Context-aware Codebook Design for 6G Extreme MIMO Systems

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***Abstract*—Beam management is the defacto approach for configuring the antennas in 5G MIMO communication systems. Extending the beam management framework to larger arrays—also known as extreme MIMO systems—is challenging as the overheads grow with the array dimensions. One solution is to make use of the wealth of sensor data that is becoming available in integrated sensing and communication (ISAC) systems. In this paper, we propose a neural architecture for codebook design using environmental context derived from sensor data. In particular, we combine beamspace transformations with local occupancy grids obtained through network sensing to maximize the achievable rate in vehicular operations. Our results show significant performance gains over traditional codebooks while requiring less overhead than standard 5G beam management.**

***Index Terms*—6G, Massive MIMO, Extreme MIMO, CSI, Codebooks**

I. Introduction

Communication systems integrated with radar or sensing information present new opportunities for fast, low-overhead link configuration. ISAC systems, where the communication signals are reused for sensing without overhead, have been proposed for 6G standardization [1]. ISAC systems seek to obtain sensing information such as user localization, object detection, and environmental awareness without dedicated wireless signals. In addition to ISAC, sensing information such as LiDAR and camera information also present possible data that can be used to configure the wireless link [2]. Effectively leveraging the environmental information, however, is challenging because it does not naturally provide complete CSI nor clearly integrate with the standard beam management framework used in mobile broadband [3].

Beam management describes the codebook-based process of obtaining partial CSI through beam training and digital feedback [3]. First, beam training is used to improve cell coverage, enable hybrid arrays, and obtain beamforming gain [4]. Second, user equipment (UE) provides feedback corresponding to beamformed CSI that enables multi-rank communication and interference mitigation [5], [6]. Applying contextual awareness to these steps requires understanding and integrating the multipath, frequency-selective environment characteristics into the codebook design and beam selection processes. While single-user (SU), line of sight (LOS) communication can be intuitively configured with environmental sensing, extending codebook design to multipath environments and multi-user (MU) is not obvious. Instead, consistent and complete CSI obtained from channel sounding or raytracing is often necessary to accurately represent the channel [7].

In this paper, we propose a novel context-aware codebook design algorithm that leverages contextual information available in vehicular communication systems. The proposed strategy combines sensing information in the form of occupancy grids with beamspace representations and end-to-end learning [6] to learn codebooks that support high-rate SU-MIMO communications. An occupancy grid is a map of the coverage area that indicates if a location is blocked or contains a target UE [8]. The proposed Contextual Codebook Learning algorithm (CCBL) generates multi-rank codebooks with multi-stream capability for each user (individually) identified in the grid.

Prior work using contextual awareness for rank-1 communications has shown that environmental sensing can help improve beamforming and reduce beam training overhead [8], [9]. Channel mapping and charting ideas have also been proposed as a method of abstracting environmental context [10], [11]. Prior work, however, has focused on a single user received power or rank-1 communications which do not show whether user data rates improved as a result. Prior work has shown the advantage of environmental context for beam training [8], [9], but does not consider how dynamic codebooks can be configured using it. Building on our prior work with codebook learning [5], we propose a strategy for designing codebooks to enable full-rank MIMO communications by leveraging environmental context. Unlike methods in [8] and [9], our approach dynamically generates multi-rank codebooks, ensuring low-latency beam management and zero-shot beam alignment.

II. System model

We consider a vehicular scenario where a dense, multi-lane roadway is served by a roadside unit (RSU). Vehicular networks are challenging because of the rapid mobility and high quality of service requirements [9], but the wealth of sensor data presents an opportunity for new algorithms to improve the communication link [12]. We assume the RSU is equipped with a hybrid planar array of size $N_{\mathrm{T}} = N_{\mathrm{X}} \times N_{\mathrm{Y}}$ with $N_{\mathrm{T,\,d}}$ digital RF chains and that there are U mobile vehicular UEs each equipped with a fully digital planar array of size

