Utilization of Beam Signatures Supporting High User Mobility with Extremely Low Feedback Overhead

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ABSTRACT Accurate beamforming under the constraint of limited-feedback for the channel state information (CSI) has always been a challenging task, despite its huge impact on the quality of multiple-input multiple-output (MIMO) transmission. The task is becoming especially important for millimeter-wave (mmWave) transmission which requires high-gain beams to overcome the severe pathloss experienced over the radio channel, since an inaccurate beam direction may cause a noticeable performance degradation. The signal blockage in the urban environment due to the mobile and human traffic can also degrade the beamforming performance, by generating blind spots for signal transmission as well as the CSI feedback.

In this paper, a new way of transmitting accurate beams to highly mobile users with a substantially reduced amount of feedback overhead is proposed, by introducing a set of beam signatures that are composed of multiple beams along the trajectories of mobile users. Instead of forming a spot beam corresponding to the precoder matrix indicator (PMI) reported by the user equipment (UE), the base station (BS) utilizes the history of previous reports to determine an appropriate beam signature and transmit beams to predicted UE positions. The proactive decision for the next beam position is made with the aid of deep learning (DL) using the train data obtained from typical mobile movements for given road conditions, thus providing the adaptability to the channel environment with progressively improving accuracy. The set of beam signatures, which are called the beambook, includes the time dimension added to the conventional spatial dimension for beams to develop into a spatio-temporal codebook. The beambook produces enhanced and reliable beamforming over the mobile’s trajectory, even when the CSI feedback interval is considerably longer than parameters supported by the current 5G new radio (NR) standard. It is demonstrated that the proposed beambook significantly outperforms the conventional codebooks based on the discrete Fourier transform (DFT) matrix and the vector quantization (VQ) in both beamforming accuracy and throughput performance.

INDEX TERMS Beamforming, codebook, 5G NR, beam tracking, mobility, deep learning.

I. INTRODUCTION

Mobile wireless systems are evolving with continuous changes and technology upgrades in each generation, to provide enhanced performance including higher data rates, increased spectral efficiency, low energy consumption and reduced latency [1]. The user-experienced data rate of 100 Mbps and the peak data rate of 1 Gbps targeted for 5G new radio (NR) are expected to further experience 100 to 1000-fold increase in the upcoming 6G wireless standard [2], [3]. Among many physical layer technologies enabling the explosive growth in data rate, multiple-input multiple-output (MIMO) transmission using a large-scale array will continue to play a key role to meet this ever-increasing demand [4].

Massive MIMO systems can generate the high beamforming gain by using focused directional beams, which in turn require an accurate alignment of the transmit and receive beams [5]. Such an alignment is performed for the initial access for link connection between the base station (BS) and the user equipment (UE) using a set of sounding beams [6]. The initial access established by identifying the best beam pair between the BS and UE is followed by beam tracking, which adjusts the direction of the beams according
to time-varying channel conditions such as UE movements, device rotation, and link blockage [7]. Beam tracking is also important for the seamless handover between BSs [8], and the radio recovery procedure has been investigated to minimize adversary effects of link failures [9]. Beam alignments can be aided by a prior knowledge of potential pointing directions, using the fingerprint database storing long-term channel characteristics of given locations [10]. Variations in the angle-of-arrival (AoA) and angle-of-departure (AoD) can be estimated from the information from the previous time slots, and the predicted result can be applied to beam tracking [11]. Different approaches have been investigated for efficient estimation of beam directions, including the Gaussian perturbation method [12] and discrete Markov process modeling for the temporal changes of AoA/AoD [13]. Extended Kalman filter (EKF)-based beam tracking is also known to efficiently decrease the beamforming angle mismatch [7], [14]. Many of beam tracking algorithms is codebook-based, i.e., a set of discrete beam vectors are used in implementing the tracking procedure. The most commonly used form of beam vectors is obtained from the discrete Fourier transform (DFT) matrix, which generates exact directional beams for the uniform linear array (ULA) and the uniform planar array (UPA). Hierarchical codebooks composed of beam vectors with different beamwidths can be applied to improve the search efficiency [15], and the search can be extended to three-dimensional space for the full spatial coverage [16].

The 3rd Generation Partnership Project (3GPP) standard for 5G NR also relies on the beamforming strategy based on the DFT codebook, which is inherited from the 4G long-term evolution (LTE) with added features such as the extension for multi-panel large-scale arrays and Type-2 operation supporting up to 6 beam directions [17], [18]. The channel state information (CSI) for each UE is estimated using the reference signal (RS) transmitted by the BS, and the estimated result is reported back to the BS via the feedback channel. Upon the reception of the CSI-RS periodically transmitted in pre-allocated time and frequency resources, the UE selects the best-matching codevector for beamforming and the selection is notified using the precoding matrix indicator (PMI). It is desired that the CSI-RS is transmitted using high directional beams in order to overcome the propagation loss, and beamformed CSI-RS serves that purpose. Unlike conventional non-precoded CSI-RS transmitted from each antenna port, beamformed CSI-RS uses multiple beamforming codevectors in the spatial domain and the UE chooses the beam with the strongest received signal strength indicator (RSSI) [19]. Beamformed CSI-RS has distinctive advantages over non-precoded CSI-RS, such as the stronger received signal power and reduced RS overhead in the transmitted resource [20].

Performance of the conventional DFT-based codebook can be further improved by employing more complex design strategies. A traditional approach is to use the vector quantization (VQ), which applies the nearest neighbor and centroid conditions to produce updated codevectors in an iterative fashion [21]. The resulting codebook reflects the specific distribution of target users to provide added efficiency of the beam coverage for the given environment. For time-varying conditions experienced by mobile users, phase tracking functions can be added to VQ using the temporal correlation property of fading channels [22]. The high computational complexity of generating VQ codebooks, however, often becomes the limiting factor in applying them to practical transmission scenarios. Codebook design in [23] lowers the complexity by proposing a dual-stage quantization method enabling an efficient CSI compression. The feedback reduction can also be achieved by using the AoD-adaptive codebook by exploiting the time-varying property of arrival angles as suggested in [24]. A practical approach of adjusting the conventional DFT-based codebook is proposed in [25], where location-wise parameters are added to customize the beamforming vectors. More recently, efforts are being made to apply deep learning (DL) algorithms to improve the efficiency of beamforming and beam management. In [26], beam patterns are predicted based on the dynamic distribution of user traffic using the recurrent neural network (RNN). A reinforcement learning (RL) based beam tracking strategy is investigated in [27], where the measured signal quality becomes the input to the Q-learning algorithm that decides the beam switching status. To predict the AoA/AoD both in terms of azimuth and elevation, a trajectory prediction method using DL is proposed to estimate the UE location information [28].

