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# **CSI Calibration for Precoding in mmWave** Massive MIMO Downlink Transmission Using Sparse Channel Prediction

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**ABSTRACT** The channel state information (CSI) obtained from channel estimation will be outdated quickly in the millimeter wave (mmWave) massive multiple-input multiple-output (MIMO) systems employing time-division duplex (TDD) setting, which results in significant performance degradation for the precoding and coherent signal detection. In order to overcome the CSI delay problem, this article proposes a novel downlink transmission scheme for the mmWave massive MIMO systems. In the proposed scheme, the base station (BS) estimates the channel coefficients by using the uplink pilots, and calibrates the CSI by employing an enhanced predictor which exploits the channel sparsity in both the angle and the time domains, followed by the interpolation to obtain the channel coefficients at the data rate. Then the signal radiated from the BS array is precoded by using the predicted channel coefficients so that the proposed scheme can overcome the CSI delay problem effectively, and improve the signal detection performance. We show that for system with 125 Hz Doppler frequency shift and 0.96 ms time slot, the uncoded bit error rate (BER) is improved from  $2.4 \times 10^{-2}$  to  $2.5 \times 10^{-3}$  by using our proposed method when the noise power ratio (SNR) is 10 dB.

**INDEX TERMS** Channel prediction, CSI calibration, massive MIMO, millimeter wave, outdated CSI, precoding.

#### I. INTRODUCTION

Recently, the millimeter wave (mmWave) communication is regarded as one of the most potential solutions for the exponentially expanding wireless data traffic in the future, due to the wide usable spectrum in the mmWave band. To compensate for the huge pathloss of communication in mmWave bands, massive multiple-input multiple-output (MIMO) technique is fundamental for providing beamforming gain to ensure coverage of a serving cell [1]. The application of massive MIMO at mmWave frequencies would be very popular in the foreseen future [2], [3].

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Despite the great potential of the mmWave massive MIMO cellular communications, there are some key technical challenges need to be addressed. The mmWave systems communicate at the extremely high-frequency band, for which the channel usually suffers from much faster variation than that in lower-frequency band communication (due to the fact that the effect of mobility in terms of Doppler shift increases linearly with frequency) [4]. Moreover, the massive MIMO systems often employ time-division duplex (TDD) setting [5], in which the time spent on uplink pilot transmission and downlink channel state information (CSI) feedback may surpass the coherence time of the channel [6], [7]. The bit error rate (BER) performance can be severely affected by the feedback delay. The delayed CSI appears due to the relative



FIGURE 1. Channel output and path gains versus sample interval. Set the velocity of terminal to 1.5 m/s and the carrier frequencies to 25 GHz (a) and 50 GHz (b), respectively. The corresponding maximum Doppler shifts are 125 Hz and 250 Hz.

movement between the antennas and the scatterers. In fact, the channel varies between when it is learned via estimation and when it is used for precoding or detection due to the time-varying nature of real channels. The study in [8] shows that the channel fading rate can be significantly reduced by using highly directional antennas. However, in order to perform beam forming and make the received signal change slowly, we also need to know the actual channel state information in advance [3].

Fig. 1 presents the step response of the channel and the corresponding path gain snapshots for different values of the sample interval property by configuring a channel with delay profile clustered-delay-line-B (CDL-B) from Technical Report (TR) 38.901 [9], where the channel power is normalized to 1. As is shown in Fig. 1, the channel will be quickly outdated even at fast walking or jogging speed (1.5 m/s), while the channel sample intervals are also very short (0.48 ms, 0.96 ms, 1.92 ms). This challenge will become more pronounced as the carrier frequency grows. In TDD systems, for downlink transmission, CSI can only be obtained by estimating uplink channel, thus resulting in unavoidable outdated problem [10], which will seriously degrade the performance of precoding and coherent signal detection.

