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Research Article

PCA-Based Adaptive Training-Feedback Scheme in Time-Varying FDD Massive MIMO Systems

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For massive multiple-input multiple-output (MIMO) systems, the real-time channel state information (CSI) acquisition is crucial but difficult in fast time-varying scenarios, especially for downlink (DL) channels in frequency division duplex (FDD) systems. This paper proposes an adaptive training-feedback scheme to estimate the CSI of DL channels. Specifically, first, base station (BS) determines a subspace containing uplink (UL) channel and an orthogonal normal basis of this subspace by using received signals in UL channel and the principle component analysis (PCA) technique. Second, by using the spatial reciprocity, it is found that the obtained subspace above also contains the DL channel vector. Thus, regarding the basis as pilots, the BS transmits pilots to mobile user (MU), and the user estimates received signals, feeds back them to the BS. Finally, according to information of the feedback, the BS can construct the DL channel vector. In this scheme, the pilots are adaptive to the change of the UL channel. Furthermore, the times of training is the dimension of the subspace, and feedback overhead is the coefficients of linear combination of DL channel vector under the basis only. Thus, cost of training and feedback can be greatly reduced. The simulation results show that the performance of the proposed scheme can approach the optimal scheme with very few training times and feedback overhead at high speed.

1. Introduction

Massive multiple-input multiple-output (MIMO) technology occupies a pivotal position in wireless communication systems, owing to its provision of excellent spectrum and energy efficiency to systems. It also brings challenges, one of which is the acquisition of accurate channel state information (CSI). The problem is severe especially for frequency division duplex (FDD) systems in mobile scenarios, since the CSI obtained through the traditional pilot-based training method is outdated immediately. The estimated CSI in one time slot is not equal to the CSI of the following time slot due to rapid time variant of the channel.

Widely efforts have been made by scholars to investigate this problem. For example, [1, 2] both performed channel prediction and channel tracking under the autoregressive (AR) model, of which [1] proposed a linear finite impulse response (FIR) Wiener predictor. [2] used Kalman filter and the minimum mean-square error (MMSE) decision feedback equalizer to solve the tracking and equalization problem of the time-varying channel and can achieve sound channel tracking performance, but the complexity is higher than traditional adaptive algorithms. [3, 4] analyzed the overall rate performance of the FIR Wiener predictor in the case of delayed CSI.

Papers [5–7] also used Kalman filters to propose their own schemes. In [5], based on an assumption that the uplink (UL)- downlink (DL) conversion problem is a linear estimation problem, an UL-DL transform algorithm by using Kalman filtering was proposed. [6] proposed a spatial-temporal basis expansion model based on the characteristics of the large-scale antenna arrays. This model can reduce the channel dimension. Furthermore, the reciprocity of the physical angle between the UL and DL channels was used to reduce the complexity of DL channel tracking. However, the time-varying spatial information tracking of UL is built based on the Kalman filter and Taylor series expansion, which leads to estimation accuracy deterioration.

for $t = 1, 2, \cdots, M$
  Receiving the received signal $\mathbf{y}_{\mathrm{u}}(t)$ as $\mathbf{Y}$ according to Eq. (10).
end for
Calculate the covariance matrix $\mathbf{R}$ of $\mathbf{Y}$ and perform SVD on it.
Take the left singular vectors $\mathbf{u}_{y_1}, \mathbf{u}_{y_2}, \cdots, \mathbf{u}_{y_K}$ corresponding to the first K largest values of $\mathbf{R}$ as pilots.
for $t = 1, 2, \cdots, K$
  Receiving the received signal $\mathbf{y}_{\mathrm{d}}(t)$ according to Eq. (13).
end for
Employ MMSE to estimate $\mathbf{h}_{\mathrm{d}}(t)\mathbf{u}_{y_t}$, $t = 1, 2, \cdots, K$ and record its combination as $\mathbf{g}_{y_0}$ according to Eq. (14).
for $j = 1, 2, \cdots, N$
  Find the index $\hat{j}_{y_0}$ of the codeword corresponding to $\mathbf{g}_{y_0}$ according to Eq. (15).
end for
Use the index $\hat{j}_{y_0}$ to construct precoder $\mathbf{p}_0$ according to Eq. (16).
for $t = 1, 2, \cdots, M$
  Receiving the received signal $\mathbf{y}_{\mathrm{d}}(t + K)$ according to Eq. (17) and estimate $\mathbf{h}_{\mathrm{d}}(t + K)\mathbf{p}_0$.
end for
Use the estimated $\mathbf{h}_{\mathrm{d}}(t + K)\mathbf{p}_0$ to transmit the data signal s.