In this paper, an enhanced beam tracking method is proposed by using a set of pre-determined trajectories which are typical paths for mobile users in a given transmission environment. A group of beamforming vectors targeting each of these trajectories is defined to be a beam signature, which covers mobile users moving along or around that path. Instead of transmitting an individual beam based on the instantaneous UE feedback or trying to predict the next beam direction from previous channel information, the proposed method performs continuous and reliable beam transmission using the pre-defined beam signatures. Each beam signature represents spatially diversified beamforming vectors that are temporally correlated, resulting in a group of spatio-temporal codevectors replacing the conventional individual codevector in spatial dimension only. Selection of specific beam signatures for the target UE is aided by the DL algorithm, that determines which beam signature to use at a given transmission time based on previous CSI feedback information. The channel information can be obtained using the PMI reports based on CSI-RS, thus the existing reference signaling and feedback mechanism can be directly combined with the proposed method. Most of the existing tracking algorithms process the previous channel data to estimate the new beam direction with the variation of processing models such as Kalman filtering [7], [14], Markov decision process [13], utilization of fingerprint database [10], etc. None of these methods, however, is specifically targeted to the given environment with specific road conditions, reflector distribution, and traffic flow characteristics. Although the fingerprint
database is a position-based model which stores the potential pointing direction for given locations, modeling is not based on a continuous set of locations or trajectories. The prediction using the deep neural network (DNN) in [28], constructs the trajectory on-the-fly basis thus may lack accuracy compared to estimation based on the pre-determined typical trajectory set built on accumulated report data.

The proposed method is an extension of the traditional codebook-based beamforming strategy in the sense that one of the beam signatures is chosen for signal transmission based on the user PMI feedback. Utilization of beam signatures is better interpreted as a generalization of the conventional codebook based beamforming with added temporal dimension, rather than another variation of tracking algorithm producing estimated beam directions. This particular work focuses on the concept and utilization of beam signatures, and the presented result is best suited in transmission environment where a good portion of mobile users follow typical movement trajectories. An environment-adaptive generation and update strategy of beam signatures is also an important research topic, and its investigation result is planned to be reported as a separate work. The key advantages and features of the proposal in this paper are as follows: (1) Near-continuous beamforming customized to given channel conditions and surrounding environment is performed, providing significantly enhanced accuracy compared to individual spot beams. (2) The signal transmission stays robust even when the CSI feedback intervals significantly increase compared to typical values supported by wireless standards, since the selection of an appropriate beam signature does not necessarily require very frequency channel feedback actions. Rather, several PMI reports with a reasonable amount of intervals suffice to make the DNN choose the correct beam signature. (3) The proposed method is universally applicable to both sub-6GHz and millimeter-wave (mmWave) transmission, although the channel matrix such that $\mathbb{E}[\|\mathbf{h}_k\|^2] = M_t$, and $\mathbf{w}_k \in \mathbb{C}^{M_t \times 1}$ is the beamforming vector for data symbol $s_k$ with power constraint $\mathbb{E}[\|s_k\|^2] = 1/K$. Noise vector $\mathbf{n}_k$ includes independent and identically distributed (i.i.d.) complex Gaussian variables following $\mathcal{CN}(0, \sigma^2)$. The received signal-to-interference-plus-noise ratio (SINR) is

$$\gamma_k = \frac{\mathbb{E}[\mathbf{h}_k \mathbf{w}_k s_k^*]}{\sum_{j \neq k} \mathbb{E}[\|\mathbf{h}_k \mathbf{w}_j s_j^*\|^2 + \sigma^2]}$$

and the achievable sum-rate for all UEs becomes

$$R = \sum_{k=1}^{K} \log_2(1 + \gamma_k).$$

The multipath channel follows the Rician fading model including the line-of-sight (LOS) component $\mathbf{h}_{k,LOS}$ and non-line-of-sight (NLOS) component $\mathbf{h}_{k,NLOS}$ as described by [29]

$$\mathbf{h}_k = \sqrt{\frac{K_R}{K_R + 1}} \mathbf{h}_{k,LOS} + \sqrt{\frac{1}{K_R + 1}} \mathbf{h}_{k,NLOS}$$

where $K_R$ is the Rician factor representing the power ratio of the LOS and NLOS channels. The channel becomes pure NLOS when no direct path exists and hence $K_R = 0$. The LOS component $\mathbf{h}_{k,LOS}$ is expressed as

$$\mathbf{h}_{k,LOS} = \Lambda_f(\phi_{k,0}, \theta_{k,0}) \Lambda_t(\phi_{k,0}, \theta_{k,0}) \mathbf{a}_b^H(\phi_{k,0}, \theta_{k,0})$$

where $\Lambda_f(\cdot)$ and $\Lambda_t(\cdot)$ respectively represent the directional gains of the receive and transmit antennas. Also, $\mathbf{a}_b(\cdot)$ is the array response vector (ARV) of the transmit antennas. The azimuth and zenith AoAs for the LOS path are respectively denoted by $\phi_{k,0}$ and $\theta_{k,0}$. Similarly, the azimuth and zenith AoDs for the NLOS path are respectively denoted by $\phi'_{k,0}$ and $\theta'_{k,0}$. Using the extended Saleh-Valenzuela model for the NLOS multipath channel, $\mathbf{h}_{k,NLOS}$ is written as [30]

$$\mathbf{h}_{k,NLOS} = \sum_{l=1}^{L} \alpha_{k,l} \mathbf{a}_b^H(\phi'_{k,l}, \theta'_{k,l})$$

where $L$ is the number of propagation paths and $\alpha_{k,l}$ is the complex gain of the $l$-th path. The azimuth and zenith AoAs

II. SYSTEM MODEL

A multi-user (MU)-MIMO downlink transmission scenario is considered, where the BS with $M_t$ antenna elements transmit the data signal to $K$ single-antenna UEs. The received signal vector for the $k$-th UE is expressed as

$$\mathbf{y}_k = \sqrt{\rho_k} \mathbf{h}_k \mathbf{w}_k s_k + \sum_{j \neq k} \sqrt{\rho_k} \mathbf{h}_k \mathbf{w}_j s_j + \mathbf{n}_k$$

where $\rho_k$ is the average received power, $\mathbf{h}_k \in \mathbb{C}^{1 \times M_t}$ is the channel matrix such that $\mathbb{E}[\|\mathbf{h}_k\|^2] = M_t$, and $\mathbf{w}_k \in \mathbb{C}^{M_t \times 1}$ is the beamforming vector for data symbol $s_k$ with power constraint $\mathbb{E}[\|s_k\|^2] = 1/K$. Noise vector $\mathbf{n}_k$ includes independent and identically distributed (i.i.d.) complex Gaussian variables following $\mathcal{CN}(0, \sigma^2)$. The received signal-to-interference-plus-noise ratio (SINR) is

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where $L$ is the number of propagation paths and $\alpha_{k,l}$ is the complex gain of the $l$-th path. The azimuth and zenith AoAs.