There have been some papers dealing with the problem of channel estimation and tracking for precoding technique in mmWave mssive MIMO systems [11]–[13]. Particularly, [14] develops a three-step multi-user channel estimation scheme for hybrid mmWave MIMO systems, and investigates the hybrid precoding system design. The prior investigations on channel estimation and tracking aim to obtain the up-to-date CSI of training symbols. However, as is shown in Fig. 1, the CSI of training stage in the uplink will be quickly outdated and could not be used for data transmission in the downlink. Channel prediction techniques have been studied to effectively compensate for the outdated CSI in the adpative transmission systems. For the MIMO systems, the minimum mean-square-error (MMSE) or adaptive channel predictors are proposed in [15], [16], and a parametric-model-based channel prediction method is proposed in [17]. They all work on each pair of antennas in the array domain. For the OFDM systems, most of the existing predictors are realized on each subcarrier in the frequency domain [18], while [19] proposes to predict the channel in the time domain. For the MIMO-OFDM systems, the previously proposed prediction methods operate on each subcarrier in each antenna pair of MIMO-OFDM channel [6], [20]. [10] comprehensively investigates the channel prediction in different domains for mmWave Massive MIMO systems.

To the best of our knowledge, general framework for mmWave massive MIMO downlink transmission and signal detection considering the outdated problem is not available in the literature. In this article, we develop a novel precoding and signal detection scheme which exploits the predicted channel coefficients to improve system performance. *The main contributions of this article are as follows*.

- We develop a novel framework for the mmWave massive MIMO downlink transmission, which consists of the uplink pilot transmission and channel estimation, the angle-time domain (Ag-TD) channel prediction, channel interpolation, massive MIMO precoding and coherent signal detection. The proposed scheme utilizes the predicted channel coefficients instead of estimated channel coefficients to overcome the CSI delay problem.
- The channel prediction and interpolation are performed in the Ag-TD, as the Ag-TD channel is composed of fewer physical paths and thus is more predictable than



FIGURE 2. The data transmission structure of mmWave massive MIMO system for TDD operations.



FIGURE 3. System blocks of the proposed precoding and signal detection scheme.

that in the other domains [10]. The channel sparsity in both the angle and time domains is also exploited for channel prediction to eliminate the noise perturbation and to reduce the computational burden.

• Unlike the prior investigations, our proposed framework does not assume that the wireless channel remains timeinvariant during channel estimation, channel prediction, or data transmission, which means that the mmWave massive MIMO channel will change sample-by-sample, resulting in highly challenging channel acquisition strategies. Therefore, we propose the new framework to make the transmitter and receiver be synchronized with the channel dynamics.

The remainder of this article is organized as follows. The system model is described in Section II. The proposed downlink transmission and coherent signal detection scheme is presented in Section III. Section IV evaluates the performance of the proposed scheme by numerical results and the paper is concluded in Section V.

#### **II. MmWave MASSIVE MIMO SYSTEM DESCRIPTION**

We consider a massive MIMO system deploying uniform linear arrays (ULA) geometry at base station (BS) with M antennas, and the terminal with one antenna. As the mmWave channel is usually wideband and frequencyselective, an orthogonal frequency division multiplexing (OFDM) technique with K sub-carriers is combined with the MIMO technique to turn the frequency-selective fading channel into a set of flat fading channels. The channel estimation of massive MIMO is operated in TDD mode, where pilots are transmitted in the uplink and then the estimated CSI is further processed and feedback in the downlink.

The data transmission structure of mmWave massive MIMO system for TDD operations is given in Fig. 2. There

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are *T* symbols in one time slot. In each time slot, the terminal first transmits  $\tau_{up}$  pilot symbols and  $\tau_{ud}$  data symbols in the uplink, and then the BS estimates the propagation channels using the pilot symbols. During the remainder of the time slot (consisting of  $T - \tau_{up} - \tau_{ud}$  symbols), the BS will transmit data to the terminal with a proper precoder. Finally, coherent signal detection can be performed at the terminal. To perform precoding and signal detection in the downlink, the BS must acquire the CSI. However, with a limited coherence time in mmWave massive MIMO systems, the estimated channel coefficients in the uplink could not be directly used for precoding and detection. Therefore, we propose a general framework for downlink transmission and signal detection to overcome the CSI delay problem.