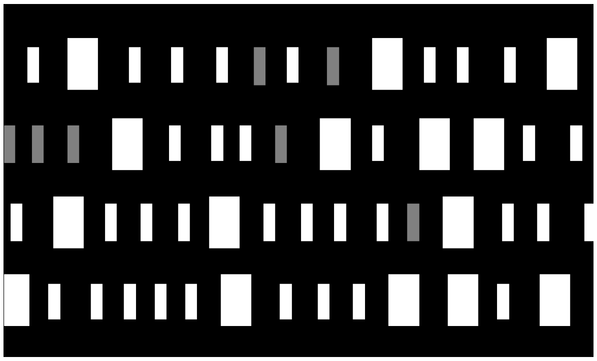

Fig. 1. An example of environmental context in the form of an occupancy grid image. The occupancy grid shows the vehicles in the 4-lane road and highlights which users are active (shown in gray) for the codebook design step compared to other vehicles that are potential blockers (shown in white). Note that the image is downsampled by a factor of 8 in the horizontal direction to reduce computational load and each pixel corresponds to approximately 0.125×1 m^2.

$N_{\mathrm{R}} = N_{\mathrm{RX}} \times N_{\mathrm{RY}}$. We assume U is a dynamic variable and corresponds to only a small number of vehicles on the roadway at a time. Following typical mobile communications, we assume an OFDM channel over T timeslots and K subcarriers $\mathbf{H} \in \mathbb{C}^{T \times K \times N_{\mathrm{R}} \times N_{\mathrm{T}}}$. A typical received signal for a user u during time-frequency resource t, k with combiner $\mathbf{W}^*$ and analog/digital precoders $\mathbf{F}_t^{\mathrm{RF}}, \mathbf{F}_{t,k}$ and symbol $\mathbf{s}$ is then

$$\mathbf{y}_{u,t,k} = \mathbf{W}^* \left(\mathbf{H}_{u,t,k} \mathbf{F}_t^{\mathrm{RF}} \mathbf{F}_{t,k} \mathbf{s}_{u,t,k} + \mathbf{N}_{u,t,k} \right). \quad (1)$$

With the generic received signal (1), we can overview how the base station can configure $\mathbf{F}_t^{\mathrm{RF}}$ and $\mathbf{F}_{t,k}$ using the standardized beam management procedure.

Beam management, as it is defined in 5G, involves a hierarchical beam search and configurable feedback formats [3]. In this work, we seek to reduce the complexity and overhead of beam management using contextual awareness to preemptively design codebooks that support high-rate MIMO communication. In prior work, we have found that well-designed codebooks could be used instead of hierarchical search with greater performance and orders of magnitude less overhead [5]. Based on these results, we now propose a beam management strategy that only uses a single stage of beam training relying only on CSI-RS.

The process starts by obtaining environmental context, which we assume corresponds to a 2D occupancy grid as shown in Fig. 1. Other formats such as 3D occupancy grids or channel charts are suggested for future work. The occupancy grid, $\mathbf{O}$, is used to prepare the upcoming codebook $\mathbf{B}^{\text{CSI-RS}}$. In essence, the codebook is assumed to be designed dynamically to support a set of users identified in the occupancy grid. In a traditional system, the codebook is dynamically configured using the hierarchical beam search. In this investigation, we focus on multi-user codebook design and SU-MIMO data transmission with extensions to multi-user and multi-cell work proposed for future work. We assume the beam training process follows typical procedures which we overview next.

A. Beam training

Beam training is classically performed over a two-tier codebook search where synchronization signal block (SSB) and channel state information reference signals (CSI-RS) are transmitted with associated beamformers to determine a multi-antenna strategy [3]. We will skip the SSB stage since it provides coarse beamforming information that is already achievable with the environmental context. CSI-RS are particularly important in the overall link configuration as they include pilot symbols for (beamformed) channel estimation and multi-rank signaling that enables MIMO transmission. UEs use the received CSI-RS to report the codebook index, rank information, and optionally precoder matrix information to the BS. The BS can then use this information either for data transmission in a SU-MIMO or MU-MIMO format. For simplicity, we focus on the achievable SU-MIMO rate in this work, although the codebook must also support multiple users that may be active in the network prior to scheduling. Therefore, we now describe the multi-user beam training process and then the SU-MIMO data transmission.

