Adaptive Channel Estimation for TDD Massive MIMO Systems with Heterogeneous User Coherence Times

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***Abstract*—In massive multiple-input-multiple-output (MIMO) systems, users periodically send pilot sequences for channel estimation in a fixed time interval, which results in pilot redundancy when a user undergoes longer coherence time than the time interval defined by LTE specification. In this paper, we propose an adaptive channel estimation scheme for time-division-duplex massive MIMO systems, which reuses the aged channel estimations by exploiting the temporal channel correlations underlying the channel aging effect. We also derive the net sum spectral efficiency of the proposed scheme and design a novel method to determine the channel estimation interval for each user. Numerical results demonstrate significant performance gains as compared to conventional ones, indicating that our proposed scheme is adaptive to diverse communication scenarios.**

***Index Terms*—channel estimation, coherence time, massive MIMO, temporal correlation.**

I. Introduction

Massive multiple-input-multiple-output (MIMO) is deemed as a critical component in 5G and beyond mobile networks due to its promised huge energy efficiency and spectral efficiency [1]. By deploying large arrays of antennas at base stations (BSs), massive MIMO systems can employ simple linear precoding techniques to serve a large number of users simultaneously. Besides, massive MIMO can mitigate small-scale fading and frequency dependence owing to channel hardening [2]–[4].

Massive MIMO requires accurate channel state information (CSI) estimates to fully realize the aforementioned gains. In time-division-duplex (TDD) massive MIMO systems, CSI is estimated by uplink training with orthogonal pilot sequences, and the length of the pilot sequence is proportional to the number of users due to channel reciprocity [5]. As a consequence, TDD massive MIMO suffers an enormous amount of CSI estimation overhead in application scenarios with high mobile device density, such as concerts and train station waiting areas. Moreover, all users estimate CSI at the same interval in the TDD massive MIMO systems, and the interval is set to be short so as to fit extreme communication scenarios where users undergo high *Doppler* frequency shifts [6]. Users in heterogeneous propagation environments have different channel coherence times, and many of them have longer coherence times than the CSI estimation interval defined by LTE specification. The mismatch between channel coherence time and fixed CSI estimation interval results in a considerable number of redundant pilot sequences in conventional CSI estimation schemes. Therefore, it is promising to design new CSI estimation schemes to exploit the heterogeneous user coherence times.

Most prior efforts primarily focus on leveraging the spatial correlation between user channels to design pilot allocation strategies that reduce channel estimation overhead for the TDD massive MIMO systems [7]–[9], while only a few studies explore temporal channel correlation underlying the pilot redundancy. In [6] and [10], the relationship between temporal channel correlation and user velocity is modeled by *Jakes* model [11]. The BS divides users into different groups according to their velocities and allocates distinct channel estimation intervals to each group to improve system capacity. In [12], the authors introduce intermittent channel estimation schemes in which case the BS can reuse aged CSI estimation accounting for the channel aging effect between time slots. Specifically, the BS schedules a fixed number of users to transmit pilot sequences in each slot to maximize the achievable sum rate. While the aforementioned channel estimation schemes achieve substantial performance improvements, they are not applicable in non-uniform scattering environments due to the assumptions inherent in *Jakes* model. Additionally, the actual channel coherence time depends not only on user mobility but also on the dynamic propagation environment. Therefore, assessing the strength of temporal channel correlation solely according to user mobility is unreasonable, leading to the aforementioned methods not fully exploiting the diversity and redundancy among actual user coherence times. We try to overcome these shortcomings by estimating the temporal channel correlation in real time. In contrast with [6], [10], [12], we adopt a more general channel model similar to the one in [13], and focus on determining the channel estimation interval for each user rather than scheduling users to estimate channel in each time slot.

In this paper, we first propose an adaptive channel estimation scheme for TDD massive MIMO systems, in which the BS assigns adaptive CSI estimation intervals to users by exploiting the temporal correlations of user channels. The net sum spectral efficiency of the adaptive scheme is also derived, accounting for channel aging and estimation errors. Then, we design a method based on high-confidence interval estimates of temporal channel correlation to determine the CSI estimation interval for each user. Specifically, the BS first uses estimated CSI samples to obtain the high-confidence lower bounds on the temporal channel correlation estimates for all users, then the BS determines the channel estimation interval for each user by comparing the lower bound with a threshold. We further derive the lower bound on the asymptotic average achievable rate obtained by this method. Subsequently, we compare the performance gains of the conventional CSI estimation scheme to those of the proposed adaptive CSI estimation scheme using COST 2100 channel model [14]. Numerical results indicate that both user mobility and signal-to-noise ratio (SNR) can affect the time interval of CSI estimation, and our proposed channel estimation scheme can greatly improve the net sum spectral efficiency as compared to the conventional one in various communication scenarios.

The rest of this paper is structured as follows. Section II describes the system model we adopt. Section III elaborates on the adaptive channel estimation scheme for TDD massive MIMO systems and derives the net sum spectral efficiency of the adaptive scheme. In Section IV, we propose a method to determine the CSI estimation intervals for different users. Finally, Sections V and VI present the numerical results and conclusions, respectively.