### III. PROPOSED FRAMEWORK FOR DOWNLINK TRANSMISSION AND COHERENT SIGNAL DETECTION

In this section, we detail the main blocks (shown in Fig. 3) of general framework for downlink transmission and signal detection in mmWave massive MIMO systems.

#### A. UPLINK TRANSMISSION AND CHANNEL ESTIMATION

In the uplink transmission, for independent Rayleigh fading, propagations between the *M* BS antennas and the terminal with one antenna are described by *M* normalized channels. The terminal transmits pilot sequence, which consists of  $\tau_{up}$  symbols. The BS correlates the received symbols with the conjugates of the pilot sequence, which yields the following processed signal:

$$y_m[i,k] = \sqrt{\tau_{up}\rho_u}h_m[i,k] + n_m[i,k],$$
 (1)

where  $h_m[i, k]$  is the normalized channel at the *k*-th subcarrier and the *i*-th symbol time for the *m*-th antenna of the BS,  $n_m[i, k]$  is the background noise plus interference term of the

*m*-th receive antenna, which can be approximated as a zero mean additive white Gaussian noise (AWGN) with variance  $\sigma_n^2$ , and  $\rho_u$  is a measure of the expected signal to noise power ratio (SNR) of the uplink channel. The MMSE estimation for  $h_m$  [*i*, *k*] can be given as

$$\tilde{h}_m[i,k] = \frac{\sqrt{\tau_{up}\rho_u}}{1 + \tau_{up}\rho_u} y_m[i,k].$$
<sup>(2)</sup>

## **B. CHANNEL PREDICTION**

The mmWave MIMO-OFDM channel prediction can be performed in four domains: the array-frequency (Ar-FD), array-time (Ar-TD), angle-frequency (Ag-FD), as well as Ag-TD. In each of the four domains, if there exist correlations between channel elements, the correlations should be exploited to improve the performance of channel prediction. The channel taps with different delays are often assumed to be wide sense stationary (WSS), independent, and narrowband complex processes. Meanwhile, in each channel tap, different physical paths (sinusoids) contribute to different angle domain bins, and thus the channel coefficients in different angle domain bins are spatially uncorrelated. Therefore, the Ag-TD channel elements are uncorrelated, and the channel prediction in the Ag-TD achieves higher accuracy than the other three domain prediction techniques without exploiting channel correlations [10]. In this article, an enhanced Ag-TD channel predictor which exploits the channel sparsity in both the angle and the time domains is employed to predict the channels.

The estimated channel in (2) is the so called Ar-FD representation of MIMO-OFDM channel. The OFDM technique employs discrete-Fourier-transform (DFT) in the receiver to transform the time domain channel into the frequency domain, and thus we can establish the relationship between the time domain and frequency domain of channel by using DFT and inverse-DFT (IDFT). Hence, the Ar-TD channel estimation can be obtained as

$$\tilde{g}_m[i,l] = IDFT\left\{\tilde{h}_m[i,k]\right\},\tag{3}$$

where  $\tilde{g}_m[i, l]$  is the channel estimation of the *l*-th channel tap at the *i*-th OFDM symbol transmitted from the terminal to the *m*-th antenna of the receiver.

A cyclic prefic (CP) is attached to every OFDM symbol to mitigate the effect of channel delay spread. As the channel's maximum delay does not exceed the CP length of OFDM system  $L_{cp}$ , for  $l = L_{cp}$ ,  $L_{cp} + 1$ , ..., K - 1, we have

$$\tilde{g}_m[i,l] = n'_m[i,l], \qquad (4)$$

where  $n'_m[i, l]$  is the transformed noise in the Ar-TD. The mmWave channel has only a few path clusters due to the limited scattering effect [21], [22], also known as multipath sparsity. Therefore, the wideband radio channel is sparse in the time domain. When the time domain channel is described as a tapped delay line, the sparseness of resolvable multipaths allows only a few taps to be nonzero. Therefore,  $\tilde{g}_m[i, l]$ ,

