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***Abstract*—We propose a novel beam-tracking algorithm based on channel charting (CC) which maintains the communication link between a base station (BS) and a mobile user equipment (UE) in a millimeter wave (mmWave) mobile communications system. Our method first uses large-scale channel state information information at the BS in order to learn a CC. The points in the channel chart are then annotated with the signal-to-noise ratio (SNR) of best beams. One can then leverage this CC-to-SNR mapping in order to track strong beams between UEs and BS efficiently and robustly at very low beam-search overhead. Simulation results in a mmWave scenario show that the performance of the CC-assisted beam tracking method approaches that of an exhaustive beam-search approach while requiring significantly lower beam-search overhead than conventional tracking methods.**

***Index Terms*—Beam tracking, channel charting, channel state information, mmWave communication, SNR prediction.**

I. Introduction

The ever-increasing demand for higher data rates for mobile users pushes wireless communication systems towards higher frequencies where large contiguous portions of bandwidth are still available. The millimeter wave (mmWave) frequency spectrum is an integral part of fifth generation (5G) new radio (NR). However, the high path loss between transmitter and receiver is a critical challenge for reliable mmWave communication systems. The relatively small wave length of mmWave signals is in favor of deploying a large number of antenna elements at both ends of the wireless link and enables beamforming, which can compensate for the high path loss [1].

Narrow beams require constant refinement in order to maintain link quality. In a mobile environment, beam alignment becomes more challenging as the channel is changing more frequently, and the base station (BS) needs to continuously update the transmitting beam. As a result, significant beam-tracking (BT) overheads are imposed on the network [2]. Thus, by devising more efficient BT methods, more resources can be utilized for data transmission rather for beam management.

The 3rd Generation Partnership Project (3GPP) has defined procedures for beam management for downlink (DL) and uplink (UL) transmission through several mechanisms [3]. The standard approach for identifying the best BS-to-User-Equipment (UE) pair is beam sweeping (i.e., an exhaustive search over all beams in a given codebook); beam-tracking is commonly carried out by probing neighboring beams [4]. The authors in [4]–[6] investigate 5G-NR beam management and discuss the associated overhead. To describe how long the BS beam provides the best possible link quality, the sensitivity of the served beam-to-UE mobility under different operating frequencies and channel dynamics was studied in [7].

The literature describes a variety of beam tracking methods. A non-standalone system was proposed in [8], so that the sub-6 GHz cell coordinates the control signals to reduce link failure. Angle and channel gain tracking was investigated in [9], where based on previous beamformers, the beam directions are estimated. Machine learning (ML) methods have received great attention due to the ability to find hidden patterns from data. The references [10], [11] proposed an ML-based beam selection strategy by considering UE location. The Neural Network (NN) model in [11] not only selects the strongest beam but also finds an alternative beam for the communication so that the beam selection remains robust to blockage. While these methods reduce the beam-tracking overhead, they require knowledge of the UEs' movement patterns.

Channel Charting (CC) is the process of learning a mapping from high dimensional channel state information (CSI) to a low dimensional chart of the network, called channel chart, in which nearby points indicate UEs that are nearby in physical space [12]. It has been shown that CC is an effective tool for applications in which absolute location information is not required, such as handover prediction [13] and mm-Wave system beam selection [14], [15].

Contributions: By building on our CC-based SNR prediction work in [14], we develop a novel CC assisted beam-tracking algorithm. The best BS-to-UE beam is predicted using a served BS beam. Our approach avoids error propagation in a conventional beam tracking approach, in which the best BS beam is determined assuming that the UE uses its previous best beam. Furthermore, our proposed CC-assisted beam tracking approach does not exploit UE mobility patterns and avoids knowledge of the UE's physical location.

Notation: Matrices and vectors are set in upper and lower boldface letters, respectively. $\mathbf{I}$ is the identity matrix. We use $[\mathbf{X}]_{ij}$ for the element of matrix $\mathbf{X}$ in the ith row and jth column. The operators $(\cdot)^H$ and $|\cdot|$ denote the Hermitian conjugate and the absolute value, respectively; $\mathbb{E}\{\cdot\}$ denotes expectation and $\|\cdot\|_F$ is the Frobenius norm. We use $\log(\cdot)$ to denote the matrix logarithm.

