm that using aged CSI has a potential to improve spectral efficiency in massive MIMO systems.

7. Conclusion

In this paper, we proposed a practical user scheduling algorithm, termed OpSAC, that uses aged CSI and opportunistically includes more users for user scheduling. Assuming the BS employs
MRT and ZF, we first analyzed the lower bound on sum-rate when aged CSI is exploited for user scheduling. According to the analytical results, we provided a heuristic user scheduling solution that comprises estimation of channel variation coefficients and valid user selection, which enables more users to be scheduled opportunistically by using aged CSI to improve performance. Through simulation, we verified our analysis results and investigated the impact of channel aging on spectral efficiency. Also, it was shown that OpSAC achieves near-optimal performance and substantially outperforms the conventional user scheduling algorithm that only uses current CSI. In addition, the simulation results revealed the impacts of various factors such as user mobility, number of BS antennas, number of pilot sequences and beamforming methods on the performance gain.

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Appendix A. Proof of Theorem 1

We obtain the lower bound on the achievable rate by evaluating the variance of each term in (19) as follows.

1) 1st term: Recall that the variance of each element of $\mathbf{g}_k[n]$ is $\delta^2[n] \phi_k$, then

$$\rho \lambda^2 \Var \left[ R \{ \mathbf{g}_k[n] \mathbf{g}_k[n] \} \right] = \rho \lambda^2 \Var \left[ \mathbf{g}_k[n] \right] = \rho \lambda^2 \Var \left[ \sum_{i \in \mathcal{K}} \mathbf{g}_i[n] \Phi_i \right] = \rho \lambda^2 \Var \left[ \mathbf{g}_k[n] \right] \Phi_k.$$

2) 2nd term: From (A.1), we have

$$\Var \left[ \mathbf{g}_k[n] \mathbf{g}_k[n] \right] = \rho \lambda^2 \Var \left[ \mathbf{g}_k[n] \right] \Phi_k.$$

Since $\Var \left[ \mathbf{g}_k[n] \mathbf{g}_k[n] \right] = \rho \lambda^2 \Var \left[ \mathbf{g}_k[n] \right] \Phi_k$, we obtain

$$\rho \lambda^2 \Var \left[ \mathbf{g}_k[n] \mathbf{g}_k[n] \right] = \rho \lambda^2 \Var \left[ \mathbf{g}_k[n] \right] \Phi_k.$$

3) 3rd term: For $i \neq k$, we have

$$\Var \left[ \mathbf{g}_i[n] \mathbf{g}_k[n] \right] = \left( \sum_{i \in \mathcal{K}} \mathbf{g}_i[n] \mathbf{g}_j[n] \Phi_i \right) \Phi_k.$$

Therefore, we obtain

$$\rho \lambda^2 \Var \left[ \mathbf{g}_i[n] \mathbf{g}_k[n] \right] = \rho \lambda^2 \Var \left[ \mathbf{g}_i[n] \mathbf{g}_k[n] \right] \Phi_k.$$

4) 4th term: Recall that the variance of each element of $\mathbf{g}_k[n]$ is $\rho \delta^2[n] \phi_k$, then

$$\rho \lambda^2 \Var \left[ \mathbf{g}_k[n] \mathbf{g}_k[n] \right] = \rho \lambda^2 \Var \left( \mathbf{g}_k[n] \mathbf{g}_k[n] \Phi_k \right) \Phi_k = \rho \lambda^2 \Var \left( \mathbf{g}_k[n] \mathbf{g}_k[n] \Phi_k \right).$$

From these results, we obtain the effective signal to interference and noise ratio (SINR) of user $k$ with MRT as

$$\text{SINR}_k = \frac{\Var(1\text{st term})}{\sum_{j=1}^{M} \Var(j\text{-th term})}.$$

Finally, we obtain the result of Eq. (20).

Appendix B. Proof of Theorem 2

We obtain the lower bound on the achievable rate by evaluating the variance of each term in (26) as follows:

1) 2nd term: Recall that the variance of each element of $\mathbf{e}_k[n]$ is $\rho \delta^2[n] \phi_k$. Then

$$\rho \lambda^2 \Var \left[ \mathbf{e}_k[n] \mathbf{e}_k[n] \right] = \rho \lambda^2 \Var \left( \mathbf{e}_k[n] \mathbf{e}_k[n] \Phi_k \right).$$

According to (B.1), we obtain the effective SINR of user $k$ with ZF

$$\text{SINR}_k = \frac{\Var(1\text{st term}) + \Var(2\text{nd term}) + \Var(3\text{rd term})}{\rho \lambda^2 (M - K)}.$$

References


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