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for the $l$-th path are respectively denoted by $\phi_{k,l}^t$ and $\theta_{k,l}^t$. The gain follows the zero-mean complex Gaussian distribution

$$
\alpha_{k,l} \sim \mathcal{CN} \left( 0, \sigma_{\phi_{k,l}^t}^2, \sigma_{\theta_{k,l}^t}^2 \right)
$$

(7)

where $\sigma_{\phi_{k,l}^t}$ is the average power, $\phi_{k,l}^t$ is the azimuth AoD, and $\theta_{k,l}^t$ is the zenith AoD of the $l$-th path. Although ray-tracing based channel generation can be better suited to specific environments [10], [31], the multipath model in (6) with random complex gains and angle values is frequently applied for performance evaluation in many transmission scenarios for its versatility to cover a wide range of environmental conditions [13], [15], [32]. In our performance analysis, evaluation results with varying channel parameters including the Rician factor and spread angle are provided to demonstrate the effectiveness of the proposal over different channel conditions. When the complex Gaussian gain in (7) with equal average power $\sigma_{\phi_{k,l}^t}^2$ is applied for each path, the power ratio of the strongest and weakest paths is approximately 17, 19, 21, and 22 dB for $L = 5, 10, 15,$ and $20$, respectively. Including more paths contributes even less to the channel, implying that $L = 20$ is a reasonable number for multipath channel generation. This observation is in general agreement to the channel based on parameters generated by ray-tracing in [10], which confirms that the power gap among 25 paths is more than 20 dB.

The ARV for the ULA with $M_h$ horizontal elements does not include the zenith angle argument and can be written as

$$
a_{\text{ULA}}(\phi) = \left[ 1, e^{j\kappa d\sin \phi}, \ldots, e^{j\kappa d(M_h-1)\sin \phi} \right]^T
$$

(8)

where $\kappa = 2\pi/\lambda$ is the wave number, $\lambda$ is the carrier wavelength, and $d$ is spacing between adjacent elements. For the UPA with $M_h$ horizontal elements and $M_v$ vertical elements, the ARV is expressed as [33]

$$
a_{\text{UPA}}(\phi, \theta) = \left[ 1, e^{j\kappa d\sin \phi \sin \theta + \phi \cos \theta}, \ldots, e^{j\kappa d((M_h-1)\sin \phi \sin \theta + (M_v-1)\cos \theta)} \right]^T.
$$

(9)

for $h = 0, 1, \ldots, M_h - 1$ and $v = 0, 1, \ldots, M_v - 1$. The total number of antenna elements in the UPA at the BS is $M_t = M_h M_v$.

### III. BEAM SIGNATURES

The codevectors used in 5G NR are obtained by taking columns from the DFT matrix. The horizontal codebook $C_h = \{v_0, v_1, \ldots, v_{I-1}\} \times I$ includes codevectors

$$
v_i = \frac{1}{\sqrt{M_h}} \left[ 1, e^{j2\pi n M_h^{-1}}, \ldots, e^{j2\pi i(M_h-1) M_h^{-1}} \right]^T
$$

(10)

for $i = 0, 1, \ldots, I - 1$, where $O_h$ is the horizontal oversampling factor which determines the codebook size $I = O_h M_h$. The codebook resolution increases for larger values of $O_h$, to perform beamforming targeted to one of $I$ horizontal directions. Similarly, the vertical codebook $C_v = \{u_0, u_1, \ldots, u_{N-1}\} \times N$ is defined by using codevectors

$$
u_n = \frac{1}{\sqrt{M_v}} \left[ 1, e^{j2\pi n M_v^{-1}}, \ldots, e^{j2\pi (N-1) M_v^{-1}} \right]^T
$$

(11)

for $n = 0, 1, \ldots, N - 1$, where $O_v$ is the vertical oversampling factor and $N = O_v M_v$ is the codebook size. Vertical beamforming can be performed to one of $N$ directions and the codebook resolution is controlled by parameter $O_v$. The two-dimensional codevectors for both horizontal and vertical beamforming are generated by taking the Kronecker product of $v_i$ and $u_n$ as

$$
c_{i,n} = v_i \otimes u_n
$$

(12)

to obtain the codebook

$$
C = \{c_{0,0}, \ldots, c_{i,n}, \ldots, c_{I-1,N-1}\}
$$

(13)

of size $Q = IN$, which is applicable to the UPA of dimension $M_h \times M_v$. For example, using $O_h = O_v = 2$ for the UPA with $M_h = M_v = 8$ results in the codebook of size $Q = 256$, corresponding to 16 horizontal beam directions and 16 vertical beam directions. The codebook in (13) can be equivalently written in one-dimensional indexing as in

$$
C = \{c_1, \ldots, c_q, \ldots, c_Q\}
$$

(14)

by letting $q = iN + n + 1$. In order to choose one of the beams from the codebook, the number of required feedback bits is $B = 8$ from the relation $Q = 2^B$. The 5G NR standard also supports the Type-2 codebook which allows weighted linear combinations of up to 6 DFT codevectors for enhanced coverage in the multipath channel environment [18]. These 3GPP codebooks, however, are universally applied to all transmission scenarios without taking into account specific geometrical conditions within the cell. Depending on environmental conditions, some of the codevectors are heavily used without sufficient beam resolution in their neighborhood while some of the codevectors are very rarely utilized. This type of inefficiency can be overcome by using VQ-based codebooks which are constructed via an iterative generation algorithm using user distribution characteristics.