The first step of the proposed beam training involves the transmission and reception of CSI-RS using each of the precoding codewords $\mathbf{F}_i \in \mathbf{B}^{\text{CSI-RS}}$. The UE u receives the CSI-RS signal $\mathbf{y}^{\text{CSI-RS}_i}$ with receive combiner $\mathbf{W}_{u,t,k}^* \in \mathbb{C}^{R \times N_{\mathrm{R}}}$ containing pilot training symbols $\mathbf{s}_{t,k}^{\mathrm{tr}}$ over the R rank precoder as

$$\mathbf{y}_{u,t,k}^{\text{CSI-RS}_i} = \mathbf{W}_{u,t,k}^* \mathbf{H}_{u,t,k} \mathbf{F}_i \mathbf{s}_{t,k}^{\mathrm{tr}} + \mathbf{W}_{u,t,k}^* \mathbf{N}_{u,t,k}. \quad (2)$$

Note that the precoding is achieved in a hybrid array with $\mathbf{F}_t^{\mathrm{RF}} \mathbf{F} \approx \mathbf{F}_i$ configured to minimize the difference between the codebook entry and the achieved hybrid precoder. There is, however, minimal reconstruction loss because $\mathrm{Rank}(\mathbf{F}_i) \ll N_{\mathrm{T,\,d}}$ even with low-resolution phase shifters [13].

For simplicity, we assume an information-theoretically optimal combining strategy for the UEs based on the embedded pilot symbols. The UE can then select a CSI-RS according to either the reference signal received power (RSRP) or higher-level metrics such as the signal-to-interference noise ratio (SINR). Because of the focus on extreme MIMO (X-MIMO), we propose beam selection using the achievable spectral efficiency arising from the multi-rank SINR as an appropriate metric. With an optimal combining strategy, the estimated spectral efficiency (SE) for CSI-RS codeword i is [14]

$$\mathrm{SE}_{u,t,k}^{\text{CSI-RS}_i} = \log_2 \det \left(\mathbf{I} + \frac{P_T}{\mathbb{E}[\mathbf{N}^2]} \mathbf{H}_{u,t,k} \mathbf{F}_i \mathbf{F}_i^* \mathbf{H}_{u,t,k}^* \right), \quad (3)$$

where $P_T / \mathbb{E}[\mathbf{N}^2]$ corresponds to the ratio of the transmit power and noise power. Then the selection simply corresponds to the codeword with the highest spectral efficiency over the CSI-RS resources $T_{\text{CSI-RS}_i}, K_{\text{CSI-RS}_i}$

$$\mathrm{SE}_u^i = \frac{1}{K} \sum_{t \in T_{\text{CSI-RS}_i}} \sum_{k \in K_{\text{CSI-RS}_i}} \mathrm{SE}_{u,t,k}^{\text{CSI-RS}_i} \quad (4)$$

$$p_u = \arg\max_i \mathrm{SE}_u^i. \quad (5)$$

Estimating the spectral efficiency is more computationally intensive than other metrics, especially for large-scale MIMO with many receiver antennas. One possible solution would be to reduce the computational load of calculating the feedback, which represents a substantial computational load on the UE [15]. Reducing the feedback calculations and overhead can provide a significant gain in low-latency and high-mobility scenarios due to the short channel coherence time.

Codeword selection is part of the minimal feedback a UE must provide, although feedback for the beamformed channel, $\mathbf{HF}_{p_u}$ is supported within the precoding matrix indicator (PMI) field of the feedback packet. In frequency division duplexing (FDD) systems it is typically assumed UEs would provide this feedback but even time-division duplexing (TDD) systems can benefit from the additional CSI [16]. This feedback can be configured in either type-I or type-II formats [17] where type-II is typically used for MU-MIMO as it allows for higher resolution feedback [18]. Feedback, however, has significant overhead and the benefits are not as clear with adaptive codebooks [5]. We assume a direct beam training scenario where users select a beam without additional feedback, thereby focusing on low-latency scenarios in this work.

B. Data transmission

In the vehicular RSU scenario, the UEs are highly mobile such that configuring MU-MIMO data transmission with up-to-date CSI is challenging without high overhead and significant processing. Therefore, we assume data precoding directly employs the beam training codewords. From the U users active in the scene, we assume a random user selection process such that each user is equally likely to be scheduled regardless of its CSI. Such an assumption is for simplicity and to prevent biasing the system towards a greedy selection process. Furthermore, by selecting a random user, we ensure that the codebooks are appropriate for any user. Integrating an advanced scheduler or predictive model into the algorithm could also be an interesting direction of work.