II. System Model

Consider a single-cell TDD massive MIMO system where a BS equipped with M antennas serves K single-antenna users. The channel vector $\boldsymbol{g}_k \in \mathbb{C}^{M\times 1}$ between the BS and the kth user is given by

$$\boldsymbol{g}_k = \sqrt{\beta_k}\boldsymbol{h}_k, \tag{1}$$

where β_k represents the large-scale fading between the BS and the kth user, and $\boldsymbol{h}_k \sim \mathcal{CN}(\mathbf{0}, \boldsymbol{I}_M)$ is a small-scale fading vector. Each slot has a length of N_c symbols and consists of two phases: uplink channel training with τ_{ul} symbols and downlink data transmission with $N_c - \tau_{ul}$ symbols. To consider the temporal correlation of the channel, we adopt a quasi-static block fading channel model where $\boldsymbol{g}_k$ stays constant in a slot but varies from slot to slot [15]. The l-delayed channel vector $\boldsymbol{g}_k[n+l]$ can be expressed as [12]

$$\boldsymbol{g}_k[n+l] = \rho_{k,l}\boldsymbol{g}_k[n] + \boldsymbol{\varepsilon}_k[n+l], \tag{2}$$

where $\boldsymbol{\varepsilon}_k[n+l] \sim \mathcal{CN}(\mathbf{0}, \beta_k(1-\rho_{k,l}^2)\boldsymbol{I}_M)$, and $\rho_{k,l}$ is the temporal correlation coefficient of the channel. β_k and $\rho_{k,l}$ are invariant in a stationary block. To simplify notation, the time slot index n is omitted in the rest of the section.

A. Uplink Training

In the uplink training phase, all users synchronously send pilot sequences $\boldsymbol{\psi}_k \in \mathbb{C}^{\tau_{ul}\times 1}$ to the BS, and $\boldsymbol{\psi}_k$ is the kth column of $\boldsymbol{\Psi} \triangleq [\boldsymbol{\psi}_1, \boldsymbol{\psi}_2, \cdots, \boldsymbol{\psi}_k, \cdots, \boldsymbol{\psi}_K]$. Since the pilot sequences of K users are pairwisely orthogonal, $\tau_{ul} \geq K$ and $\boldsymbol{\Psi}^H\boldsymbol{\Psi} = \boldsymbol{I}_K$ must hold. Then the received signal matrix $\boldsymbol{Y}_p$ at the BS can be expressed as

$$\boldsymbol{Y}_p = \sqrt{\tau_{ul}p_{ul}}\boldsymbol{G}\boldsymbol{\Psi}^H + \boldsymbol{W}_p, \tag{3}$$

where $\boldsymbol{G} \triangleq [\boldsymbol{g}_1, \cdots, \boldsymbol{g}_k, \cdots, \boldsymbol{g}_K]$, p_{ul} denotes the SNR for uplink pilot transmission and $\boldsymbol{W}_p \in \mathbb{C}^{M\times\tau_{ul}}$ is the additive noise matrix whose elements are i.i.d. complex Gaussian random variables with zero mean and unit variance. After receiving the signal $\boldsymbol{Y}_p$, the BS can acquire the channel estimate via the minimum mean-square error (MMSE) estimator. The linear MMSE estimate of $\boldsymbol{g}_k$ is given by

$$\hat{\boldsymbol{g}}_k = \frac{\tau_{ul}p_{ul}\beta_k}{\tau_{ul}p_{ul}\beta_k + 1}\boldsymbol{g}_k + \frac{\sqrt{\tau_{ul}p_{ul}}\beta_k}{\tau_{ul}p_{ul}\beta_k + 1}\boldsymbol{w}_{p,k}, \tag{4}$$

where $\boldsymbol{w}_{p,k} \sim \mathcal{CN}(\mathbf{0}, \boldsymbol{I}_M)$ is the noise vector mutually independent of $\boldsymbol{g}_k$. The average power of the mth component of the channel estimation vector $\hat{\boldsymbol{g}}_k$ is

$$\gamma_k \triangleq \mathbb{E}\left\{\|\hat{g}_k^m\|^2\right\} = \frac{\tau_{ul}p_{ul}\beta_k^2}{1+\tau_{ul}p_{ul}\beta_k}. \tag{5}$$

Let $\tilde{\boldsymbol{g}}_k = \hat{\boldsymbol{g}}_k - \boldsymbol{g}_k$ denote the channel estimation error, with $\tilde{g}_k^m$ representing the mth component of the vector $\tilde{\boldsymbol{g}}_k$. Due to the orthogonality of the MMSE estimator, $\tilde{g}_k^m$ and $\hat{g}_k^m$ are uncorrelated. $\mathbb{E}\left\{\|\tilde{g}_k^m\|^2\right\}$ can be calculated as

$$\mathbb{E}\left\{\|\tilde{g}_k^m\|^2\right\} = \beta_k - \gamma_k \geq 0. \tag{6}$$