The proposed beambook is an alternative solution to avoid the inefficiency of the 3GPP codebooks by including multiple beam signatures tailored to given transmission conditions. These beam signatures provide an efficient coverage to target areas and the capability to perform trajectory-based beamforming. A specific beam signature is chosen by multiple PMI reports by the UE, upon the reception of beamformed CSI-RS using the conventional DFT codebook in (13). Once the beam signature is correctly chosen, near-continuous fine-resolution beams can be generated along the mobile trajectory. Each beam signature is expressed as the matrix including column vectors generating spot beams along the given trajectory. The total number of beam signatures and the number of spot beams in each beam signature are design parameters which can be appropriately adjusted for given environmental conditions. The $j$-th beam signature is defined by $M_t$-by-$L_j$ matrix

$$
S_j = [b_{j,1}, b_{j,2}, \ldots, b_{j,L_j}]
$$

(15)

where $L_j$ is the number of spot beams called the signature length, and $b_{j,l}$ is the $l$-th spot beamforming vector in $S_j$. 
An $M_j \times 1$ column vector $\mathbf{b}_{j,l}$ directs the beam to azimuth angle $\phi_{j,l}$ and zenith angle $\theta_{j,l}$. Such a beamforming vector can be described using the ARV expression in (9) as

$$\mathbf{b}_{j,l} = \frac{1}{\sqrt{M_j}} \mathbf{a}_{\text{UPA}}(\phi_{j,l}, \theta_{j,l}). \quad (16)$$

Combining (15) and (16), the $j$-th beam signature is written as

$$\mathbf{S}_j = \frac{1}{\sqrt{M_j}} \left[ \mathbf{a}_{\text{UPA}}(\phi_{j,1}, \theta_{j,1}) \ldots \mathbf{a}_{\text{UPA}}(\phi_{j,L_j}, \theta_{j,L_j}) \right]. \quad (17)$$

The beambook $\mathbf{B}$ is the set of all beam signatures used for signal transmission and is given as

$$\mathbf{B} = \{ \mathbf{S}_1, \mathbf{S}_2, \ldots, \mathbf{S}_J \}. \quad (18)$$

An urban intersection with the BS near the center of the intersection is considered to illustrate the generation and utilization of beam signatures. As shown in Fig. 1, The BS is separated from the intersection center in horizontal distance of $x_{\text{BS}}$ and vertical distance of $y_{\text{BS}}$. The height of the base station is denoted by $h_{\text{BS}}$. The bearing, downtilt, and slant angles of the antenna array as defined in [34] are respectively denoted by $\alpha$, $\beta$, and $\gamma$. A number of users exist in the cell covered by the BS, with different amounts of mobility and moving directions. Three exemplary movement paths are indicated by black solid lines with arrows, which correspond to left-turn, go-straight, and right-turn traffic from the bottom entrance to the intersection in the map. In practical situations, numerous paths can be drawn for actual mobile users with different departure and destination points with possible lane changes. UE movements can be described in the form of location coordinates as a function of time. A series of such location coordinates of a mobile UE is referred to as a movement path. For efficient modeling of the real-world mobile traffic and practical generation of representative trajectories, we use the simulation of urban mobility (SUMO) package which is an open-source traffic simulation software [35]. The SUMO simulation package produces user movement patterns with the consideration of various realistic factors such as traffic lights, changing lanes of vehicles, and deceleration when approaching vehicles in front [36]. Using this model, UEs and their movement paths are generated inside the coverage area. Once a sufficient number of movement paths for mobile vehicles are generated by SUMO, the generated paths can be sorted into groups with similar movement patterns. In typical urban intersections, 12 groups of movement paths can be chosen with four different departure points and three different moving directions.

Each group of movement paths is represented by a trajectory, which is a series of $k$ location coordinates determined by the $k$-means clustering algorithm. The $k$-means clustering algorithm is an iterative clustering method commonly used in similarity grouping or clustering problem as described in [37]. The algorithm separates the data samples into $k$ clusters in which each data sample belongs to the cluster with the nearest mean. In our case, the $k$-means clustering algorithm is applied to each of 12 groups of movement paths. The execution of the algorithm is repeated for all groups of movement paths to obtain 12 trajectories. The two-dimensional location coordinates of all mobile movement paths in a group are initially collected to form the set of data samples. Suppose, for example, 100 movement paths are generated with the common departure and arrival positions, with each path described by 1,000 coordinates. Then the set of 100,000 data samples is applied as the input to the $k$-means clustering algorithm, which produces $k$ representative centroids by clustering these data samples. These representative coordinates are referred to as centroids. Finally, the $k$ cluster centroids obtained as the output of the algorithm are connected by line segments to produce the trajectory for
generated, the beam signature in (17) is defined using the corresponding azimuth and zenith angles. The number of trajectories chosen for the beam signature generation can vary depending on specific road conditions and traffic patterns. The beambook size needs to be selected in consideration of the expected beamforming performance versus the complexity, since including redundant trajectories for additional beam signature generation only increases the operational complexity. There exist a discrete number of spot beamforming vectors in each signature, and different approaches can be taken to locate these spot beams. The method adopted here is to separate the neighboring beams by a constant angle value, since each spot beam then presents an approximately identical angular coverage. Let \( \mathbf{u}(\phi, \theta) \) denote the unit vector pointing to the direction of the azimuth and zenith angle pair \((\phi, \theta)\), which can be written as the 3-tuple

\[
\mathbf{u}(\phi, \theta) = [\sin \theta \cos \phi, \sin \theta \sin \phi, \cos \theta].
\]

The separation angle \( \delta \) between two adjacent spot beams \( \mathbf{b}_{j,l} \) and \( \mathbf{b}_{j,l+1} \) in beam signature \( \mathbf{S}_j \) in (15) is defined as the angle between the two unit vectors pointing to the beam directions. Thus \( \delta \) satisfies the relation

\[
\delta = \arccos \{ \mathbf{u}(\phi_{j,l}, \theta_{j,l}) \cdot \mathbf{u}(\phi_{j,l+1}, \theta_{j,l+1}) \}.
\]

for \( l = 1, 2, \ldots, L_j - 1 \), where \( \cdot \) denotes the inner product between two vectors. The separation angle determines the resolution of the beam signature, and signature lengths become longer as \( \delta \) decreases.

Figure 3 shows the trajectories and corresponding beam signatures for the urban intersection model. 12 trajectories obtained by the SUMO traffic generation followed by \( k \)-means clustering are shown in Fig. 3(a), with some irregularities in trajectory curves due to the random traffic generation. Three beam signatures \( \mathbf{S}_1 \), \( \mathbf{S}_2 \) and \( \mathbf{S}_3 \) are indicated in the figure, and adjacent spot beams within the same beam signature are separated by angle \( \delta \). The separation angle is better illustrated from the view point of the BS as shown in Fig. 3(b), where the red circle indicates the BS and blue cross marks are beam locations. When the beams are projected on the ground surface, the distance between two projected points can vary despite the fact that the constant separation angle is applied for the beam generation. For example, let us suppose \( \delta = 20^\circ \) is applied to the crossroad in the figure with both horizontal and vertical lane lengths of 100m. The BS is located at \( x_{BS} = y_{BS} = 25 \) and \( h_{BS} = 15 \) m. The signature lengths vary from 3 to 5, and the angle parameters for the