Algorithm 1: PCA-based Adaptive Training-Feedback Scheme.

Under the assumption of channel sparsity in massive MIMO systems, [7] proposed a sparse Bayesian learning framework based on the expectation maximization. [8] proposed a structured compressed sampling matching tracking algorithm, which can obtain reliable CSI. In [9], a channel prediction algorithm was proposed based on the first-order Taylor expansion channel model, and the interval of effective prediction was derived. [10] proposed a dynamic turbo orthogonal approximate message passing algorithm based on a two-dimensional Markov model, which can recursively track dynamic channels. However, the computational complexity is high in all these mentioned methods.

In this paper, based on the principal component analysis (PCA) technology and the spatial reciprocity of adjacent frequency bands in the FDD system, we propose an adaptive training-feedback scheme to estimate and track CSI. The main steps of our scheme are as follows: the first, the base station (BS) utilizes the PCA technology to construct a covariance matrix from the received signals, and the singular value decomposition (SVD) is performed on this matrix. The second, the left singular vectors corresponding to the first K largest singular values are selected to form an orthonormal basis of the subspace of UL channel. According to the spatial reciprocity, this subspace is same as the subspace generated by the DL channel. Thus, an orthogonal basis to linearly represent the DL channel is obtained. The third, elements of this basis are transmitted to the mobile station (MS) as pilots, and the MS can estimate the received signals. These estimations can be regarded as coefficients of linear representation of DL channel under the orthonormal basis. The fourth, the MS finds a precoder in predesigned precodebook to match the coefficients, and sends the index of this precoder to the BS. The last, the BS utilizes the index, the precodebook and the orthonormal basis to construct a precoder and transmits data signals. It is worth mentioning that the pilots designed in this paper can adapt to the channel, and the proposed PCA-based adaptive training-feedback scheme has few training times, and the required feedback overhead is also very small.

The paper is organized as follows: in the next section, the 3D time-varying channel model, the spatial reciprocity in the FDD system and the PCA principle are briefly described. In Section 3, a PCA-based adaptive training-feedback scheme is proposed, and the specific steps of this scheme are described. The simulation results are shown in Section 4 and Section 5 summarizes the paper.

The following notations are given: a, **a**, and **A** denote scalar, vector and matrix, respectively. $(\cdot)^{\mathrm{T}}$, $(\cdot)^{H}$ denote transpose and conjugate transpose, respectively. $[\mathbf{A}]_{i,j}$ denotes the $(i, j)^{th}$ element in the matrix $\mathbf{A}$ and rank $(\mathbf{A})$ denotes its rank. $|\cdot|$ and $\|\cdot\|$ are the absolute value and normed space, respectively. "$\otimes$" denotes the tensor product of matrices.

2. Preliminary

In this section, we will describe the system model, spatial reciprocity in FDD systems, and the principles of PCA.

2.1. System Model. We consider a massive MIMO system with a single-antenna user in FDD transmission mode, where the frequency of the UL channel is f_{u}, the frequency of the DL channel is f_{d}, and the frequency interval between them is Δf. Assume that the M_t antennas provided by the BS are arranged by an antenna array of $M_v \times M_h$, where M_v and M_h are the number of columns and rows of the BS antenna array and $M_t = M_v M_h$.

The channel model involved in this paper is given by the standard time-varying channel model proposed by the 3rd Generation Partnership Project (3GPP) Organization, see the document [11] for details. Assume that there are L_c

Table 1: Parameter value.