B. Downlink Data Transmission

Let s_k be the symbol the BS transmits to user k during the downlink transmission phase. The transmitted symbol vector is denoted as $\boldsymbol{s} \triangleq [s_1, \cdots, s_K]^T$, which satisfies $\mathbb{E}\{\boldsymbol{s}\boldsymbol{s}^H\} = \boldsymbol{I}_K$. The transmitted signal after linear precoding is given by

$$\boldsymbol{x} = \boldsymbol{A}\boldsymbol{D}_\eta^{1/2}\boldsymbol{s}, \tag{7}$$

where $\boldsymbol{A} \in \mathbb{C}^{M\times K}$ is the precoding matrix, which is a function of $\hat{\boldsymbol{G}} \triangleq [\hat{\boldsymbol{g}}_1, \cdots, \hat{\boldsymbol{g}}_K]$. $\boldsymbol{D}_\eta \triangleq \mathrm{diag}\{\eta_1, \eta_2, \cdots, \eta_K\}$ is a power scaling matrix satisfying the power normalization $\mathbb{E}\{\|\boldsymbol{x}\|^2\} = 1$, where η_k is the power scaling parameter corresponding to the signal for user k. In this paper, we employ the zero-forcing (ZF) precoding. Consequently, the ZF precoding matrix is

$$\boldsymbol{A} = \sqrt{M-K}\hat{\boldsymbol{G}}^*(\hat{\boldsymbol{G}}^T\hat{\boldsymbol{G}}^*)^{-1}\boldsymbol{D}_\gamma^{1/2}, \tag{8}$$

where $\boldsymbol{D}_\gamma \triangleq \mathrm{diag}\{\gamma_1, \gamma_2, \cdots, \gamma_K\}$. After the BS transmits the precoded signal $\boldsymbol{x}$, the received signal vector which denoted as $\boldsymbol{y}$ is given by

$$\boldsymbol{y} = \sqrt{p_{dl}}\boldsymbol{G}^T\boldsymbol{x} + \boldsymbol{w}, \tag{9}$$

where $\boldsymbol{y} \triangleq [y_1, \cdots, y_k, \cdots, y_K]^T$, p_{dl} is the average downlink SNR, and $\boldsymbol{w} \triangleq [w_1, \cdots, w_k, \cdots, w_K]^T$, with each element $w_k \sim \mathcal{CN}(0,1)$ representing the noise at the kth user. Let $\boldsymbol{a}_k$ be the kth column of $\boldsymbol{A}$. Accordingly, the kth user observes

$$y_k = \sqrt{p_{dl}\eta_k}\boldsymbol{g}_k^T\boldsymbol{a}_k s_k + \sum_{k'\neq k}^{K}\sqrt{p_{dl}\eta_{k'}}\boldsymbol{g}_k^T\boldsymbol{a}_{k'}s_{k'} + w_k. \tag{10}$$

III. Adaptive Channel Estimation Scheme for TDD Massive MIMO Systems

The conventional TDD massive MIMO systems apply a constant CSI estimation interval T_s to all users, where T_s is the duration of a slot. All users need to send pilot sequences in each slot, which results in pilot redundancy since the coherence times of many users exceed T_s. Considering the impact of channel aging, the BS can reuse the aged CSI estimation to precode data in the current slot if the channel varies minimally, as aged channels with strong temporal correlations can still provide effective spectral efficiency in massive MIMO systems [15]. The part of training resources freed by reusing aged estimated CSI can be used for data transmission. Based on the idea, we propose an adaptive channel estimation scheme and then derive the formula for the net sum spectral efficiency of our proposed scheme. Recall that the user temporal channel correlations are constant in each stationary block. For the convenience of scheme design, we use the stationary block duration as the update period for the channel estimation intervals. Let N_s denote the length of the stationary block. The intervals of channel estimation for all users in a stationary block are denoted by $u_1 T_s, \ldots, u_k T_s, \ldots, u_K T_s$, where $u_k \in \mathbb{N}^+$. The BS estimates the channel in a conventional scheme when $u_k = 1$. For those users with $u_k > 1$, the BS reuses the latest aged CSI estimation to precode and transmit data, respectively.

Compared to conventional schemes where the BS estimates the channel in each slot, the adaptive channel estimation scheme reuses the latest channel estimation matrix $\hat{\dot{\boldsymbol{G}}}[n]$ for linear precoding in the current slot n. Let $\hat{\dot{\boldsymbol{g}}}_k[n]$ denote the kth column of $\hat{\dot{\boldsymbol{G}}}[n]$, representing the channel estimate for the aging channel $\dot{\boldsymbol{g}}_k[n]$. It satisfies $\boldsymbol{g}_k[n] = \dot{\rho}_k[n]\dot{\boldsymbol{g}}_k[n] + \dot{\boldsymbol{\varepsilon}}_k[n]$, where $\dot{\rho}_k[n]$ is the temporal correlation coefficient between $\boldsymbol{g}_k[n]$ and $\dot{\boldsymbol{g}}_k[n]$, $\dot{\boldsymbol{\varepsilon}}_k[n] \sim \mathcal{CN}(\boldsymbol{0}, \beta_k(1-\dot{\rho}_k[n]^2)\boldsymbol{I}_M)$. After the BS sends the precoded signal $\boldsymbol{x}[n]$, the received signal at the kth user is