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**TABLE 1.** Angular parameters for beam signatures using separation angle \( \delta = 20^\circ \)

| \( \mathbf{S}_1 \) | \( \mathbf{S}_2 \) | \( \mathbf{S}_3 \) |
|-------------------|-------------------|-------------------|
| \((\phi_{1,1}, \theta_{1,1})\) | \((\phi_{2,1}, \theta_{2,1})\) | \((\phi_{3,1}, \theta_{3,1})\) |
| \((-19^\circ, 89^\circ)\) | \((-20^\circ, 89^\circ)\) | \((-21^\circ, 89^\circ)\) |
| \((-9^\circ, 93^\circ)\) | \((-1^\circ, 95^\circ)\) | \((-26^\circ, 108^\circ)\) |
| \((20^\circ, 88^\circ)\) | \((18^\circ, 103^\circ)\) | \((-47^\circ, 112^\circ)\) |
| \((9^\circ, 105^\circ)\) | \((38^\circ, 105^\circ)\) | \((-68^\circ, 113^\circ)\) |
spot beam directions are determined as given in Table 1. Note that numeric representations for the azimuth and zenith angles follow the description in [34], with \((\phi, \theta) = (0^\circ, 90^\circ)\) directing to the array boresight.

The separation angle can be adjusted to minimize the beamforming accuracy loss. To assess the beamforming accuracy, the average correlation power

\[
e = \mathbb{E} [ || \hat{h}_k b_{j', l'} ||^2 ]
\]

is evaluated where \(\hat{h}_k = h_k / ||h_k||\) is the normalized channel with unit power, and \(b_{j', l'}\) is the spot beamforming vector in (16) which maximizes the correlation to the channel for \(j' \in \{1, \ldots, J\}\) and \(l' \in \{1, \ldots, L_{j'}\}\). Beambooks including 12 beam signatures with varying values of \(\delta\) are constructed, to evaluate the corresponding average correlation to the channel \(h_k\) generated using the model in (4) for randomly distributed users. The evaluation result is shown in Fig. 4, indicating a rapid decrease in accuracy as the separation angle increases. Since the correlation performance tends to saturate in the range \(\delta \leq 1^\circ\), the separation angle of \(\delta = 1^\circ\) is chosen for the subsequent beambook construction. By choosing this separation angle, near-continuous beamforming can be performed without a noticeable loss in accuracy. The signature lengths for 12 beam signatures for the trajectories described in Fig. 3 range from 40 to 160. Increasing signature lengths does not affect the complexity of the DL algorithm used for predictive beam tracking, as discussed in the next section.

### IV. DEEP-LEARNING BASED BEAM TRACKING

In 5G NR signal transmission, the BS periodically broadcasts the beamformed CSI-RS, and the UE reports back to the BS which beam is received with the strongest power. The report is feedback in the form of the PMI, which is the integer index for the strongest beam. The BS uses the reported PMI to estimate the user channel and generates the precoding matrix accordingly. The time interval between the PMI reports, denoted by \(P_{\text{PMI}}\), ranges from 5 to 80ms based on the current 3GPP specifications [38]. The beams for reference signaling are taken from the DFT codebook \(C = \{ c_1, \ldots, c_Q \}\), such as the one described in (14). The PMI index \(i_k\) for the \(k\)-th UE with a single antenna is chosen by

\[
i_k = \arg \max_{q \in \{1, 2, \ldots, Q\}} || h_k c_q ||^2
\]

to maximize the received signal power. The beamforming is based on this PMI report and does not change until the next CSI feedback is obtained. As the PMI feedback period \(P_{\text{PMI}}\) increases, inaccurate beam transmission may occur for UEs making spatial displacements. More frequent CSI feedbacks are required to maintain the beamforming accuracy at a desired level, which is achieved at the expense of higher resource overhead for control signaling.

Using the proposed beambook, accurate beamforming can be performed with a significantly reduced amount of feedback overhead. We use DL to determine the beam signature index \(j\) in (15) and the spot beam index \(l\) in (16) for the target UE, by applying the history of PMI reports as the input to the DNN. Figure 5 illustrates the beam tracking operation scenario where the BS periodically transmits beamformed CSI-RS using the conventional DFT-codebook, and the UE reports back the preferred codevector index via the PMI feedback channel. A history of PMI reports becomes the input to the DNN, which produces estimated indices for both the beam signature and its spot beamforming vector. Since the estimation has been made by the DNN which trajectory the UE is moving along as well as what specific location on the trajectory the UE sent the most recent PMI report at, the BS can update beamforming directions even without new feedback information. Let \(P_{\text{beam}}\) denote the time interval between beamforming vector updates, which can be chosen to be substantially smaller than the PMI report interval, i.e., operation parameters \(P_{\text{beam}}\) and \(P_{\text{PMI}}\) can be chosen to satisfy

\[
P_{\text{beam}} \ll P_{\text{PMI}}.
\]

Hence beamforming vector updates can be frequently made between adjacent PMI reports to provide seamless signal transmission to the target UE, despite relatively sparse actions for the CSI-RS transmission and PMI report to reduce the resource overhead for control signaling.

Figure 6 shows the details of the DNN structure including the dimensions for the data and network nodes. There are two identically-structured networks, one to generate the beam signature index \(j\) and the other to produce the spot beamforming vector index \(l\). The input to the networks is the PMI reports accumulated for \(N_{\text{PMI}}\) feedback instances, forming an \(N_{\text{PMI}} \times Q\) matrix with binary elements. Each row of the matrix represents the CSI feedback result from the target UE, with the indication of the PMI index. One nonzero element “1” is written in each row, with the column number representing the index. All other \(Q - 1\) elements in each row are zeros. The input matrix is flattened to one-dimensional data at the input layer, followed by multiple hidden layers and the output layer. Two dense layers with the rectifier linear unit (ReLU) for the activation function are used as hidden layers, including \(N_1\) and \(N_2\) nodes respectively. All function types and parameter sizes are determined based on the evaluation results to minimize the DNN loss function. \(N_1 = N_2 = 16\) nodes are used for the hidden layers, since using more than 16 nodes does not further decrease the output of the DNN loss.
function. The output layer employs the softmax activation function and is composed of \( N_3 \) nodes. As the result of the softmax activation operation, each node produces the prediction probability of the DNN output. DNN #1 in the figure generates the prediction probabilities for the possible \( J \) trajectories in \( N_3 = J \) nodes, and the beam signature with the highest probability is selected. Similarly, the spot beamforming vector index is selected from the prediction probabilities stored at the output layer of DNN #2. The number of output nodes are chosen as \( N_3 = L_{\text{max}} \) to include the maximum number of beams in all beam signatures, i.e., \( L_{\text{max}} = \max_j L_j \). Both DNNs use the categorical cross entropy for the loss function, and the weights are updated using the Adam optimizer. Supervised learning is used for initial training of the weights to increase the accuracy for the prediction probabilities. A SUMO-generated dataset including 100,000 examples is used for training, with 20% of them used for validation. Each example is composed of 64 PMI values with highest correlation to moving UE channels along a path generated by SUMO. The corresponding labels are the beam signature index and the spot beam index. The batch size is set to 512 for repeated training of 1000 epochs, with the learning rate of 0.001. An early stopping criterion with the 100 epoch patience is applied, i.e., learning stops when the minimum validation loss does not decrease for 100 consecutive epochs.