Parameter	Meaning	Value
L_c	Number of clusters	19
L_p	Number of propagation paths	1
M_r	Number of receiving antennas at the MS	1
M_t	Number of transmitting antennas at the BS	32, 64, 128
d_{2D}	Distance between BS and MS	10 m
h_{m}	Antenna height at the MS	1.5 m
h_{b}	Antenna height at the BS	10 m
$\phi_{LOS,AOA}$	LOS AOA (azimuth arrival angle in the line-of-sight (LOS) scenario)	Uniform(0,360°)
$\phi_{LOS,AOD}$	LOS AOD (azimuth departure angle in the LOS scenario)	Uniform(0,360°)
$\theta_{LOS,ZOA}$	LOS ZOA (elevation arrival angle in the LOS scenario)	Uniform(0,180°)
$\theta_{LOS,ZOD}$	LOS ZOD (elevation departure angle in the LOS scenario)	Uniform(0,180°)
f_{ul}	UL carrier frequency	2.1GHz
λ_{ul}	UL carrier wavelength	0.143 m
d_{rx}	Three-dimensional coordinates of the receiving antenna in the global coordinate system	(0 m, 0 m, 700 m)
$d_{tx,1}$	Three-dimensional coordinates of the first transmitting antenna in the global coordinate system	(0 m, 0 m, 710 m)
d_H	Horizontal spacing between transmit antennas	$0.5\lambda_0$
d_V	Vertical spacing between transmit antennas	$0.8\lambda_0$
Δf	UL and DL channel frequency interval	10^8Hz
T	The first transmitting antenna	10s
Δt	Time interval	$0.5\lambda_0$
v	Speed of MS	120 km/h

clusters per channel and L_p propagation paths per cluster, we only consider the main propagation path of each cluster; that is, $L_p = 1$. Then the UL channel from the MS antenna to M_t BS antennas at time slot t, denoted as $\mathbf{h}_{\mathrm{u}}(t)$, can be expressed as

$$\mathbf{h}_{\mathrm{u}} = \mathbf{A}_{\mathrm{u}}\left[e^{jv_{\mathrm{u},1}t} \quad e^{jv_{\mathrm{u},2}t} \cdots e^{jv_{\mathrm{u},L_c}t}\right]^T, \tag{1}$$

where

$$\mathbf{A}_{\mathrm{u}} = \mathbf{A}_1 \operatorname{diag}\left(\alpha_{u_1}, \alpha_{u_2}, \cdots, \alpha_{u_{L_c}}\right). \tag{2}$$

$\mathbf{A}_1 \in \mathbb{C}^{M_t \times L_c}$ is a steering matrix, and $\alpha_{u_1}, \alpha_{u_2}, \cdots, \alpha_{u_{L_c}}$ are the UL channel gains of different clusters. In this paper, we assume that they are independently and identically distributed (i.i.d.) complex Gaussian random variables with zero-mean and unit variance. In Eq. (1)

$$v_{\mathrm{u},l_c} = 2\pi \frac{\bar{\mathbf{v}}\,\hat{\mathbf{r}}_{rx,l_c}}{\lambda_{\mathrm{u}}}, l_c = 1, 2, \cdots, L_c, \tag{3}$$

where λ_{u} is the wavelength of UL carrier frequency, $\bar{\mathbf{v}} = v[\sin(\theta_v)\cos(\phi_v) \ \sin(\theta_v)\sin(\phi_v) \ \cos(\phi_v)]$ and v is the speed of MS, θ_v and ϕ_v are the travel elevations angle and azimuth angle of MS, respectively. The definition of the elevation angle in this paper is the direction of the signal propagation with respect to the z-axis in the global coordinate systems. The definition of $\hat{\mathbf{r}}_{rx,l_c}$ is as follows

$$\hat{\mathbf{r}}_{rx,l_c} = \begin{bmatrix} \sin\left(\theta_{l_c,ZOA}\right)\cos\left(\phi_{l_c,AOA}\right) \\ \sin\left(\theta_{l_c,ZOA}\right)\sin\left(\phi_{l_c,AOA}\right) \\ \cos\left(\theta_{l_c,ZOA}\right) \end{bmatrix}, \tag{4}$$

where $\theta_{l_c,ZOA}$ and $\phi_{l_c,AOA}$ are the elevation arrival angle (ZOA) and the azimuth arrival angle (AOA) in l_c-th cluster, respectively.