$$\begin{aligned} y_k[n] &= \sqrt{p_{dl}\eta_k}\dot{\rho}_k[n]\hat{\dot{\boldsymbol{g}}}_k^T[n]\boldsymbol{a}_k[n]s_k[n] \\ &+ w_k[n] - \sum_{k'=1}^{K}\sqrt{p_{dl}\eta_{k'}}(\dot{\rho}_k[n]\hat{\dot{\boldsymbol{g}}}_k[n] - \boldsymbol{g}_k[n])^T\boldsymbol{a}_{k'}[n]s_{k'}[n]. \end{aligned} \tag{11}$$

Let $\tilde{g}_k^m[n]$ be the mth component of the vector $\tilde{\boldsymbol{g}}_k[n]$ where $\tilde{\boldsymbol{g}}_k[n] \triangleq \dot{\rho}_k[n]\hat{\dot{\boldsymbol{g}}}_k[n] - \boldsymbol{g}_k[n]$ represents errors caused by channel estimation and channel aging. The signal received by the kth user can be rewritten as

$$\begin{aligned} y_k[n] =& \sqrt{(M-K)p_{dl}\gamma_k\eta_k}\dot{\rho}_k[n]s_k[n] \\ &+ \underbrace{w_k[n] - \sqrt{p_{dl}}\tilde{\boldsymbol{g}}_k^T[n]\boldsymbol{x}[n]}_{\text{effective noise}}, \end{aligned} \tag{12}$$

where the three terms are mutually uncorrelated and we treat the last two terms as effective noise. Therefore, the effective signal-to-interference-plus-noise ratio (SINR) for user k in the adaptive scheme can be expressed as, respectively,

$$\mathrm{SINR}_k[n] = \frac{(M-K)p_{dl}\gamma_k\eta_k\dot{\rho}_k[n]^2}{1 + p_{dl}\mathbb{E}\left\{\|\tilde{g}_k^m[n]\|^2\right\}\sum_{k=1}^{K}\eta_k}. \tag{13}$$

The achievable rate for user k can be calculated as

$$C_k[n] = \log_2\left(1 + \mathrm{SINR}_k[n]\right). \tag{14}$$

Then we obtain the net sum spectral efficiency of our proposed scheme as

$$C_{net}[n] = \frac{N_c - \tau_{ul}[n]}{N_c}\sum_{k=1}^{K}C_k[n], \tag{15}$$

where $\tau_{ul}[n]$ is the number of users that need to send pilots in the nth slot of a stationary block. The average net sum spectral efficiency in each stationary block is

$$\overline{C}_{net} = \frac{1}{N_s}\sum_{n=1}^{N_s}C_{net}[n] = \frac{1}{N_s}\sum_{n=1}^{N_s}\frac{N_c - \tau_{ul}[n]}{N_c}\sum_{k=1}^{K}C_k[n]. \tag{16}$$

Note that the channel coherence time is prolonged with strong temporal channel correlations in each stationary block, which enables a longer u_k to increase the net sum spectral efficiency. Conversely, when the temporal channel correlations are weak, long u_k can lead to great CSI aging errors, thereby decreasing system performance. Hence it is natural to think of setting $\{u_k\}_{1\le k\le K}$ based on the temporal channel correlation in each stationary block.

IV. High-Confidence Temporal Correlation Interval Estimation-Based CSI Tntervals Design

Under the assumption of a uniform scattering scenario, the well-known *Jakes* channel model is typically employed to characterize temporal channel correlation, but the assumption is invalid in certain communication scenarios, leading to the absence of a closed-form expression for temporal channel correlation in such cases. Therefore, it is essential to estimate the temporal channel correlations for each stationary block using estimated CSI samples, whereas the temporal correlation coefficient is likely to be either overestimated or underestimated, with overestimation potentially leading to inaccurate assessments of temporal channel correlation. To control the occurrence of overestimation, we adopt high-confidence temporal correlation interval estimates and use the lower bound of the confidence interval as the temporal correlation indicator. In the remainder of this section, we propose a method for setting $\{u_k\}_{1\le k\le K}$ according to high-confidence interval estimates of temporal channel correlations in each stationary block, and then we present the lower bound on the asymptotic average achievable rate obtained by this method when p_{ul} goes to infinity. The structure of the method for setting the channel estimation interval is illustrated in Fig. 1, where the length of the time window used for temporal channel correlation estimation is N_m slots. During the N_m time slots at the beginning of each stationary block, the BS can obtain the channel estimate vector $\hat{\boldsymbol{g}}_k[n] = \left[\hat{g}_k^1[n], \cdots, \hat{g}_k^m[n], \cdots, \hat{g}_k^M[n]\right]$ for the kth user in each time slot, where $\hat{g}_k^m[n]$ is the CSI estimation of mth antenna. We denote the in-phase component vector of $\hat{\boldsymbol{g}}_k[n]$ as $\hat{\boldsymbol{g}}_{I,k}[n] = \left[\hat{g}_{I,k}^1[n], \cdots, \hat{g}_{I,k}^m[n], \cdots, \hat{g}_{I,k}^M[n]\right]$, then the BS can collect the estimated CSI sample set $\{\hat{\boldsymbol{g}}_{I,k}[n]\}_{1\le n\le N_m}$.