The utilization of the beambook can be applied to mobile users with different speeds. Each UE travels along a certain moving path at a different speed in practical transmission scenarios, and the DL algorithm is trained accordingly to produce the indices for beam signature and spot beamforming vector. Figure 7 illustrates examples of the DNN operation, where \( c_q \)'s surrounded by the green circle indicate the beam directions for beamformed CSI-RS projected to the road surface. Similarly, symbol \( b_{j,l} \) indicates the beam direction for the \( l \)-th spot beamforming vector of the \( j \)-th beam signature. In Fig. 7(a), the first UE following the beam signature indicated by the red arrow sequentially selects \( c_{16} \),

![Figure 5](image-url)  
**FIGURE 5.** Beam tracking operation using a beam signature and deep learning for the BS performing conventional beamformed CSI-RS transmission.

![Figure 6](image-url)  
**FIGURE 6.** DNN structure using UE PMI reports as input to produce estimated indices for the beam signature and spot beamforming vector.
The DNN produces beamforming vectors $b_{7,1}$, $b_{7,14}$, $b_{7,26}$ and $b_{7,39}$ on beam signature $S_7$. The UE in Figure 7(b) moves along the same blue trajectory but at a slower speed. The DNN produces beamforming vectors $b_{7,1}$, $b_{7,7}$, $b_{7,15}$ and $b_{7,22}$ which are more densely populated on the same beam signature $S_7$ due to the lower mobility. As illustrated by these examples, the operation of the DNN remains the same regardless of the direction and speed of the target UE. The DNN produces the desired beam indices for continuous beamforming by taking the PMI reports from UEs of any movement characteristics. For two UEs moving along the identical trajectory with sufficiently different velocities, for example, the same beam signature is likely to be chosen by the DNN. The corresponding spot beam indices for these UEs will be either sparsely or densely located on the same beam signature to reflect the amounts of their mobility.

The procedure to obtain the beam indices using the DNN is further visualized in Fig. 8. At each PMI report instance, the UE determines the codevector with the strongest received power and sends the corresponding codevector index to the BS. The DNN at the BS uses the most recent $N_{\text{PMI}} = 3$ report values as its input to generate the desired beam signature indices. Beamforming vector $b_{7,26}$ is chosen from PMI reports $\{c_{16}, c_{49}, c_{25}\}$, and $b_{7,34}$ is generated from $\{c_{48}, c_{25}, c_9\}$. The procedure continues utilizing the PMI reports in a sliding-window of size $N_{\text{PMI}}$. The indices obtained as the DNN output are then applied to produce predictive beamforming vectors until the next channel feedback instance. Among many different approaches that can be taken for predictive beamforming, a simple and effective way of generating beams is to extrapolate the spot beam indices obtained by the DNN. The procedure to perform index extrapolation is shown in Fig. 9, where the red circles indicate the beam indices produced as the DNN output in the intervals of $T_{\text{PMI}} = 1$ sec. Dotted line segments in the figure are formed by connecting two adjacent red circles. The solid line segments are the extrapolated extension of the dotted line segments, and predictive beamforming indices are obtained from these extensions. Predictive beamforming vectors can
be obtained in any arbitrary resolution, until the next DNN index generation based on a new PMI report occurs. If the beam update interval is set to be $P_{\text{beam}} = 5$ msc, for example, $P_{\text{PMI}} / P_{\text{beam}} = 200$ updates are made between two consecutive PMI reports to provide the enhanced beamforming precision. The extrapolation for beam indices can be performed based on higher-order polynomials using increased numbers of past DNN output indices if desired. The resulting performance is compared in the next section, to determine the prediction strategy for beam signature transmission.

It should be noted that labeled data is required for supervised learning introduced in this section. When the correct beam indices for the actual moving vehicles used as labels are not available or hard to obtain in practice, the labeling procedure can be approximated by using the labeled dataset generated by the beambook itself. Since the beambook is chosen based on UE movement paths, spot beam vectors in each beam signature represent typical paths for UEs. Thus in the training stage of the DNN, random segments of a beam signature composed of consecutive beam vectors are selected, and the corresponding PMI values with the largest correlation to those beam vectors can be used as the input to the DNN. The indices of the beam signature and the last beam vector for the input are known, thus can be applied as the labels. Repeated selections of random segments of the beam signatures in the beambook provide samples for the labeled dataset. This type of dataset generation can be verified to effectively train the DNN. For codebook size $Q = 16$, for example, the resulting beamforming gain performance evaluated in the next section lies within approximately a few percentile from the performance obtained by using the correct labels for moving UEs. Introducing intentional random deviations from the beam vectors used for the dataset generation can further provide resemblance to the actual UE traffic if desired. Since we intend to demonstrate the full potential gain of the beambook utilization, the rest of the paper assumes that the labeled dataset has been collected from the moving UEs which is applied for supervised learning.

V. PERFORMANCE EVALUATION

Mobile users are randomly generated by the SUMO simulator using the urban crossroad environment setup in Fig. 1. The road includes 6 two-way lanes, with horizontal and vertical lengths of 100 m. Each lane has the width of 3.5 m. The BS is equipped with the UPA including $M_B = M_v = 8$ antenna elements with half-lambda spacing at location coordinates $x_{BS} = y_{BS} = 25$ m and $h_{BS} = 15$ m. The bearing, downtilt, and slant angles are respectively set to be $\alpha = 315^\circ$, $\beta = 12^\circ$, and $\gamma = 0^\circ$. Single-antenna UE with height $h_{UE} = 1.5$ m are moving at velocity $v_{UE}$. The radiation pattern for all antenna elements is isotropic and the channel coefficients in (4) are generated using $L = 20$ NLOS paths with equal average power. The azimuth and zenith AoDs of NLOS path components follow the Laplacian distribution centered around the LOS component. Rician factor $K_R = 10$ dB and the Laplace standard deviation of $10^\circ$ are assumed unless otherwise specified. The DFT codebook in (14) is used for beamformed CSI-RS transmission using $B = 4, 6$, and 8 bits. The corresponding codebook sizes are $Q = 16, 64$, and 256, constructed by using oversampling factors $O_b = O_a = 0.5, 1$, and 2, respectively. The beambook in (18) of size $J = 12$ is generated using separation angle $\delta = 1^\circ$ and applied for performance evaluation. Beamforming vector updates are made with period $P_{\text{beam}} = 5$ msc for beam signature transmission, and the channel feedback period of up $P_{\text{PMI}} = 2$ msc is applied for performance evaluation. The default values for