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 $l = 0, 1, \ldots, L_{cp}$ -1, can be modeled as

$$\tilde{g}_{m}[i,l] = \begin{cases}
g_{m}[i,l] + n'_{m}[i,l], & \text{significant tap} \\
n'_{m}[i,l], & \text{zero-valued tap,}
\end{cases}$$
(5)

where  $g_m[i, l]$  is the real channel of the *l*-th channel tap at the *i*-th OFDM symbol transmitted from the terminal to the *m*-th antenna of the receiver.

Then, by the nonzero channel taps identification algorithm, we can revise the result of channel estimation as

for 
$$l = 0, 1, \dots, L_{cp} - 1$$
  
 $\tilde{\mathbf{g}}[i, l] = \begin{cases} \tilde{\mathbf{g}}[i, l], & \text{if } \sigma_{g_l}^2 - \sigma_{n'}^2 \ge \sigma_{n'}^2 \\ 0, & \text{if } \sigma_{g_l}^2 - \sigma_{n'}^2 < \sigma_{n'}^2 \end{cases}$   
for  $l = L_{cp}, L_{cp} + 1, \dots, K - 1$   
 $\tilde{\mathbf{g}}[i, l] = 0,$ 

where  $\tilde{\mathbf{g}}[i, l]$  is the column wise arrangement of  $\tilde{g}_m[i, l], m = 0, 1, \dots, M - 1, \sigma_{g_l}^2$  is the average power of the *l*-th Ar-TD channel tap given as

$$\sigma_{g_l}^2 = E\left\{\left\|\tilde{\mathbf{g}}\left[i,l\right]\right\|^2\right\},\,$$

which can be computed from the past channel estimates, and the noise power  $\sigma_{n'}^2$  can be estimated by

$$\sigma_{n'}^2 = \frac{1}{K - L_{cp}} \sum_{l=L_{cp}}^{K-1} \sigma_{g_l}^2,$$
(6)

because for  $l = L_{cp}, L_{cp} + 1, \dots, K - 1$ , the channel tap  $\tilde{\mathbf{g}}[i, l]$  is only composed of noise.

The MIMO technique extends the radio channel into space, for which we can abstract the array domain model into the angle domain model in terms of spatially resolvable paths. Therefore, we can transform the Ar-TD channel representation into Ag-TD representation as [23], [24]

$$\tilde{\mathbf{g}}^{a}\left[i,l\right] = \mathbf{U}_{r}^{H}\tilde{\mathbf{g}}\left[i,l\right],\tag{7}$$

where the superscript "*H*" denotes conjugate transpose, the superscript "*a*" denotes the angle domain variables,  $\mathbf{U}_r$  is the  $M \times M$  unitary matrix of which the (u, v)-th entry is  $\frac{1}{\sqrt{M}} \exp\left(\frac{-j2\pi uv}{M}\right)$  for  $u, v = 0, 1, \ldots, M - 1$ ,  $\tilde{\mathbf{g}}^a[i, l]$  is the column wise arrangement of  $\tilde{g}^a_{\phi}[i, l], \phi = 0, 1, \ldots, M - 1$ , and  $\tilde{g}^a_{\phi}[i, l]$  is the estimate of the channel from the transmitter to the  $\phi$ -th receive angle in the *l*-th channel tap at the *i*-th OFDM symbol.