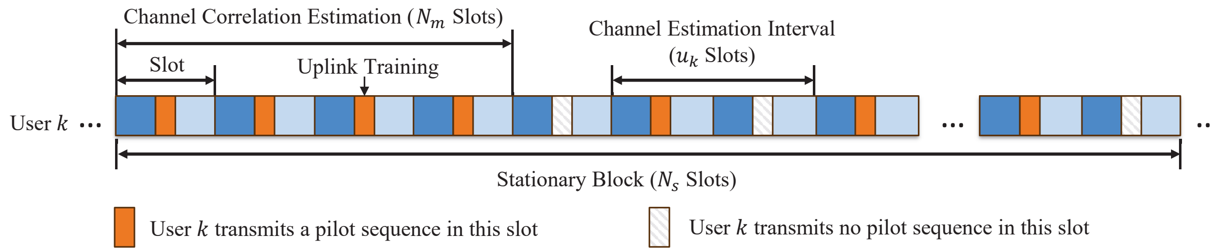

Fig. 1. The structure of our proposed method for setting channel estimation interval.

Let $\hat{\rho}_{k,l}$ be the temporal correlation coefficient between two CSI estimations separated by l time slots, the BS can estimate $\hat{\boldsymbol{\rho}}_k \triangleq [\hat{\rho}_{k,1}, \cdots, \hat{\rho}_{k,l}, \cdots, \hat{\rho}_{k,N_m-1}]$ with $\{\hat{\boldsymbol{g}}_{I,k}[n]\}_{1\leq n\leq N_m}$. According to (2) and the assumption that γ_k remains constant in a stationary block, the relationship between the channel estimates $\hat{\boldsymbol{g}}_k[n+l]$ and $\hat{\boldsymbol{g}}_k[n]$ separated by l time slots can be expressed as

$$\hat{\boldsymbol{g}}_k[n+l] = \hat{\rho}_{k,l}\hat{\boldsymbol{g}}_k[n] + \hat{\boldsymbol{\varepsilon}}_k[n+l], \tag{17}$$

where $\hat{\boldsymbol{\varepsilon}}_k[n+l] \sim \mathcal{CN}(\mathbf{0}, \gamma_k(1-\hat{\rho}_{k,l}^2)\boldsymbol{I}_M)$, and $\hat{\rho}_{k,l} = \frac{\rho_{k,l}\gamma_k}{\beta_k}$ gradually diminishes as the p_{ul} decreases. Then $\hat{\rho}_{k,l}$ can be estimated by the sample correlation coefficient $r_{k,l}$, which is calculated as

$$r_{k,l} = \frac{\sum_{m=1}^{M}\left(\hat{g}_{I,k}^m[n] - \bar{\hat{\boldsymbol{g}}}_n\right)\left(\hat{g}_{I,k}^m[n+l] - \bar{\hat{\boldsymbol{g}}}_{n+l}\right)}{\sqrt{\sum_{m=1}^{M}\left(\hat{g}_{I,k}^m[n] - \bar{\hat{\boldsymbol{g}}}_n\right)^2}\sqrt{\sum_{m=1}^{M}\left(\hat{g}_{I,k}^m[n+l] - \bar{\hat{\boldsymbol{g}}}_{n+l}\right)^2}}, \tag{18}$$

where $\bar{\hat{\boldsymbol{g}}}_n = \frac{1}{M}\sum_{m=1}^{M}\hat{g}_{I,k}^m[n]$ and $\bar{\hat{\boldsymbol{g}}}_{n+l} = \frac{1}{M}\sum_{m=1}^{M}\hat{g}_{I,k}^m[n+l]$. Subsequently, we get the sample correlation coefficient vector $\boldsymbol{r}_k = [r_{k,1}, ..., r_{k,l}, \cdots, r_{k,N_m-1}]$. Let the joint confidence level for $\hat{\boldsymbol{\rho}}_k$ be $1-\alpha$, the confidence level for $\hat{\rho}_{k,l}$ is $1-\zeta = 1 - \frac{\alpha}{N_m-1}$ by the *Bonferroni* correction. Then we apply *Fisher* transformation for variance stabilization to $r_{k,l}$ [16]:

$$z_{k,l} = \tanh^{-1} r_{k,l} = \frac{1}{2}\ln\left(\frac{1+r_{k,l}}{1-r_{k,l}}\right), \tag{19}$$