A user $u_a \sim \mathcal{U}(1, U)$ known to the BS is selected as the active user. The resulting spectral efficiency follows (3) with the user-reported precoder applied over the entire resource grid. We further define the effective spectral efficiency as the total spectral efficiency excluding beam management resources $(T_{\text{BM}}, K_{\text{BM}})$, highlighting performance relative to overhead as

$$\text{ESE} = \frac{1}{K} \sum_{\substack{t \notin T_{\text{BM}} \\ k \notin K_{\text{BM}}}} \text{SE}_{u_a,t,k}. \tag{6}$$

With the goal of maximizing the ESE, we now present the context-aware codebook algorithm CCBL.

III. Proposed algorithm

In this paper, we propose CCBL, an end-to-end codebook learning strategy that uses contextual awareness to optimize multi-user codebooks for SU-MIMO data transmission. In particular, our proposal optimizes codebooks for high-rate

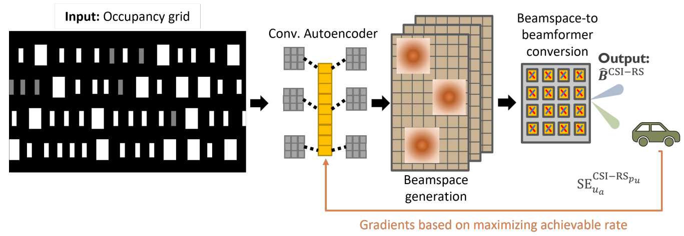

Fig. 2. A visual dedication of the CCBL algorithm. The network predicts codebooks to serve the identified users in the occupancy grid and then updates the model in an end-to-end fashion to maximize the per-user MIMO spectral efficiency.

and low-latency communication to support vehicular networks. The challenge in these scenarios arises from the limitations of current beam management [3] which involves multiple beam training and feedback steps prior to multi-stream communication. Furthermore, designed codebooks often seek to maximize the rank-1 power, which does not necessarily maximize the MIMO performance. Our proposed CCBL remedies this optimization mismatch while also integrating the beam training and site-specific characteristics into the codebook operation to obtain rate-maximizing codebooks.

The first step of the CCBL algorithm is feeding the environmental context $\mathbf{O}$ into a convolutional autoencoder neural network. The neural architecture is composed of 4 convolutional layers with 5×5 filters and max pooling. The decoding layers include 4 inverse convolution (convolution transpose in machine learning (ML) terminology) layers and an additional convolutional layer to size the outputs appropriately. We design the outputs to correspond to beamspace representations [5] which are a visual representation of the beamformers. This representation was shown to improve learning and improve generalization performance with a simple matrix multiplication to transform to and from complex beamformers [5].

We define the transformation matrices $\mathbf{U}_{N_{\text{X}},N_{\text{X,O}}}$, $\mathbf{U}_{N_{\text{Y}},N_{\text{Y,O}}}$ where $(N_{\text{X,O}}, N_{\text{Y,O}})$ are the beamspace samples along the azimuth and elevation directions [5]. The beamspace-to-beamformer conversion for the ith predicted codebook entry $\widehat{\mathbf{B}_i^{\text{sub}}}$ and corresponding beamspace $\mathbf{O}_i$ is

$$\widehat{\mathbf{B}_i^{\text{sub}}} = (\mathbf{U}^*_{N_{\text{X}},N_{\text{X,O}}})^\dagger \mathbf{O}_i \mathbf{U}^\dagger_{N_{\text{Y}},N_{\text{Y,O}}} \quad \forall i. \tag{7}$$

The beamspace dimensions $(N_{\text{X,O}}, N_{\text{Y,O}})$ determine the largest unaliased antenna array that can be supported, i.e. $N_{\text{X,O}} \geq N_{\text{X}}, N_{\text{Y,O}} \geq N_{\text{Y}}$.