Correspondingly, the DL channel at time t from BS to MS is obtained by

$$\mathbf{h}_{\mathrm{d}} = \mathbf{A}_{\mathrm{d}}\left[e^{jv_{\mathrm{d},1}t} \quad e^{jv_{\mathrm{d},2}t} \quad \cdots e^{jv_{\mathrm{d},L_c}t}\right]^T, \tag{5}$$

where

$$\mathbf{A}_{\mathrm{d}} = \mathbf{A}_2 \operatorname{diag}\left(\alpha_{d_1}, \alpha_{d_2}, \cdots, \alpha_{d_{L_c}}\right), \tag{6}$$

and $\alpha_{d_1}, \alpha_{d_2}, \cdots, \alpha_{d_{L_c}}$ are the DL channel gains of different clusters. Matrix $\mathbf{A}_2$ is a steering matrix. Also, assume that they are i.i.d. complex Gaussian random variables with

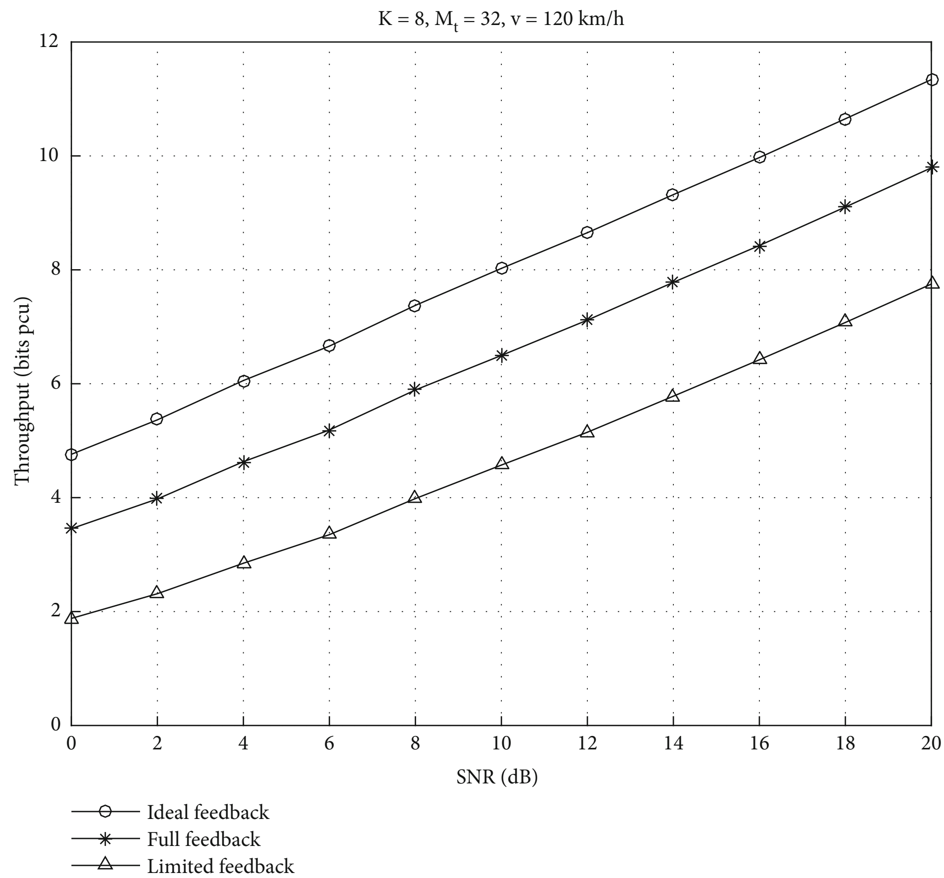

FIGURE 1: Comparison of throughput in three feedback situations.

zero-mean and unit variables. In Eq. (5)

$$\nu_{\mathrm{d},l_c} = 2\pi \frac{\bar{\mathbf{v}}\,\hat{\mathbf{r}}_{tx,l_c}}{\lambda_{\mathrm{d}}}, l_c = 1, 2, \cdots, L_c, \tag{7}$$

where λ_{d} is the wavelength of DL carrier frequency, and the transmit spherical unit vector $\hat{\mathbf{r}}_{tx,l_c}$ is defined as

$$\hat{\mathbf{r}}_{tx,l_c} = \begin{bmatrix} \sin\left(\theta_{l_c,ZOD}\right) \cos\left(\phi_{l_c,AOD}\right) \\ \sin\left(\theta_{l_c,ZOD}\right) \sin\left(\phi_{l_c,AOD}\right) \\ \cos\left(\theta_{l_c,ZOD}\right) \end{bmatrix}, \tag{8}$$

where $\theta_{l_c,ZOD}$ and $\phi_{l_c,AOD}$ are the elevation departure angle (ZOD) and the azimuth departure angle (AOD) in l_c-th cluster, respectively.