where $z_{k,l} \sim \mathcal{N}\left(\frac{1}{2}\ln\left(\frac{1+\hat{\rho}_{k,l}}{1-\hat{\rho}_{k,l}}\right), \frac{1}{n-3}\right)$. Hence the $1-\zeta$ confidence interval for $\frac{1}{2}\ln\left(\frac{1+\hat{\rho}_{k,l}}{1-\hat{\rho}_{k,l}}\right)$ can be expressed as

$$\left(L_{k,l}^z, U_{k,l}^z\right) = \left(z_{k,l} - \frac{u_{\zeta/2}}{\sqrt{n-3}}, z_{k,l} + \frac{u_{\zeta/2}}{\sqrt{n-3}}\right), \tag{20}$$

where $u_{\zeta/2}$ represents the upper $\zeta/2$ quantile of the standard normal distribution. We apply the hyperbolic tangent transformation to $(L_{k,l}^z, U_{k,l}^z)$, and then the $1-\zeta$ confidence interval for the channel correlation coefficient $\hat{\rho}_{k,l}$ is calculated as

$$\begin{aligned}(L_{k,l}, U_{k,l}) &= (\tanh L_{k,l}^z, \tanh U_{k,l}^z) \\ &= \left(\frac{e^{2L_{k,l}^z}-1}{e^{2L_{k,l}^z}+1}, \frac{e^{2U_{k,l}^z}-1}{e^{2U_{k,l}^z}+1}\right).\end{aligned} \tag{21}$$

Next, we use $L_{k,l}$ as the temporal correlation indicator and define b as the threshold for judging the strength of temporal channel correlation. When $L_{k,l} \geq b$, the temporal correlation between $\hat{\boldsymbol{g}}_k[n+l]$ and $\hat{\boldsymbol{g}}_k[n]$ is strong, indicating that the coherence time is longer than l slots. Conversely, the temporal channel correlation is weak and the coherence time is less than l slots between channels when $L_{k,l} \leq b$. The coherence time can be estimated by sequentially comparing $L_{k,l}$ against b and we set

$$u_k = \max\{l \mid L_{k,l} \geq b, L_{k,l+1} \leq b, 0 \leq l \leq N_m - 1, l \in Z\}. \tag{22}$$

Finally, we analyze the lower bound on the asymptotic average achievable rate as p_{ul} approaches infinity. Before derivation, we suggest the following lemma.

Lemma 1. *The variance of the mth component of the vector $\tilde{\boldsymbol{g}}_k[n]$ is given by*

$$\mathbb{E}\left\{\|\tilde{g}_k^m[n]\|^2\right\} = \beta_k(1-\dot{\rho}_k[n]^2) + \dot{\rho}_k[n]^2\mathbb{E}\left\{\|\tilde{g}_k^m[n]\|^2\right\}. \tag{23}$$

Proof: The proof is omitted due to space limitation. ■

Then we have the following theorem which gives the effective SINR of our proposed scheme.

Theorem 1. *The lower bound on effective SINR for user k in the adaptive scheme at a confidence level of $1-\alpha$ is given by*

$$\mathrm{SINR}_k \geq \frac{(M-K)\gamma_k\eta_k}{\frac{1}{b^2 p_{dl}} + (\beta_k(\frac{1}{b^2}-1) + \beta_k - \gamma_k)\sum_{k=1}^{K}\eta_k}, \tag{24}$$

where $\beta_k(\frac{1}{b^2}-1)$ represents the error caused by channel aging, and $\beta_k - \gamma_k$ is the error introduced by channel estimation.

Proof: Let $\hat{\dot{\rho}}_k[n]$ be the estimation of $\dot{\rho}_k[n]$. According to (6), (22) and the definitions of $\dot{\rho}_k[n]$ and $\hat{\dot{\rho}}_k[n]$, we have

$$\dot{\rho}_k[n] = \frac{\hat{\dot{\rho}}_k[n]\beta_k}{\gamma_k} \geq \hat{\dot{\rho}}_k[n] \geq b. \tag{25}$$

Then we can directly derive the above SINR_k by substituting (6), (25) and *Lemma 1* into (13). ■

Theorem 1 indicates that the error introduced by channel estimation is independent of the channel aging error, which is related to b. Thus, b should be appropriately set to control the channel aging effect. To figure out the effect of channel aging only, we derive the downlink SINR with ideal channel estimation.