II. System Model and Background

We consider a Millimeter Wave (mmWave) system, where the UE and BS have multiple antennas following 5G NR. The BS is equipped with an antenna array with B elements and each UE antenna array has U elements. At both the BS and the UE beamformers are used. The UE beamformer is autonomous such that the UE uses the best UE beam towards a BS beam. For simplicity, the number of Radio Frequency (RF) chains is equal to the number of antenna elements at the BS and the UEs. We assume that wideband beams are used at both the BS and the UE, i.e., for all subcarriers, the same beam is employed.

A. Channel and Beam Models

We consider a Time Division Duplex (TDD) system. The channel matrix between a UE and the BS at subcarrier ω is represented by $\mathbf{H}_\omega \in \mathbb{C}^{B\times U}$. Beam management is carried out by a beam sweeping approach, which is an exhaustive search over beam pairs at the BS and the UE. The entire angular space is scanned by narrow beams at the BS and UEs [5].

The received signal at the BS from a UE transmission at one subcarrier is:

$$y_\omega = \mathbf{w}^H \mathbf{H}_\omega \mathbf{v}\, s_\omega + n_\omega, \tag{1}$$

where $\mathbf{w} \in \mathbb{C}^{B\times 1}$ is a BS beamformer, $\mathbf{v} \in \mathbb{C}^{U\times 1}$ is a UE beamformer, n_ω is circularly symmetric Gaussian noise with variance N_0 and s_ω is the transmitted signal from the UE with unit power, i.e., $\mathbb{E}|s|^2 = 1$.

Let, $\mathbf{w}_b \in \mathbb{C}^{B\times 1}$ for $b = 1,\dots,B$ denote the set of BS beamformers and $\mathbf{v}_u \in \mathbb{C}^{U\times 1}$ for $u = 1,\dots,U$ denote the set of UE beamformers. Assuming Uniform Linear Array (ULA) antennas with M elements, the unitary $M\times M$ Discrete Fourier Transform (DFT) based codebook, $\mathbf{F}_M = [\mathbf{f}_1,\dots,\mathbf{f}_M]$ is used with:

$$\begin{aligned}\mathbf{f}_m = \frac{1}{\sqrt{M}}[1, e^{-j2\pi\frac{(m-1)}{M}},\dots,e^{-j2\pi\frac{(M-1)(m-1)}{M}}]^T,\\ m = 1,\dots,M.\end{aligned} \tag{2}$$

For the BS, a codebook containing a set of B DFT codewords defined as $\mathbf{W} = \mathbf{F}_B$ and for the UE a codebook containing a set of U DFT codewords defined as $\mathbf{V} = \mathbf{F}_U$ is used.

Assuming an uplink based beam management approach, the received signal at the BS implementing exhaustive search through all the BS and UE beams can be expressed as:

$$\mathbf{Y}_\omega = \mathbf{W}^H \mathbf{H}_\omega \mathbf{V} + \mathbf{N} = \mathbf{Y}'_\omega + \mathbf{N}, \tag{3}$$

where $\mathbf{Y}_\omega \in \mathbb{C}^{B\times U}$, $[\mathbf{Y}_\omega]_{i,j}$ is the received signal using the ith BS beam and jth UE beam and $\mathbf{N} \in \mathbb{C}^{B\times U}$ is the noise matrix. The best BS-UE beam pair can be obtained as:

$$(\hat{i},\hat{j}) = \underset{\substack{i\in\{1,\dots,B\}\\ j\in\{1,\dots,U\}}}{\arg\max} \sum_{\omega=1}^{\Omega} |[\mathbf{Y}'_\omega]_{i,j}|^2, \tag{4}$$

where Ω is the number of subcarriers. The average Signal-to-Noise-Ratio (SNR) for a transmission at the best beam pair $(\hat{i},\hat{j})$ is computed as:

$$\gamma = \frac{1}{\Omega N_0} \sum_{\omega=1}^{\Omega} |[\mathbf{Y}'_\omega]_{\hat{i},\hat{j}}|^2. \tag{5}$$

Assuming the transmission from UE best beam

$$\hat{j}(b) \triangleq \hat{j}(\mathbf{w}_b) = \underset{j\in\{1,\dots,U\}}{\arg\max} \sum_{\omega=1}^{\Omega} |\mathbf{w}_b^H \mathbf{H}_\omega \mathbf{v}_j|^2, \tag{6}$$

towards beam $\mathbf{w}_b$ of the BS, the effective channel is defined as

$$\mathbf{h}_{\omega,\hat{j}(b)} = \mathbf{H}_\omega \mathbf{v}_{\hat{j}(b)}. \tag{7}$$