For each significant channel tap, as some angle domain bins contain no physical signal due to limited scattering, the corresponding channel coefficients approach zeros. If the l-th channel tap is significant, we can further identify the significant angle domain coefficients of this channel tap by

$$\tilde{g}^{a}_{\phi}[i,l] = \begin{cases} \tilde{g}^{a}_{\phi}[i,l], & \text{if } \sigma^{2}_{g^{a}_{\phi,l}} - \sigma^{2}_{n^{a}} \ge \sigma^{2}_{n^{a}} \\ 0, & \text{if } \sigma^{2}_{g^{a}_{\phi,l}} - \sigma^{2}_{n^{a}} < \sigma^{2}_{n^{a}}, \end{cases}$$
(8)

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where

$$\sigma_{g_{\phi,l}^a}^2 = E\left\{ \left| \tilde{g}_{\phi}^a \left[ i, l \right] \right|^2 \right\}$$

is the average channel power of the channel from the transmitter to the  $\phi$ -th receive angle in the *l*-th channel tap at the *i*-th OFDM symbol, and  $\sigma_{n^a}^2$  is the noise power of each Ag-TD bin, which can be estimated as

$$\sigma_{n^a}^2 = \frac{1}{(K - L_{cp})M} \sum_{l=L_{cp}}^{K-1} \sum_{\phi=0}^{M-1} \sigma_{g_{\phi,l}^a}^2.$$
 (9)

Finally, the channel prediction can be performed on each significant element in the Ag-TD, and the autoregressive (AR) based method [25] is employed to perform channel prediction as

$$\hat{g}^{a}_{\phi}\left[i+T,l\right] = \sum_{p=0}^{P-1} d_{g^{a}_{\phi,l}}\left(p\right) \tilde{g}^{a}_{\phi}\left[i-pT,l\right], \quad (10)$$

where *T* is the slot symbol number shown in Fig. 2 (also known as prediction interval), *P* is the prediction order, and  $d_{g_{\phi,l}^a}(p)$ , for  $p = 0, 1, \dots, P-1$  are the prediction coefficients for the channel from the transmitter to the  $\phi$ -th receive angle in the *l*-th channel tap. The prediction coefficient in the vector form

$$\mathbf{d}_{g_{\phi,l}^{a}} = \left[ d_{g_{\phi,l}^{a}}(0), d_{g_{\phi,l}^{a}}(1), \cdots, d_{g_{\phi,l}^{a}}(P-1) \right]^{T}$$

can be calculated based on MMSE principle as [26]

$$\mathbf{d}_{g^a_{\phi,l}} = \left(\mathbf{R}_{g^a_{\phi,l}} + \sigma^2_{n^a}\mathbf{I}\right)^{-1}\mathbf{r}_{g^a_{\phi,l}},\tag{11}$$

where **I** is the identity matrix,  $\mathbf{R}_{g_{\phi,l}^a}$  is the channel autocorrelation matrix, and  $\mathbf{r}_{g_{\phi,l}^a}$  is the channel auto-correlation vector, as defined in [10].

#### TABLE 1. The procedure of prediction block.

- 1. Transforming the Ar-FD estimates into the Ar-TD using IDFT block.
- 2. Identifying significant channel tap positions in the time domain.
- 3. Transforming the Ar-TD estimates into the Ag-TD using the transformation matrix  $\mathbf{U}_r^H$ .
- 4. For each significant channel tap, identifying significant channel elements in the angle domain.
- 5. Performing AR-based channel prediction on each non-zero element of the Ag-TD channel.

The prediction block procedure is summarized in Table 1. The performance of channel prediction has been evaluated in some paper. Reference [27] analyzes the theoretical performance of the channel prediction as a function of several parameters: the number of scatterers, model order, sampling rate and the Signal-to-Noise ratio (SNR). [10] investigates and presents the prediction performance in the Ar-FD, Ar-TD, Ag-FD, as well as Ag-TD.

#### C. CHANNEL INTERPOLATION AND TRANSFORMATION

In an OFDM system using pilots for channel estimation, time interpolation among pilots of different OFDM symbols is commonly used to improve the estimation. As is shown in Fig. 2, the channel coefficients can be estimated at the begining of each time slot. As the channel estimating rate (perform estimation once every *T* OFDM symbols) is much lower than the OFDM symbol rate, interpolation is employed to estimate the channel coefficients at the symbol rate. In our interpolation method,  $N_I$  consecutively time slots are firstly used to obtain the channel coefficients, including  $N_I - 1$ estimated coefficients and 1 predicted coefficient. The  $N_I$ channel coefficients are interpolated by a cubic spline interpolator [28] to generate estimates of the channel coefficients at the symbol rate, between the channel prediction sample and the last of channel estimation samples, as shown in Fig. 2.