In Eq. (2), the $M_t \times L_c$ steering matrix $\mathbf{A}_1$ is composed of L_c steering vectors $\mathbf{a}(\Theta_{l_c}, \Phi_{l_c})$, $l_c = 1, 2, \cdots, L_c$, where Θ_{l_c} and Φ_{l_c} are the elevation angles (ZOD, ZOA) and the azimuth angles (AOD, AOA) of the l_c-cluster, respectively. $[\mathbf{A}]_{i,j} = e^{j2\pi\lambda_{\mathrm{d}}^{-1}(\hat{\mathbf{r}}_{rx,j}^{\mathrm{T}}\cdot\bar{d}_{rx})} e^{j2\pi\lambda_{\mathrm{d}}^{-1}(\hat{\mathbf{r}}_{tx,j}^{\mathrm{T}}\cdot\bar{d}_{tx,i})}$, where $\bar{d}_{rx}$ and $\bar{d}_{tx,i}$ are the MS antenna 3D position coordinates and the BS antennas 3D position coordinates. Since MS has only one antenna, where $e^{j2\pi\lambda_{\mathrm{u}}^{-1}(\hat{\mathbf{r}}_{rx,j}^{\mathrm{T}}\cdot\bar{d}_{rx})}$ is a complex number. Matrix $\mathbf{A}_2$ given in (6) is a $M_t \times L_c$ steering matrix, and its components are then similar with the above. The details can be found in the following subsection.

2.2. The Spatial Reciprocity in FDD Systems. In FDD systems, since the reflections and propagation paths experienced by signals transmitted between the UL and DL channels are the same, the angles (AOA, ZOA, AOD, and ZOD) and delay of the UL and DL channels are all the same, which has been confirmed in [12]. The phenomenon is also called spatial reciprocity or channel reciprocity. This phenomenon is utilized to estimate the DL channel at different conditions, see [13–15]. Recently, specific details on the spatial reciprocity can be found in [16].

For the time-varying channel in this paper, the initial positions of the BS antennas and the MS antenna are determined, and the subsequent changes in antenna positions are mainly reflected in speed and delay, which means that $\bar{d}_{tx,i}$, $i = 1, 2, \cdots, M_t$ and $\bar{d}_{rx}$ do not change with time.

According to the above analysis and the definition of the steering matrix, the difference in steering matrices of the UL and DL channels are only caused by the frequency interval between the UL and DL channels. In most cases, the frequency of the UL and DL channels is very high (such as GHz), and the frequency interval between the UL and DL