The measured covariance matrix from the effective channel at the BS is defined as:

$$\mathbf{R} = \frac{1}{\Omega}\sum_{\omega=1}^{\Omega} \mathbf{h}_{\omega,\hat{j}(b)} \mathbf{h}^H_{\omega,\hat{j}(b)} + N_0 \mathbf{I}. \tag{8}$$

B. Channel Charting and SNR Prediction

We assume a mobile UE in the radio environment served by a given BS beam and we would like to predict the SNR of the UE at other BS beams. We are going to predict beam SNR based on the channel chart location of the UE at the served beam.

Channel charting maps high dimensional CSI to low dimensional chart that reflects relative spatial distance of the corresponding UEs. Channel chart is constructed from channel features that capture large scale fading effects. In this paper, we shall use channel covariance matrices at the BS as feature:

$$\{\mathbf{R}_k\}_{k=1}^{K}, \tag{9}$$

where $\mathbf{R}_k$ is the channel covariance of the kth UE, and K is the number of UEs in the radio environment. The charting function is defined as:

$$\begin{aligned}\mathcal{C} : \mathbb{C}^{B\times B} &\rightarrow \mathbb{R}^{d'\times 1},\\ \mathbf{R}_k &\rightarrow \mathbf{z}_k \triangleq \mathcal{C}(\mathbf{R}_k),\end{aligned} \tag{10}$$

where $\mathbf{z} \in \mathbb{R}^{d'\times 1}$ is the channel chart location associated to channel covariance matrix $\mathbf{R}_k$ and d' is the chart dimension.

By using a suitable Dimensionality Reduction (DR) technique a chart of the radio environment will be constructed in which local geometry of UEs are preserved. To do so, a conventional DR method such as t-SNE can be used [16].. First, pairwise feature distance between UEs should be calculated and a distance matrix $\mathbf{D}$ is formed. We use the log-Euclidean distance to compute the distance between covariance matrices of UE k and UE k', i.e.,

$$[\mathbf{D}]_{k,k'} = \left\|\tilde{\mathbf{R}}_k - \tilde{\mathbf{R}}_{k'}\right\|_F, \tag{11}$$

where $\tilde{\mathbf{R}} = \log(\mathbf{R})$. A low dimensional representation of the CSI features is obtained by applying t-SNE DR.

For each BS beam, we construct the corresponding CC, and annotate the CC locations with SNR values of other beams. We assume, each UE uses its best beam towards a BS beam. In the offline phase, the SNR at different BS beams needs to be measured. The UE needs to transmit towards different BS beams. If a UE has a single antenna, the best BS beam can be directly measured at the BS. However, when the UE has multiple antennas, and autonomously uses a beamformer, the BS cannot unilaterally measure and find the best beam towards the user. We train a model to predict SNR of other beams given

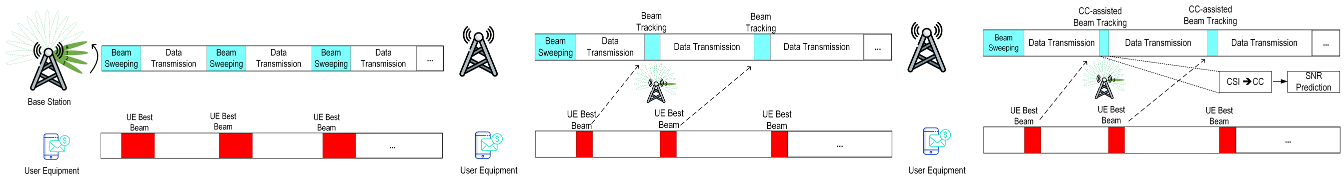

Fig. 1: An illustration of beam tracking Approaches: (Left); beam sweeping. (Middle); beam tracking, (Right); CC-assisted beam tracking.

the CC location of the serving beam. We predict SNR value of the UE at other beams, thereby switching to another beam can be handled. In this regard, a CC is constructed for each BS beam, and a NN is then trained so as to predict the SNRs of all other BS beams:

$$\boldsymbol{\gamma}_{\mathrm{CC}} = g(\mathbf{z}), \tag{12}$$

where, $g(\cdot)$ is the SNR predictor function and $\boldsymbol{\gamma}_{\mathrm{CC}}$ is the vector of predicted SNR at other BS beams. All these processes are done in an offline phase. In the online phase, once the UE establishes its connection to the BS, it will be mapped on the CC and using SNR predictors, the SNR at other beams can be predicted.