After the outputs of the neural network are transformed into the new codebook, $\widehat{\mathbf{B}^{\text{sub}}}$, the end-to-end training strategy is used to optimize the neural network. Because the codebook should be capable of serving any of the users and no advanced scheduler is considered, we evaluate the achievable spectral efficiency for each user in parallel and determine the loss as the average over the users. To be precise, we train the neural network to minimize the spectral efficiency difference between the maximum SU-MIMO rate (vectorized for all users as $\mathbf{r}$) and the rate achievable with the codebook as

$$\mathcal{L}(\mathbf{r}, \{\mathrm{SE}_u^{p_u}\}^U) = \frac{1}{U}\sum_u^U (r_u - \mathrm{SE}_u^{p_u})^2. \tag{8}$$

Gradients are backpropagated through the loss, beam reception, and selection, and finally used to update the model weights with respect to the occupancy grid. This end-to-end or metric-based learning is especially beneficial when it is unclear how the codebook entries should be designed given a limited number of beams.

IV. Simulation setup

Simulating spatially consistent and realistic channels is important for evaluating the proposed codebook algorithm for vehicular scenarios. We employ the Sionna raytracing simulator [19] along with a custom vehicular overlay described in detail in [20]. The RSU is located at 10m above the road height and is equipped with an $N_\mathrm{T} = 16 \times 16$ array with 16 digital ports. The vehicles are equipped with $N_\mathrm{R} = 4 \times 4$ arrays and channels are sampled over a short bandwidth $K = 60$ resource blocks each corresponding to 12×30 kHz subcarriers. This band represents one physical resource group of a potentially larger bandwidth. We generate 50 possible scenes with over 100 initial user locations to form a dataset of possible configurations. Note that users from different configurations or scenes cannot be combined as the multipath channels correspond to the surrounding vehicle placements so that some vehicles may be blocked by nearby buses [20].

To prepare the training and validation datasets, a scene and $U \sim \mathcal{U}(4, 12)$ users are selected for a data sample. The corresponding channels are stored along with a matching occupancy grid with the selected users highlighted. In addition, the SU-MIMO rates corresponding to each user channel's singular values are stored for end-to-end training. The dataset is then split into train and validation subsets (80% and 20% respectively) while a test set is generated independently. All training is performed until the validation performance stops improving with learning rate reduction.

V. Simulation results

ML algorithms naturally tend to fit the underlying characteristics in the data and loss function. Because of this, it's often the case that ML algorithms show significant gains in principle but experience catastrophic failures. To counter this, we carefully evaluate and investigate the CCBL algorithm with respect to the distribution of results. In particular, we characterize the performance of codebook-based SU-MIMO data transmission with industry-standard DFT codebooks and the proposed CCBL codebooks. The DFT codebooks correspond to potential beams in the direction of the users based on the occupancy grid, so that the two methods are both using sensing information for dynamically allocating beams.

Firstly, we characterize the CDF of the spectral efficiency of CCBL compared to DFT codebooks in Fig. 3. Note that the vehicular RSU scenario has very high SNR due to the large antenna arrays and the short distance separating the RSU from the vehicles leading to high MIMO spectral efficiency. It can be seen from Fig. 3 that CCBL codebooks average more than 9 bps/Hz improvement over DFT codebooks. The proposed algorithm shows substantial improvements over DFT codebooks in general, arising from the improved beamformer design and multi-rank support that is atypical of DFT codebooks [6].

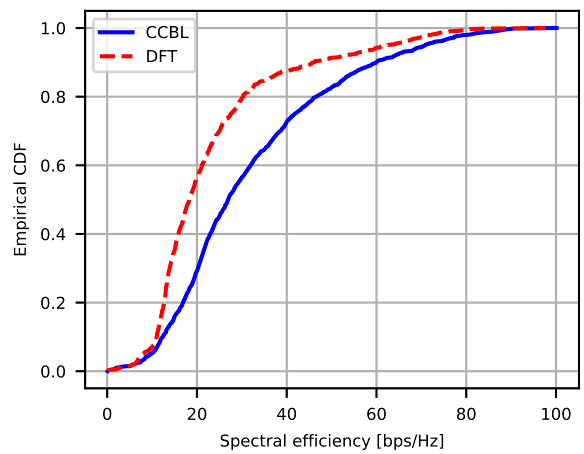

Fig. 3. A graph of the empirical CDF of the SE of CCBL vs DFT codebooks. DFT codebooks tend to be best suited for sparse and low rank channels which are not representative of realistic channels even at 28 GHz. We find that DFT codebooks are adequate but ultimately outperformed by CCBL codebooks that are designed for the specific environment and mobility patterns.