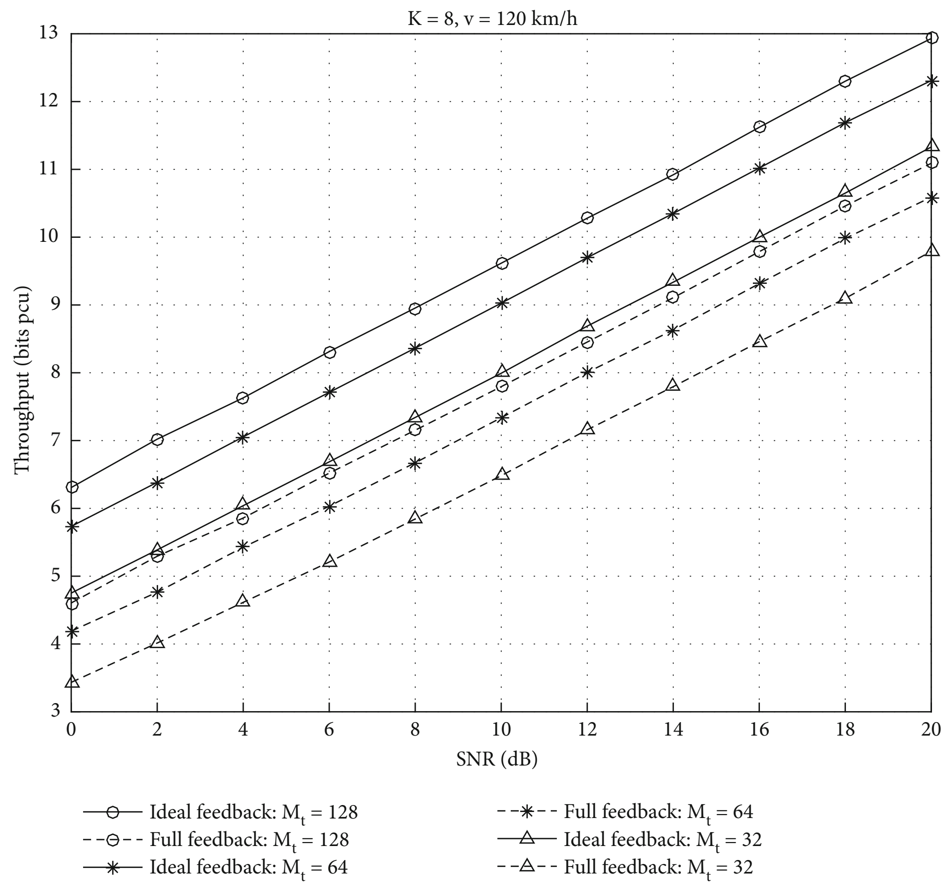

FIGURE 2: Comparison of two feedback situations under different BS antenna numbers.

is very small compared to the carrier frequency, then, according to the calculations given in [16], the difference between the UL and DL steering matrices caused by the frequency interval can basically be ignored. Consequently, we can make the assumption that the following holds

$$\mathbf{A}_1 = \mathbf{A}_2. \tag{9}$$

3. PCA-Based Adaptive Training-Feedback Scheme

From equations (1), (5), and assumption $\mathbf{A} = \mathbf{A}_u = \mathbf{A}_d$ we can see that the UL channel vector $\mathbf{h}_u$ and the DL channel vector $\mathbf{h}_d$ lying on the same subspace, the subspace generated by the columns of matrix $\mathbf{A}$. Thus, the precoder used in the DL transmissions should be in this subspace, and hence, it is worth getting this subspace.

To determine this subspace at the BS, it is useful to take the advantage of PCA based on the UL transmissions. After that, an orthonormal base of this subspace is transmitted on the DL channel as pilots, and from these received signals, the MS can evaluate the coefficients of combination of $\mathbf{h}_d$ on this base. Using the designed codebook, information of these coefficients can be sent back to the BS, and the BS makes the precoder and data transmissions.

Based on the above, we give specific steps of the PCA-based adaptive training-feedback scheme, as shown in following algorithm.

For the proposed algorithm, we give further explanation as follows:

Step 1. Design a K-dimensional precoding codebook $\mathcal{F}$ containing N codewords. There are a lot of methods to design the codebook $\mathcal{F}$ in the existing literatures, for example, see [17].

Step 2. The MS sends a signal x to BS, and the received signal at the t-th time slot of BS is

$$\mathbf{y}_u(t) = \sqrt{\rho}\mathbf{h}_u(t)x + \mathbf{w}_t, \tag{10}$$

where ρ is the signal-to-noise ratio (SNR), $\mathbf{h}_u(t) \in \mathbb{C}^{M_t \times 1}$ is the UL channel at time slot t, $\mathbf{w}_t$ is a Gaussian standard noise.

Step 3. The BS combines the M received signals at different times with a time interval Δt in the period T as $\mathbf{Y} = [\mathbf{y}_u(1), \mathbf{y}_u(2), \cdots, \mathbf{y}_u(M)] \in \mathbb{C}^{M_t \times M}$, and takes its row mean $\bar{\mathbf{y}} \in \mathbb{C}^{M_t \times 1}$.