It should be noted that channel prediction and interpolation are performed in the Ag-TD in this article. However, as the precoding and coherent signal detection are performed in the Ar-FD, the prediction results in other domain representations should be transformed back into Ar-FD. The transformation can be conducted by inverse operations of (3) and (7). Thus, we can obtain the Ar-FD channel prediction  $\hat{h}_m$  [*i*, *k*].

#### D. DOWNLINK PRECODING AND SIGNAL DETECTION

The downlink data symbol received by the mobile terminal at the k-th subcarrier and the i-th symbol time is given by

$$x[i,k] = \sqrt{\rho_d} \mathbf{h}^T[i,k] \mathbf{s}[i,k] + z[i,k], \qquad (12)$$

where the superscript "*T*" denotes transpose,  $\mathbf{h}[i, k]$  is the column wise arrangement of the channel  $h_m[i, k]$ ,  $m = 0, 1, \ldots, M-1, \mathbf{s}[i, k]$  is the  $M \times 1$  input to the BS's antennas,  $\rho_d$  is the transmitted power coefficient, and z[i, k] is the noise at the terminal. Here we assume that the z[i, k] is AWGN with unit variance.

As the channel has been obtained and known to the BS, the signal radiated from each BS antenna should be weighted [29] so that the propagated signal can be added coherently at the receiver. In this article, the BS precodes data of its user through an  $M \times 1$  vector  $\mathbf{w}[i, k]$  such that

$$\mathbf{s}[i,k] = \mathbf{w}[i,k] d[i,k], \qquad (13)$$

where d[i, k] is the message-bearing symbol intended for the terminal, and the *m*-th weight coefficient of **w**[*i*, *k*] is

$$w_m[i,k] = \frac{\hat{h}_m^*[i,k]}{\hat{\mathbf{h}}^H[i,k]\hat{\mathbf{h}}[i,k]},$$
(14)

where the superscript "\*" denotes conjugation. Finally, the terminal can directly detect the received signal using traditional methods.

We assume that the message-bearing symbols are uncorrelated with unit variance

$$E\left\{d^{*}\left[i,k\right]d\left[i,k\right]\right\} = 1.$$

Hence, the expected SNR of the received signal at the terminal would be equal to  $\rho_d$ .

## E. COMPUTATIONAL COMPLEXITY

This article employs the channel prediction instead of channel estimation to overcome the CSI delay problem. Compared with the traditional methods, the computational complexity is increased due to the use of 3 modules: the MMSE channel prediction, the channel interpolation and the transformation between different domains.

The MMSE channel prediction technique can compute optimal predictor coefficients using the Levinson recursion, and its computational complexity is  $O(P^2)$ . The cubic spline interpolator using  $N_I$  consecutively channel coefficients is employed for channel interpolation, and the computational complexity of the interpolation is  $O(N_I + log(N_I))$ . Meanwhile, two types of transformations are employed in the proposed prediction techniques: the first type is transformation between the array domain and the angle domain, which requires a computational complexity of O(2M) for each channel coefficient; the second one is the transformation between the frequency domain and the time domain, which gives a computational complexity of  $O(\log_2 K)$  (the DFT/IDFT can be conducted using FFT/IFFT) for each channel coefficient. The increased complexity of the proposed scheme is summarized in Table 2.

#### TABLE 2. The increased computational complexity.

Transformation	Prediction	Interpolation
$O\left(2M + \log_2 K\right)$	$O\left(P^2\right)$	$O\left(N_{I}+log\left(N_{I} ight) ight)$

The precoding and coherent signal detection performance improvement of the proposed scheme comes at the expense of increasing the computational complexity. Nevertheless, it is important to note that the proposed scheme exploits the channel sparsity in both the angle and the time domains to find the nonzero tap positions and nonzero angle domain coefficients for channel prediction, thereby reducing computational complexity of the proposed scheme.