![Figure 9](image1.png)

**FIGURE 9.** Beam index prediction via extrapolating line segments determined by the DNN output.

![Figure 10](image2.png)

**FIGURE 10.** Feedback distance $\Delta$ determined as the product of the mobile speed and the channel feedback period.
the channel feedback period, the feedback overhead and the UE velocity are respectively $P_{PMI} = 2 \text{ msec}$, $B = 6$ bits and $v_{UE} = 10 \text{ m/sec}$, when they are not explicitly specified.

Both user mobility $v_{UE}$ and channel feedback period $P_{PMI}$ have a significant impact on beamforming accuracy, since they jointly determine the distance of the locations at two consecutive channel feedback instances. The feedback distance is the product of these two parameters, expressed as

\[ \Delta = v_{UE} P_{PMI}. \]  

Figure 10 shows different values of feedback distance $\Delta$ obtained by multiplying $v_{UE}$ in $y$-axis and $P_{PMI}$ in $x$-axis. The current 3GPP standard provides the channel feedback in the range of 5 to 80 msec, with the mobility support of up to 500 km/h for 5G NR which is increased from 350 km/h for LTE-Advanced [38], [39]. These support ranges for the 5G NR and LTE-Advanced are indicated by shaded areas in Fig. 10. Beam tracking using the beamform vector significantly enhances the transmission performance over a wider range of the feedback distance. To verify the enhanced performance, the number of PMI reports to be used for the index estimation is determined first.

Figure 11 shows the beamforming gain of the proposed scheme as the number of PMI reports used as the input to the DNN increases. The beamforming gain is defined as [40]

\[ G_{BF} = \mathbb{E}[\|\bar{h}_k w_k\|^2] \]  

where $\bar{h}_k = h_k/\|h_k\|$ is the channel with power normalization, and $w_k$ is the beamforming vector obtained by the proposed beam tracking method. As indicated in the figure, the gain increases rapidly until $N_{PMI}$ increases to 64 for all values of $B$. Therefore $N_{PMI} = 64$ is chosen as the input dimension for the DNN. The linear extrapolation using two previous DNN output beam indices is applied for predictive beamforming, which is verified to provide a superior beamforming gain over other schemes with higher complexity. As shown in Fig. 12, using more than two beam indices or the higher-order polynomial for prediction does not improve the performance over the wide range of $P_{PMI}$ values.

The construction of the VQ-based codebook begins by obtaining a sufficient number of random location samples from the mobile traffic generated by SUMO. The set of these location coordinates on the two-dimensional street map is then applied to the Linde-Buzo-Gray (LBG) algorithm in [21], which produces $Q$ centroid locations representing the whole set of samples. The azimuth and zenith angles from the antenna array to each of these locations are used to generate the codevector in the form of the expression in (16). The VQ-based codebook is obtained by including $Q$ such codevectors. In Fig. 13, the beamforming gains of the VQ-based codebook and DFT-based codebook are evaluated for different $P_{PMI}$ values and compared with that of the proposed beambook. Beamforming gains for the VQ and DFT-
Figure 15 presents the beamforming gain comparison under different mobility conditions, with the training dataset obtained for mobile speeds uniformly distributed over [5, 15] m/sec.

For each of UE speed values in Fig. 13, the DNN weights are trained using the SUMO-generated UE samples with the corresponding vehicle speed conditions. In practical situations, mobile UEs with a mixture of speeds exist within the coverage of beam transmission and performance needs to be evaluated accordingly. In order to better assess the generalization capability and robustness of the proposed method, samples in the training set are generated by SUMO with different mobile speed conditions and the test set is composed of samples generated by intentionally mismatched mobile speeds. Figure 14 is the result of such evaluation. For all performance curves in the figure, the training set is based on the mixture of mobile speeds that are uniformly distributed over [5, 15] m/sec. As indicated in the legend of the figure, the test set is based on different mobility conditions, including the varying speeds over [5, 15] and [5, 10] m/sec. The beamforming performance for UEs with fixed speeds $v_{UE} = 10$ and 15 m/sec is also shown in the figure. As these curves indicate, the proposed DL-based beam tracking works well for a variety of mobility conditions using the DNN trained by samples with a mixture of mismatching speeds. The figure also shows that the performance tends to improve when the test mobile speed decreases, and a degradation occurs for the highest speed of $v_{UE} = 15$ m/sec. In fact, degraded performance for higher mobile speeds also occurs for conventional codebooks due to the lack of ability to appropriately update beams. Figure 15 compares the beamforming gains in Fig. 14 with those of VQ and DFT codebooks. As can be verified from the figure, the proposed method outperforms conventional codebooks for all speed conditions over a wide range of $P_{PMI}$ values under the mismatching training condition. Such codebooks are determined by the expression in (25) with the substitution of $w_k = c_{ik}$, i.e., codevector $c_{ik}$ is chosen as the beamforming vector from the corresponding codebook $C = \{c_1, \ldots, c_Q\}$. Here $i_k$ is the codevector index which maximizes the correlation to the channel as described in (22). As indicated in the figure, the proposed beambook outperforms the conventional codebooks over the entire range of feedback periods for three different mobile speeds tested. This is due to its capability of performing more frequent updates for beamforming vectors using the selected beam signature, whereas the conventional codebooks can only provide the identical codevector until the next channel report is available. The proposed method stays more robust for longer channel report intervals despite the user mobility, producing an improved beamforming accuracy. As the mobile speed increases from 5 to 15 m/sec, the feedback distance in (24) also increases for a given value of $P_{PMI}$, resulting in degraded beamforming gains. However, proposed beamforming with enhanced accuracy is shown to achieve a significant amount of gains under different UE mobility scenarios.

For each of UE speed values in Fig. 13, the DNN weights are trained using the SUMO-generated UE samples with the corresponding vehicle speed conditions. In practical situations, mobile UEs with a mixture of speeds exist within the coverage of beam transmission and performance needs to be evaluated accordingly. In order to better assess the generalization capability and robustness of the proposed method, samples in the training set are generated by SUMO with different mobile speed conditions and the test set is composed of samples generated by intentionally mismatched mobile speeds. Figure 14 is the result of such evaluation. For all performance curves in the figure, the training set is based on the
a mismatching mixture of speeds is assumed for training and test sets used for the evaluation results in the remainder of this section, with mobile speeds uniformly distributed over [5, 15] m/sec.