Step 4. Calculate the covariance matrix of the received signals and normalize as

$$\mathbf{R}=\frac{1}{M-1}\sum_{t=1}^{M}[\mathbf{y}_{\mathrm{u}}(t)-\bar{\mathbf{y}}][\mathbf{y}_{\mathrm{u}}(t)-\bar{\mathbf{y}}]^{H}. \tag{11}$$

Step 5. Implement SVD on the covariance matrix $\mathbf{R}$ as follows:

$$\mathbf{R}=\mathbf{U}_y\mathbf{D}_y\mathbf{V}_y^{\mathrm{H}}, \tag{12}$$

where $\mathbf{U}_y=[\mathbf{u}_{y_1},\mathbf{u}_{y_2},\cdots,\mathbf{u}_{y_{M_t}}]\in\mathbb{C}^{M_t\times M_t}$, $\mathbf{V}_y\in\mathbb{C}^{M_t\times M_t}$, satisfying with $\mathbf{U}_y^{\mathrm{H}}\mathbf{U}_y=\mathbf{I}_{M_t}$, $\mathbf{V}_y^{\mathrm{H}}\mathbf{V}_y=\mathbf{I}_{M_t}$, $\mathbf{D}_y=\operatorname{diag}(\lambda_{y_1},\lambda_{y_2},\cdots,\lambda_{y_{M_t}})$, and $\lambda_{y_1}\geq\lambda_{y_2}\geq\cdots\geq\lambda_{y_{M_t}}$.

Step 6. Take the left singular vectors $\mathbf{u}_{y_1},\mathbf{u}_{y_2},\cdots,\mathbf{u}_{y_K}$ corresponding to the first K largest singular values of $\mathbf{R}$ as pilots and send them to the MS through the DL channel. The received signals are

$$y_{\mathrm{d}}(t)=\sqrt{\rho}\mathbf{h}_{\mathrm{d}}(t)\mathbf{u}_{y_t}+w_t, t=1,2\cdots K, \tag{13}$$

where $\mathbf{h}_{\mathrm{d}}(t)\in\mathbb{C}^{1\times M_t}$ is the DL channel at time slot t, $\mathbf{u}_{y_t}\in\mathbb{C}^{M_t\times 1}$, $w_t\sim\mathscr{CN}(0,1)$ denote the noises. The Minimum Mean Square Error (MMSE) estimation is implemented on Eq. (13) to estimate values $\mathbf{h}_{\mathrm{d}}(t)\mathbf{u}_{y_t}$ $(t=1,2,\cdots,K)$. Denote the estimation of $\mathbf{h}_{\mathrm{d}}(t)\mathbf{u}_{y_t}$ as g_{y_t}, $t=1,2,\cdots,K$. Put

$$\mathbf{g}_{y_0}=\begin{bmatrix}g_{y_1} & g_{y_2} & \cdots & g_{y_K}\end{bmatrix}^T. \tag{14}$$

Step 7. Find the index $\hat{j}_{y_0}$ of the codeword $\mathbf{f}_{\hat{j}_{y_0}}$ corresponding to $\mathbf{g}_{y_0}$ in the precoding codebook $\mathscr{F}$, which is given by

$$\hat{j}_{y_0}=\underset{1\leq j\leq N}{\operatorname{argmax}}\left|\mathbf{g}_{y_0}^H\mathbf{f}_j\right|, \tag{15}$$

where $\mathbf{f}_j$ is the j-th K-dimensional codeword in the precoding codebook. Then, MS sends the index $\hat{j}_{y_0}$ to the BS.

Step 8. The BS constructs the following precoder $\mathbf{p}_0$ according to the index obtained by the feedback:

$$\mathbf{p}_0=\begin{bmatrix}\mathbf{u}_{y_1} & \mathbf{u}_{y_2} & \cdots & \mathbf{u}_{y_K}\end{bmatrix}\mathbf{f}_{\hat{j}_{y_0}}, \tag{16}$$

where $\mathbf{p}_0\in\mathbb{C}^{M_t\times 1}$, $\mathbf{f}_{\hat{j}_{y_0}}\in\mathbb{C}^{K\times 1}$.

Step 9. With the precoder constructed above, the BS first sends a pilot (namely 1) to the MS. The signal received by the MS can be expressed as

$$\mathbf{y}_{\mathrm{d}}(t+K)=\sqrt{\rho}\mathbf{h}_{\mathrm{d}}(t+K)\mathbf{p}_0+\mathbf{w}. \tag{17}$$

Furthermore, the MS can estimate $\mathbf{h}_{\mathrm{d}}(t+K)\mathbf{p}_0$.