III. Beam Tracking

Beam tracking is introduced to reduce the number of beam measurements as few as possible, and find the optimal beam pair in a mobile scenario. Once the initial access connection is established, due to mobility of the UE, link quality degradation should be handled by beam refinement. Exhaustive search (beam sweeping) gives the most accurate transmission direction. However, it is time and resource consuming.

A. Beam Sweeping

Fig. 1 (Left) illustrates the beam sweeping approach where all beams have to be examined so that the best BS-UE beam pair is found. The BS sequentially sweeps its beams by sending synchronization signal blocks. Then, the BS beam is fixed and the UE performs beam sweeping. This is the standard method to find best beam pairs. While beam sweeping gives the most accurate transmission direction, it requires a significant amount of resources. The best beam pair is determined using (4).

B. Beam Tracking

In Fig. 1 (Middle) the beam tracking approach is shown where, first the best UE beam is determined, conditioned on previous location best BS beam. A pilot signal is then transmitted towards the BS, and the best BS beam is determined based on the received signal.

Considering this beam tracking approach, we assume that an exhaustive search is conducted at the starting point of a UE mobility path. Thus, from the previous transmission, the BS beamformer $\hat{\mathbf{w}}$ is used for the current transmission. Given $\hat{\mathbf{w}}$, the UE measures the received power at all its beams by forming a vector:

$$\bar{\mathbf{y}}_{\omega} = \mathbf{V}^{H}\mathbf{H}_{\omega}^{H}\hat{\mathbf{w}}, \tag{13}$$

where $\bar{\mathbf{y}} \in \mathbb{C}^{U\times 1}$. The UE determines its best beam for a transmission from the previous best BS beam as:

$$\bar{u} = \underset{u\in\{1,\ldots,U\}}{\arg\max} \mid [\bar{\mathbf{y}}_{\omega}]_{u} \mid^{2}. \tag{14}$$

The UE sends a pilot to the BS given the UE beam $\mathbf{v}_{\bar{u}}$. At the BS the effective channel from UE transmitting towards beam $\hat{\mathbf{w}}$ is:

$$\mathbf{h}_{\omega,\bar{u}} = \mathbf{H}_{\omega}\mathbf{v}_{\bar{u}}. \tag{15}$$

The corresponding channel covarinace for the transmission towards beam $\hat{\mathbf{w}}$ is:

$$\bar{\mathbf{R}} = \frac{1}{\Omega}\sum_{\omega=1}^{\Omega}\mathbf{h}_{\omega,\bar{u}}(\mathbf{h}_{\omega,\bar{u}})^{H}. \tag{16}$$

The best BS beam for the UE is then determined by finding the beam that provides highest SNR as:

$$\bar{i} = \underset{b\in\{1,\ldots,B\}}{\arg\max}\ \mathbf{w}_{b}^{H}\bar{\mathbf{R}}\mathbf{w}_{b}. \tag{17}$$

The beam $\mathbf{w}_{\bar{i}}$ will be used for the next position and this procedure repeats until the next exhaustive search is carried out. However, the main issue with this approach is that after few steps, due to error propagation, the UE loses the best beam and is not able to recover the best beam pairs. Consequently, a new exhaustive search is needed. Furthermore, since the UE beamformer is based on the previous best BS beam, the UE may be pointing towards a wrong direction and the BS cannot find the best beam from this transmission.

C. CC-assisted Beam Tracking

In Fig. 1 (Right), the CC-assisted beam tracking is depicted. In this approach after receiving the pilot signal from the UE, the covariance matrix is estimated, the UE is then mapped to beam $\hat{\mathbf{w}}$ CC, using SNR predictors, the best BS beam is found. CC-based beam SNR prediction showed excellent prediction accuracy. The SNR predictor is able to predict other beam SNRs quite accurately, thereby correcting misaligned beams [14]. In the CC-assisted beam tracking approach, the same procedures as in (13) to (16) are followed. Given the effective channel covariance matrix $\mathbf{R}$, the UE is mapped to beam $\hat{\mathbf{w}}$ CC. Due to non-parametric nature of t-SNE DR, the out-of-sample extension for the new UE is applied by averaging over the n nearest CC locations. Then, the SNR at other beams is predicted using SNR predictors. Therefore, by measuring the SNR at the current beam and predicted SNR at other beams, a decision regarding choosing the best beam can be made.