Corollary 1. *We assume ideal uplink training, i.e., $p_{ul} \to \infty$. The lower bound on the effective SINR for user k with equal*

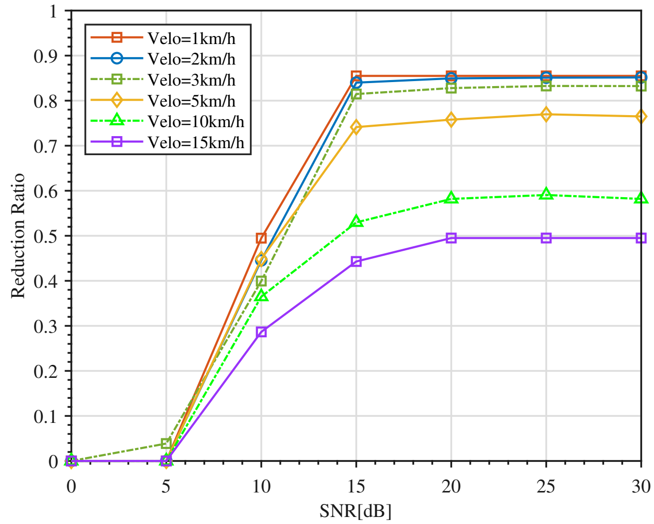

Fig. 2. Reduction ratio of channel estimation frequency versus different user velocities.

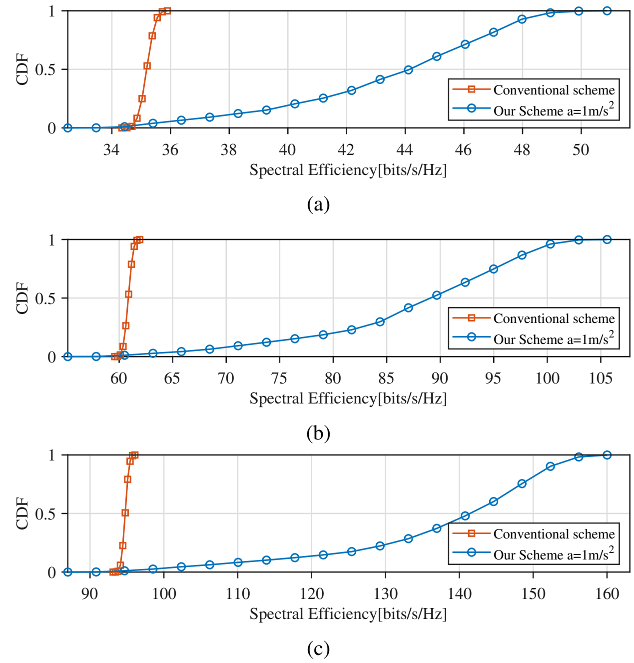

Fig. 3. CDF of net sum spectral efficiency for our proposed scheme and the conventional scheme. a) p_{ul} = p_{dl} = 10 dB; b) p_{ul} = p_{dl} = 15 dB; c) p_{ul} = p_{dl} = 20 dB.

power allocation at a confidence level of $1-\alpha$ *is expressed as*

$$\lim_{p_{ul}\to\infty} \mathrm{SINR}_k \geq \frac{\frac{M}{K}-1}{\frac{1}{b^2}-1}. \tag{26}$$

Let c represent the predefined asymptotic downlink effective SINR. When $\lim_{p_{ul}\to\infty} \mathrm{SINR}_k = c$, we can ensure that the error introduced by channel aging is bounded by $\frac{(\frac{M}{K}-1)\beta_k}{c}$. Thus, the threshold b can be calculated as

$$b = \sqrt{\frac{c}{\frac{M}{K}+c-1}}, \tag{27}$$

and the lower bound on the asymptotic average achievable rate for user k can be given by

$$\lim_{p_{ul}\to\infty} \overline{C}_k \geq (1-\alpha)\log_2(1+c), \tag{28}$$

V. Numerical Results

We use COST 2100 channel model to evaluate the performance of our proposed channel estimation scheme. We consider a TDD massive MIMO system with $M = 128$, $K = 40$, $N_s = 100$, $N_m = 10$, $T_s = 1$ ms. The OFDM symbol delay spread is 5 μs, so the coherent bandwidth is 100 kHz which contains $N_b = 7$ subcarriers. A slot in TDD LTE standard consists of $N_s = 14$ symbols, therefore, $N_c = N_s N_b = 98$. Using COST 2100 model, we simulate an outdoor channel environment with a central frequency of 2.6 GHz and a bandwidth of 20 MHz. Mobile users are uniformly located in a circle of radius 100 m with the base station located at the center of the circle. Unless otherwise specified, user speeds are uniformly drawn from $[1\text{km/h}, 40\text{km/h}]$, c = 20 dB and $p_{ul} = p_{dl}$. The acceleration of mobile users is denoted by a, and the number of stationary blocks in the simulation is set to 500.