The range of \( P_{\text{PMI}} \) up to 2 sec in the \( x \)-axis of Figs. 13, 14 and 15 is substantially larger than the coverage of the current standard indicated in Fig. 10. This range is equivalent to feedback distance \( 0 \leq \Delta \leq 20 \) m for the mobile speed of \( v_{\text{UE}} = 10 \) m/sec. Figure 16 shows the required number of feedback bits as a function of PMI feedback period \( P_{\text{PMI}} \). As can be seen from the figure, a rapid decrease of the feedback overhead can be achieved by sparse PMI report actions. By using \( P_{\text{PMI}} = 1 \) sec, for instance, the feedback overhead decreases by the factor of 12.5 when compared to the \( P_{\text{PMI}} = 80 \) msec case, which is the largest feedback interval for 5G NR.

As an alternative measure of beamforming accuracy, the difference between the beamforming direction and the target UE direction from the viewpoint of the BS can be evaluated. Although multiple wireless links exist in the actual channel, many of them are distributed around the LOS link as in the Laplacian model adopted for the channel in (6). Using the unit vector notation in (19), the angular distance between the UE direction and the beam direction is defined as

\[
\psi = \arccos \{ \mathbf{u}(\phi_k, \theta_k) \cdot \mathbf{u}(\phi_{ik}, \theta_{ik}) \} \tag{26}
\]

where \( (\phi_k, \theta_k) \) is the azimuth-zenith angle pair for the \( k \)-th UE, and \( (\phi_{ik}, \theta_{ik}) \) is the azimuth-zenith angle pair for the closest beamforming vector. Figure 17 shows the cumulative distribution functions (CDFs) for the angular distance obtained from randomly distributed UEs on the road surface. For a given UE location, the closest codevector is chosen from the proposed beambook as well as the conventional codebooks to collect the angular distance samples. As can be observed from the figure, the CDF curves for the proposed beambook is shifted to the left from the rest of the CDF curves, suggesting reduced angular distance values. The beambook outperforms conventional codebooks over the entire range of user percentiles for \( B = 6 \) and 8. When \( B = 6 \) bits are used for the PMI feedback, the distribution of angular distance becomes very close to the \( B = 8 \) case, suggesting the beambook size of \( Q = 64 \) achieves the most of the gains.

The sum-rate performance is also evaluated for the proposed method when data transmission is simultaneously made to multiple users. For MU-MIMO transmission, selected beams for target users are combined to form an estimated channel, and the zero-forcing (ZF) precoder is generated based on the channel. The users are randomly selected in a rank-adaptive fashion, i.e., user are additionally selected until the sum-rate begins to decrease. When \( K' \) UEs are selected for MU-MIMO transmission, the estimated channel is

\[
\hat{\mathbf{H}} = [ \mathbf{w}_1 \; \mathbf{w}_2 \; \ldots \; \mathbf{w}_{K'} ]^T
\]

where \( \mathbf{w}_k \) is the beamforming vector for the \( k \)-th user for \( k = 1, \ldots, K' \). The ZF precoder under the total power constraint is determined as \( \mathbf{W}_{\text{ZF}} = \mathbf{W}_{\text{ZF}} / \| \mathbf{W}_{\text{ZF}} \| \) where

\[
\mathbf{W}_{\text{ZF}} = \hat{\mathbf{H}}^H ( \hat{\mathbf{H}} \hat{\mathbf{H}}^H )^{-1} \tag{28}
\]

Figure 18 compares the sum-rates evaluated using (3) for the proposed beambook, VQ codebook, and DFT codebook. For the VQ and DFT codebooks, the estimated channel is constructed as \( \hat{\mathbf{H}} = [ \mathbf{c}_{i_1} \mathbf{c}_{i_2} \ldots \mathbf{c}_{i_Q} ]^T \) where \( \mathbf{c}_{i_k} \) is the selected beamforming vector from the corresponding codebook. The signal-to-noise ratio (SNR) of \( \rho_k / \sigma^2 = 20 \) dB is applied for evaluation, and transmission ranks with less than 1% occurrence probability are not shown in the figure. Over the entire range of transmission ranks, the proposed beambook
achieves substantially higher sum-rates than both VQ and DFT codebooks. The sum-rate evaluation result verifies that more frequent beam updates by using beam signatures not only increases the beamforming gain for individual users, but enhances the system throughput performance with a significant amount of gain.

Performance comparison for varying channel parameters is given in Figs. 19 and 20. In Fig. 19, the Rician factor changes from 0 to 20 dB and the corresponding beamforming gains are plotted. For all three codebooks in consideration, the beamforming gains increase as the channel becomes close to the LOS-only condition with larger values of Rician factor $K_{LR}$. The NLOS component becomes more significant when $K_{LR}$ becomes smaller, and the performance degradation occurs for all codebooks as shown in the figure. Note that the performance difference between the proposed and VQ codebooks becomes smaller as $K_{LR}$ decreases, since the NLOS dominance causes less accurate beam index estimation by the DNN. The difference becomes also smaller as $P_{PMI}$ decreases, because the conventional codebooks perform better with shorter PMI report intervals. Nevertheless, as the evaluation result in the figure indicates, the proposed codebook outperforms the conventional codebooks over the wide range of $K_{LR}$ and $P_{PMI}$ values due to its beam update capability enabled by the relation $P_{beam} \ll P_{PMI}$. A similar advantage can be observed over the wide range of the spread angle, which is the standard deviation of the Laplacian distribution for NLOS AoDs. In Fig. 20, the spread angle increases up to $100^\circ$ for the NLOS paths for the $K_{LR} = 10$ dB channel and the corresponding beamforming gains are compared. Performance tends to decrease as the spread angle increases up to $40^\circ$, after which the performance stays at a constant level. Regardless of the amount of spatial dispersion experienced by multiple paths of the channel, the performance advantage of the beambook can be confirmed from the figure.

VI. CONCLUSIONS

Unlike most of conventional beam tracking algorithms generating beams on an individual case basis, we apply a set of beam signatures to provide seamless beamforming to users with mobility using simple beam index selection procedure. The proposed method is shown to be robust over the wide range of channel feedback intervals by utilizing the beambook constructed for the given channel environment. The proposed beambook is shown to outperform the conventional codebooks in both beamforming accuracy and data throughput with the reduced feedback overhead.

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