TABLE I: Simulation Parameters

Parameter	Value	Parameter	Value
Center Freq.	28 GHz	Subcarriers	256
Scenario	3GPP 38.901 UMa-NLOS	Subcarrier Bandwidth	240 KHz
BS Array	32 ULA	UE Array	8 ULA
BS Height	25 m	UE Height	1.5 m

IV. Simulation Results

In our simulations, we consider a 10 m $\times$ 10 m street segment. The BS is equipped with ULA antenna with 32 elements, and UEs are equipped with ULA antennna with 8 elements. Quadriga channel simulator is used to generate the radio environment [17]. Simulation parameters are listed in Table I. We uniformly scattered 1600 UEs in the area of interest for training and validation of the NN SNR predictors.

t-SNE DR with perplexity 200 is chosen for beam CC construction. The quality of channel charts are evaluated by Continuity (CT) and Trustworthiness (TW) which are widely used performance measures in DR methods [18]. CT shows whether nearby UEs in the physical space are mapped to nearby points on the CC. On the other hand, TW determines whether nearby points on the CC correspond to UEs who are spatially close to each other in the physical space. The value of both CT and TW are in the range $[0, 1]$, and the larger the value the higher is quality of channel chart. The CT and TW performance metric for the constructed CCs are 0.98 and 0.98 respectively.

Fig. 2 shows the constructed CC where the boundaries for the dominant beams are shown. Also, one mobility path is shown with black dot markers which corresponds to a mobility path in the middle of the street.

A NN with 3 layers and 30 neurons in each layer with ReLu activation function is used for SNR prediction. The input layer of NN gets 2D CC location and current beam SNR value, and the output layer has SNR values for the other beams.

In the street segment, we consider 20 mobility paths along the positive x-axis. Each path consist of 60 locations where a UE is assumed to travel through. At the beginning of each path, exhaustive search is carried out and UEs are supposed to track the best beam for their connection to the BS.

Fig. 3 shows best BS beam for each location. In the area of interest, seven dominant beams are observed. Once the best beam changes, the beam tracking approach shows error in tracking the best beam; Magenta circles shows UEs that cannot follow the best beam through their path based on beam tracking approach. Black circles show UEs that have erroneous best beam based on CC-assisted beam tracking. We see that CC-assisted beam tracking approach has fewer erroneous beams compared to the beam tracking approach.

In Fig. 4, we evaluate beam tracking accuracy in terms of SNR difference. For each location, the reference SNR is obtained from exhaustive search. For performance comparison, we introduce a baseline scheme that after some steps in each mobility path, an exhaustive search is carried out so as to refresh the beam information for next steps. We consider every

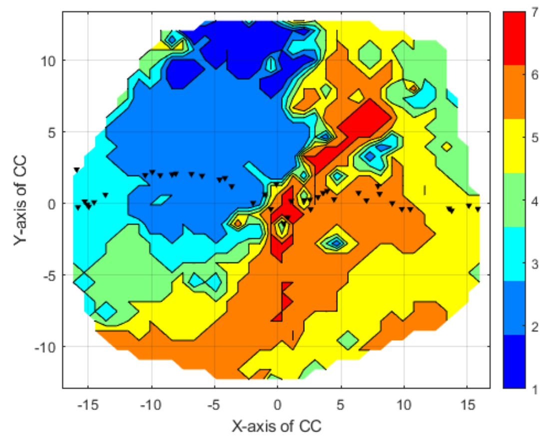

Fig. 2: CC of the training data set. Black triangle markers depict a mobility path in the middle of street.

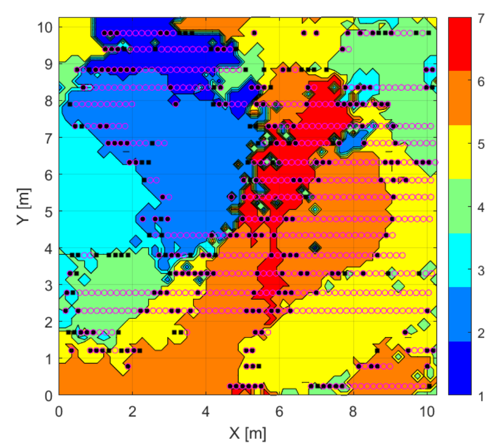

Fig. 3: Beam dominance areas as a function of the x-y coordinates of the street. Black dots shows points that the UE has error in CC-assisted beam tracking. Magenta circles show points that the UE has error in beam tracking.