Step 10. The subsequent data signal s is transmitted using the precoder $\mathbf{p}_0$ and the estimated value of $\mathbf{h}_{\mathrm{d}}(t+K)\mathbf{p}_0$.

4. Simulations

In this section, we will demonstrate the performance of the proposed PCA-based adaptive training-feedback scheme. The channel established in the simulation of this paper is established according to Section 7 of [11]. The Root-Mean-Square (RMS) delay spread is 10°, the delay distribution proportionality factor is 3, and the per cluster shadowing std is 3 dB. The scaling factors for azimuth angles generation and the scaling factors for elevation angles generation are 1.273 and 1.1764, respectively. The RMS azimuth spread of arrival angles (ASA) and departure angles (ASD) are 9° and 10°, respectively. The RMS elevation spread of arrival angles (ZSA) and departure angles (ZSD) are both 10°. The cluster ASA is 22°, the cluster ASD is 10°, and the cluster ZSA is 7°. In addition, we select the values of the remaining parameters as shown in Table 1.

Based on the above channel model, for the case of 8 trainings ($K=8$), we first designed an 8-dimensional precoding codebook containing 16 codewords, (see [17]), defined as

$$\mathscr{F}_1=\left\{(\boldsymbol{\theta}_0)^l\boldsymbol{\phi}_0\,;l=0,1,\cdots,15\right\}, \tag{18}$$

where $\boldsymbol{\phi}_0=1/\sqrt{8}[1\quad 1\quad\cdots\quad 1]^T\in\mathbb{R}^{8\times 1}$, and $\boldsymbol{\theta}_0=\operatorname{diag}(e^{-j(2\pi u_1/16)},e^{-j(2\pi u_2/16)},\cdots,e^{-j(2\pi u_8/16)})$. $\{u_1,u_2,\cdots,u_8\}=\{0,1,7,5,47,14,15,12\}$.

The calculation formula of the throughput is as follows:

$$C=\log_2\left(1+\rho\left|\mathbf{h}_{\mathrm{d}}^H\mathbf{p}_0\right|^2\right), \tag{19}$$

where $\mathbf{p}_0$ denotes the precoder. In the following, when $\mathbf{p}_0=\mathbf{h}_{\mathrm{d}}^H/\|\mathbf{h}_{\mathrm{d}}^H\|$, it is called as "ideal feedback", and when the BS uses the coefficients given in (14) to construct $\mathbf{p}_0$, it is called as "full feedback".

Simulation 1. According to the above precoding codebook, when $K=8$, in the case of 32 BS antennas and the speed of the MS being 120 km/h, as shown in Figure 1, we simulated the throughput in the three feedback situations: ideal feedback, full feedback, and limited feedback based on the above precoding codebook. Notice that the ideal feedback involved in simulations refers to full feeding back the true DL channel at the current time slot to the BS. It can be seen from the figure that at a speed of 120 km/h, the throughput of the proposed scheme under full feedback is close to the throughput under ideal feedback.

Simulation 2. In order to further demonstrate the effect of this scheme at high speed, taking 120 km/h and 8 trainings as examples, we compare the full feedback throughput of this scheme and the ideal feedback throughput under different BS antenna numbers ($M_t=32,64,128$), as shown in Figure 2. This figure illustrates that even with a large number of BS antennas ($M_t = 128$), the throughput of the proposed scheme under full feedback is also close to that of ideal feedback.

5. Conclusions

In this paper, by utilizing the spatial reciprocity between the UL and DL channels in the FDD system, we propose a PCA-based adaptive training-feedback scheme for time-varying massive MIMO systems. The proposed scheme combines PCA technology and SVD method to extract the K principal singular vectors of the covariance matrix of UL received signals. According to the spatial reciprocity of the FDD system, it is shown that K singular vectors can constitute a subspace of the DL covariance matrix. Therefore, the pilots designed are based on these singular vectors and could be adaptive, which greatly reduces the number of training times and feedback bits. Simulation results show that the throughput of the proposed scheme is close to that of ideal feedback even under high speed, with low training and feedback overhead.

Data Availability

Data is available upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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