While the CDF curve from Fig. 3 provides a high-level comparison, it is also important to understand the user-for-user difference in performance. A histogram of the difference in SE is shown in Fig. 4 with an overlay of the resulting CDF. It can be seen that the proposed CCBL improves over DFT codebooks in 95% of cases with the potential to improve SE by 30 bps/Hz. Based on Fig. 3-4, CCBL codebooks present a significant benefit in low-latency SU-MIMO scenarios with contextual awareness.

Finally, Fig. 5 highlights a comparison of the algorithm performance with different dataset sizes. Neural networks are often envisioned for large datasets, which may not be possible to obtain in realistic settings. The end-to-end nature of CCBL codebooks enables more efficient training [5], [6] that is especially helpful in data-constrained settings such as a network operator might experience deploying an RSU. It can be seen that performance gains with increasing dataset size are relatively small after $10,000$ training samples. This highlights the sample efficiency of our proposed CCBL end-to-end framework on top of its performance capabilities.

VI. Conclusion

In this paper, we proposed a dynamic codebook algorithm using environmental context. This algorithm, CCBL, combines sensing information with end-to-end learning to generate code-

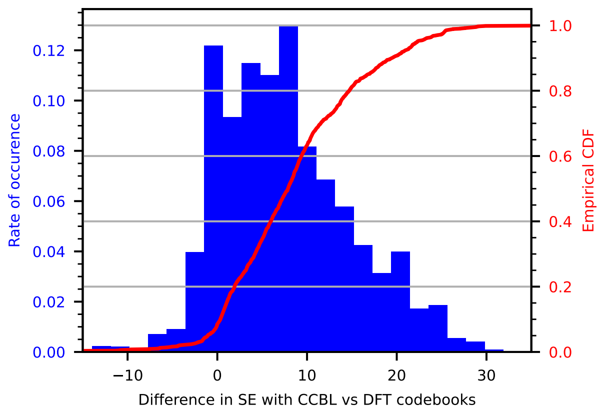

Fig. 4. A histogram of the SE difference between CCBL and DFT codebooks. A secondary axis in red shows the CDF of the performance delta. The performance difference highlights how often CCBL codebooks are worse than DFT codebooks, which only occurs $\leq 5\%$ of the time or less. Typically, CCBL improves performance by more than 8 bps/Hz.

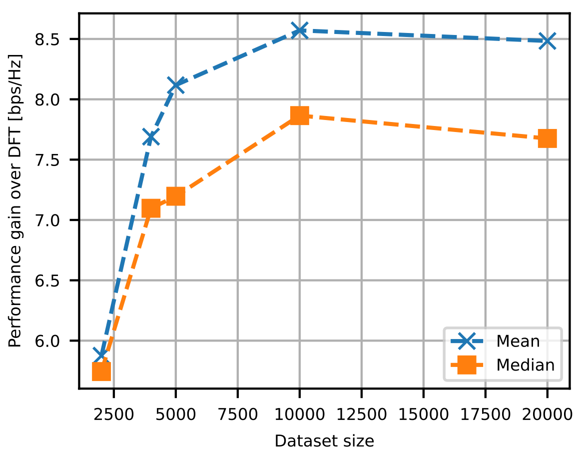

Fig. 5. A chart of CCBL performance with different dataset sizes. The performance shows significant gains from 2000 to $10,000$ but little gain is seen beyond that point. This highlights the effectiveness of the proposed end-to-end strategy which requires very few data samples to reach nearly the maximum performance.

books that maximize user spectral efficiency. We found that this formulation was very sample-efficient and significantly outperformed traditional codebooks for low-latency high-rate communications. These results suggest that combining sensing and AI/ML in 6G can enable new applications with high-rate communications. The site generalization evaluation of the proposed algorithm is left as an interesting future work.

VII. Acknowledgments

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