$[2^{\text{nd}}, 5^{\text{th}}, 10^{\text{th}}, 15^{\text{th}}, 30^{\text{th}}]$ step, a refreshing of the best beam information is conducted. We define the percentage of total number of exhaustive searches in a mobility path to the total number of points in the mobility path as:

$$\rho = \frac{\#\ \text{exhaustive search}}{\#\ \text{points in the mobility path}} \times 100, \qquad (18)$$

where the number of points in the mobility path is 60 points. The blue solid line corresponds to the exhaustive search, it is a baseline for performance comparison. The blue dashed line represents the case where only at the start of mobility path we have an exhaustive search beam information. Our proposed CC-assisted beam tracking approach outperforms conventional beam tracking for different refreshing criteria. Moreover, the largest SNR prediction error for CC-assisted method is less than 1.5 dB, whereas for beam tracking, the SNR prediction error can reach 4.0 dB.

The motivation for beam tracking is to avoid the exhaustive search over all BS beams. Assuming each exhaustive search counts as one unit of overhead, in Fig. 5 we have depicted the

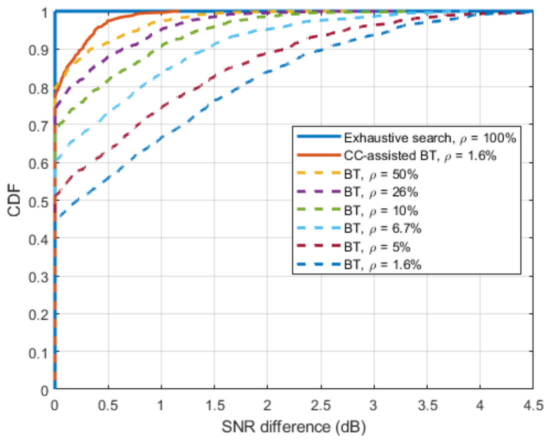

Fig. 4: The CDF of SNR prediction error in dB for beam tracking and CC-assisted beam tracking approaches. For beam tracking different refreshing criteria are considered. The CC-assisted beam tracking approach outperforms beam tracking approach with different refreshing frequencies.

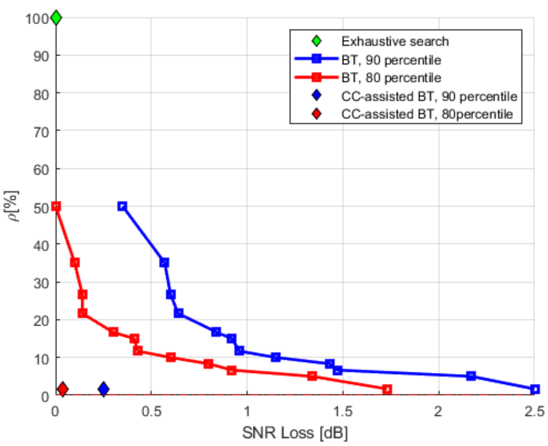

Fig. 5: Overhead-SNR difference trade-off for beam tracking and CC-assisted beam tracking. The 80 / 90 percentile SNR difference in dB is used as the performance measure.

percentage of exhaustive searches to the total number of points in a mobility path to achieve 80 / 90 percentile SNR difference for various exhaustive search frequencies on the mobility path. CC-assisted approach has a significant overhead reduction as it only needs the exhaustive search at the beginning of the mobility path.

V. Conclusion

In this paper we have considered beam tracking for 5G mm-Wave networks. CC-assisted beam tracking is proposed and compared to conventional beam tracking approach. In this regard, beam SNRs are predicted based on CC locations. Accordingly, the best beam is chosen from predicted SNRs and compared to the reference SNR obtained from exhaustive search. Simulation results demonstrate that the proposed CC-assisted approach can significantly reduce overhead and accurately enable beam refinement.

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References

[1] T. S. Rappaport, S. Sun, R. Mayzus, H. Zhao, Y. Azar, K. Wang, G. N. Wong, J. K. Schulz, M. Samimi, and F. Gutierrez, "Millimeter wave mobile communications for 5G cellular: It will work!" *IEEE Access*, vol. 1, pp. 335–349, 2013.