First, we compare the reduction ratio of the channel estimation frequency using the adaptive channel estimation scheme with respect to the value of p_{ul} in Fig. 2. The mobile user speeds are set to [1, 2, 3, 5, 10, 15] km/h. Fig. 2 shows that the channel estimation intervals for users increase as p_{ul} rises. The phenomenon is consistent with the theoretical analysis, as channel noise significantly affects time correlation estimation under lower uplink training SNR, leading to an underestimation of the temporal channel correlation. In this case, our proposed channel estimation scheme degrades to the conventional channel estimation scheme. Conversely, the temporal channel correlation can be estimated accurately when p_{ul} is high. This enables our proposed scheme to set appropriate channel estimation intervals. Moreover, as shown in Fig. 2, we observe that the reduction ratio of channel estimation frequency becomes higher as user velocity decreases. The reason lies in the fact that users of lower velocities usually have stronger temporal channel correlation, in which case longer channel estimation intervals can effectively enhance the net sum spectral efficiency. From Fig. 2, we also see that in the scenario of high uplink training SNR where $p_{ul} \geq 15$ dB, the reduction ratio of the channel estimation frequency is almost the same if the velocities of users are less than 5 km/h. The reason behind this is that the BS needs to estimate the channel at least once every N_m time slots, so N_m limits the maximum channel estimation interval and thus constrains the maximum reduction ratio of all users. Hence, N_m should be set based on specific scenarios.

Since SNR is the primary factor influencing the frequency of channel estimation, we then compare the cumulative distribution function (CDF) of the net sum spectral efficiency for the conventional scheme and the adaptive channel estimation

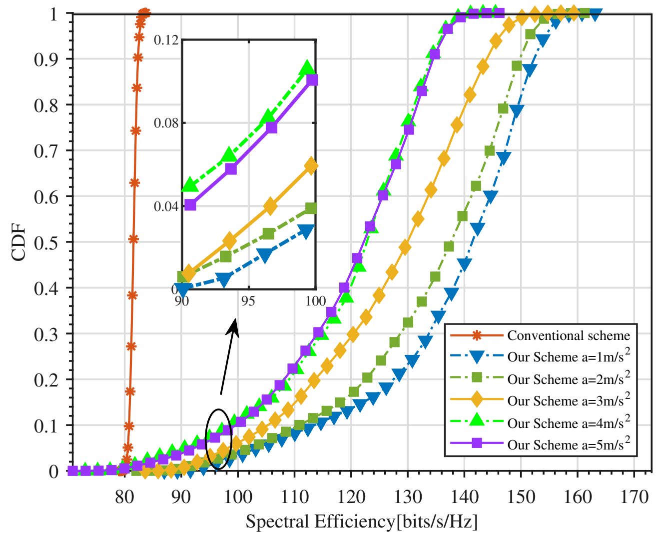

Fig. 4. CDF of net sum spectral efficiency among the conventional estimation scheme and the proposed ones under different a.

scheme under different p_{ul} and p_{dl}, as depicted in Fig. 3. We set $a = 1$ m/s^2 and SNR of Fig. 3a-c as 10 dB, 15 dB and 20 dB, respectively. From Fig. 3, we can observe that the adaptive channel estimation scheme can obtain 20%-50% performance gains in net sum spectral efficiency compared to the conventional scheme. For instance, in Fig. 3b, the average net sum spectral efficiency of the adaptive channel estimation scheme is around 60 bit/s/Hz, while the average net sum spectral efficiency obtained by the conventional scheme is approximately 90 bit/s/Hz. Thus, the adaptive scheme approximately achieves a gain of 30 bit/s/Hz, equivalently 600 Mbit/s in a communication system of 20 MHz bandwidth. This demonstrates that in communication scenarios with high p_{ul} and p_{dl}, effectively utilizing outdated CSI estimation in time-correlated channels can remarkably improve the performance gains of massive MIMO systems.

Fig. 4 compares the CDF of the net sum spectral efficiency among the conventional channel estimation scheme and the proposed schemes with different a. We set $p_{ul} = p_{dl} = 20$ dB, and a is set to be [1, 2, 3, 4, 5] m/s^2 in this scenario, respectively. From Fig. 4, we can observe that the net sum spectral efficiencies obtained by the adaptive channel estimation scheme are mainly in [110, 150] bits/s/Hz, while those of the conventional scheme are primarily in the range of [80, 90] bits/s/Hz. Furthermore, we can see that the CDF curves of net sum spectral efficiency for the adaptive channel estimation scheme shift slightly to the left as user acceleration increases. The shift arises from shorter stationary block lengths as user acceleration increases, which leads to the update of temporal channel correlation estimates slightly lagging behind the changes of channel time correlation in some slots, and consequently the net sum spectral efficiency of our proposed channel estimation scheme would decrease. Although high user accelerations lead to spectral efficiency losses, the range and the CDF growth trends of the net sum spectral efficiency remain approximately consistent with different user accelerations, which demonstrates that the adaptive channel estimation scheme can effectively adapt to changes in temporal channel correlation and is applicable to various communication scenarios.

VI. Conclusion

In this paper, we investigated how to set appropriate channel estimation intervals to utilize the redundant spectral resources in the uplink training phase. We developed a novel channel estimation scheme based on the temporal channel correlation and derived the net sum spectral efficiency of the proposed scheme. Moreover, we employed *Fisher* transformation on estimated CSI samples to obtain high-confidence temporal channel correlation interval estimates and determined the channel estimation interval by comparing the lower bound of the interval estimates to a threshold. Numerical results demonstrate that our proposed scheme effectively enhances net sum spectral efficiency over the conventional one and is adaptable to various communication scenarios.

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