## **IV. SIMULATION RESULTS**

MATLAB simulations are carried out to evaluate the performance of the proposed scheme in a mmWave massive MIMO-OFDM system. The standardized 3GPP channel model TR 38.901 [9] is employed to test our proposed scheme, and the simulated channel is constructed by using the clustered delay line model with delay profile CDL-B. It should be noted that the CDL-B of 3GPP TR 38.901 is double directional 3D channel model with both azimuth and elevation angles. However, only azimuth angle is considered in this article.

The velocity of the terminal is set as 1.5 m/s, modeling slow velocity scenarios like fast walking or jogging. The deployed antenna number at BS is set as M=128. We set the normalized separation between antennas of BS as  $\Delta r=0.5\lambda$ , where  $\lambda$  is the wave length. There are K = 256 OFDM subcarriers, and the CP length is  $L_{cp} = K/4$ , which is larger



FIGURE 4. BER performance comparison for downlink transmission, maximum Doppler frequency 125 Hz.



**FIGURE 5.** BER performance comparison for downlink transmission, maximum Doppler frequency 250 Hz.

than the maximum channel delay. 200 slots are simulated: the first 100 slots are used for computing prediction coefficients, while the second 100 for performance evaluation. The data sampling rate is set as 10 MHz. We assume that the symbol numbers of uplink and downlink transmission are equal  $\tau_{up} + \tau_{ud} = \tau_{dd}$ , and the pilot symbol number in the uplink is  $\tau_{up} = 10$ . Then, the specific symbol numbers can be decided by slot duration and data sampling rate. Note that in order to perform channel prediction, the channel sampling rate (pilot density) is set as higher than the Nyquist rate which is twice of the maximum Doppler frequency occurring with the wireless channel. The message-bearing quadrature amplitude modulation (QAM) symbols with unit power are used. The SNR of uplink channel is  $\rho_u = 10$  dB. The prediction order is P = 10. The channel coefficients number used for interpolation is  $N_I = 10$ , including 9 estimated coefficients

and 1 predicted coefficient. The channel coefficients number used for computing average power  $\sigma_{g_l}^2$  and  $\sigma_{g_{\phi,l}^a}^2$  is also set as 10.

We simulate the uncoded BER performance of the mmWave massive MIMO-OFDM system with the novel downlink transmission and signal detection scheme using predicted channel coefficients. The traditional scheme employing estimated CSI and ideal case employing perfect CSI are also simulated for comparison. The results are showed in Fig. 4 and Fig. 5, with carrier frequencies set as 25 GHz and 50 GHz (the resulting maximum Doppler frequencies are 125 Hz and 250 Hz, respectively). In the simulations, each figure tests two slots (channel sample intervals) to evaluate the performance improvement. As is observed in the simulations, the detection error caused by the delay of estimated CSI is unacceptable, even when the terminal moves at fast walking or jogging speed. Therefore, we expect to improve the precoding and coherent signal detection utilizing the predicted channel information. The simulations show that the proposed precoding and signal detection scheme using the predicted channel coefficients outperforms the traditional methods.

#### **V. CONCLUSION**

Motivated by the fact that the TDD reciprocal assumption, which indicates that the uplink and downlink channel paths are similar, is invalid even when the terminal moves at just fast walking or jogging speed in mmWave massive MIMO communications, a novel framework for downlink transmission and signal detection is proposed in this article. Instead of using estimated channels for precoding and detection, an enhanced channel predictor followed by interpolation exploiting the channel sparsity in both the angle and the time domains is employed by the proposed scheme to acquire CSI. Our main contribution in this article is to propose a novel framework of the downlink transmission and signal detection, which employs Ag-TD sparse channel prediction algorithm to improve system performance.

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