[2] Y. Heng, J. G. Andrews, J. Mo, V. Va, A. Ali, B. L. Ng, and J. C. Zhang, "Six key challenges for beam management in 5.5G and 6G systems," *IEEE Commun. Mag.*, vol. 59, no. 7, pp. 74–79, 2021.

[3] 3GPP, "Study on new radio (NR) access technology," 3rd Generation Partnership Project (3GPP), Technical document number 38.912, version 14.0.0, May 2017.

[4] Y. R. Li, B. Gao, X. Zhang, and K. Huang, "Beam management in millimeter-wave communications for 5G and beyond," *IEEE Access*, vol. 8, pp. 13 282–13 293, 2020.

[5] M. Giordani, M. Polese, A. Roy, D. Castor, and M. Zorzi, "A tutorial on beam management for 3GPP NR at mmWave frequencies," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 1, pp. 173–196, 2019.

[6] E. Gures, I. Shayea, A. Alhammadi, M. Ergen, and H. Mohamad, "A comprehensive survey on mobility management in 5G heterogeneous networks: Architectures, challenges and solutions," *IEEE Access*, vol. 8, pp. 195 883–195 913, 2020.

[7] F. Fernandes, C. Rom, J. Harrebek, and G. Berardinelli, "Beam management in mmwave 5G NR: an intra-cell mobility study," in *Proc. IEEE Veh. Technol. Conf. (VTC-Spring)*, 2021, pp. 1–7.

[8] M. Giordani, M. Mezzavilla, S. Rangan, and M. Zorzi, "Multi-connectivity in 5G mmwave cellular networks," in *Proc. Mediterranean Ad Hoc Networking Workshop (Med-Hoc-Net)*, 2016, pp. 1–7.

[9] V. Va, H. Vikalo, and R. W. Heath, "Beam tracking for mobile millimeter wave communication systems," in *Proc. IEEE Global Conf. on Signal and Information Processing (GlobalSIP)*, 2016, pp. 743–747.

[10] Y. Heng and J. G. Andrews, "Machine learning-assisted beam alignment for mmWave systems," *IEEE Trans. Cogn. Commun. Netw.*, pp. 1–6, 2021.

[11] S. Rezaie, C. N. Manchón, and E. de Carvalho, "Location- and orientation-aided millimeter wave beam selection using deep learning," in *IEEE Int. Conf. on Commun. (ICC)*, 2020, pp. 1–6.

[12] C. Studer, S. Medjkouh, E. Gönültaş, T. Goldstein, and O. Tirkkonen, "Channel charting: Locating users within the radio environment using channel state information," *IEEE Access*, vol. 6, pp. 47 682–47 698, 2018.

[13] P. Kazemi, H. Al-Tous, C. Studer, and O. Tirkkonen, "SNR prediction in cellular systems based on channel charting," in *Proc. of the IEEE Int. Conf. on Commun. and Netw. (ComNet)*, 2020, pp. 1–8.

[14] P. Kazemi, T. Ponnada, H. Al-Tous, Y.-C. Liang, and O. Tirkkonen, "Channel charting based beam SNR prediction," in *Proc. of Eur. Conf. Netw. and Commun. 6G Summit (EuCNC/6G Summit)*, 2021, pp. 72–77.

[15] T. Ponnada, P. Kazemi, H. Al-Tous, Y.-C. Liang, and O. Tirkkonen, "Best beam prediction in non-standalone mmwave systems," in *Proc. of Eur. Conf. Netw. and Commun. 6G Summit (EuCNC/6G Summit)*, 2021, pp. 532–537.

[16] L. van der Maaten and G. Hinton, "Visualizing data using tSNE," *Journal of Machine Learning Research*, vol. 9, pp. 2579–2605, nov. 2008.

[17] S. Jaeckel, L. Raschkowski, K. Borner, and L. Thiele, "QuaDRiGa: A 3-D multi-cell channel model with time evolution for enabling virtual field trials," *IEEE Trans. Antennas Propag.*, vol. 62, no. 6, pp. 3242–3256, Jun. 2014.

[18] J. Venna and S. Kaski, "Neighborhood preservation in nonlinear projection methods: An experimental study," in *Proc. of the International Conference on Artificial Neural Networks, (ICANN)*, 2001, pp. 485–491.