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AI-based Hybrid Beamforming for Vehicular to Infrastructure Networks

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Hybrid Beamforming in V2I Scenario using machine learning based techniques

Abstract-*Hybrid beamforming (HBF) is an important approach for improving millimeter-wave (mmWave) communication, notably in 5G vehicular-to-infrastructure (V2I) networks. This research investigates the use of hybrid beamforming and machine learning to address the challenges of signal transmission in dynamic situations. Hybrid beamforming, which blends digital and analog techniques, improves MIMO system performance by decreasing the requirement for fully digital beamformers and maximizing network capacity. The mmWave frequency provide prospects to ease spectrum shortages, allowing systems to support large data speeds and better signal quality even in demanding propagation situations. Recent advances have seen the introduction of machine learning to beamforming, which improves system efficiency by predicting interference and dynamically changing the direction of beam steering.*

In this paper, a machine learning approach is proposed to optimize hybrid beamforming in V2I communication, with a geometric channel model simulating real-world situations. The model uses a deep neural network to govern both digital and analog beamforming operations, resulting in considerable improvements in prediction accuracy and real-time signal transmission. We use realistic modeling tools such as SUMO and OpenStreetMap to provide a complete analysis of the system's performance in terms of signal-to-noise ratio (SNR) and network efficiency. Our findings show that the Optimizable Tree model provides the best balance of accuracy and speed, with the lowest RMSE (1.42e-09) and the fastest prediction time (12,000 observations per second), making it ideal for real-time V2I applications. Despite the longer training period, this model excels at jobs requiring both precision and rapid prediction, making it appropriate for next-generation vehicular communication systems.

1. INTRODUCTION

Hybrid beamforming (HBF) serves as a pivotal technique poised to facilitate the forthcoming multitude of millimeter wave (mmWave) communication advancements. The MIMO (Multiple Input Multiple Output) systems, characterized by the provision of efficient beamforming methodologies, are distinguished by their cost-effectiveness and the minimal requirement for fully-digital beamformers [1-4]. In light of the heightened data rates and augmented network utilization inherent in mobile communication, the fifth generation network (5G) serves as a crucial advancement, particularly in the realm of vehicular to everything (V2X) communication. The proliferation of millimeter wave bands, spanning from 30 GHz to 300 GHz, presents a plethora of opportunities to enhance existing technologies such as LTE-based MIMO systems, while simultaneously facilitating the advancement of future applications reliant on machine learning and deep learning methodologies. The millimeter-wave systems address the challenges of spectrum scarcity through the implementation of extensive antenna arrays, typically configured in a MIMO arrangement, to attain substantial multiplexing gains, thereby mitigating the propagation losses encountered at elevated frequencies. Grateful for the advancements in Massive MIMO technology, which significantly augment system capacity and possess the capability to concurrently process signals, thereby providing a substantially greater array gain and more refined spatial multiplexing compared to traditional MIMO systems. The progression of inquiry into the electronic steering of beams towards the intended user orientation elucidates the concept of beamforming. As the quantity of antennas utilized within a singular array escalates, both the gain and path loss are affected, necessitating the implementation of directional beam forming.

This encompasses a range of analog and digital beamforming methodologies that are pertinent to the realm of millimeter wave communication systems. A variety of concepts has been executed for the beam formers utilized in hybrid beamforming methodologies [5-6], aimed at augmenting the capacity of networks comprising multiple transmit and receive antennas, each equipped with a dedicated radio frequency (RF) chain. The architecture of digital beamforming, characterized by its combinational approach, has yielded a hybrid configuration that operates with a reduced quantity of RF chains. The system predominantly comprises an analog beamformer characterized by its high dimensionality, alongside a digital beamformer that operates within a lower dimensional framework. Hybrid beamforming technology, primarily engineered for single-user MIMO systems. and multi-user MIMO systems has been evaluated across various application contexts. Through the examination of these scenarios, a novel concept emerges to explore the intricacies of machine learning techniques. Over recent years, machine learning has notably advanced within its specialized domains, particularly in wireless technologies, and has ventured into the realms of beamforming.

This approach has consistently yielded substantial enhancements across various application domains within deep learning, including but not limited to pedestrian detection, voice recognition, and natural language processing, as referenced in the literature[7-9]. Consequently, to manage the surplus data streams and achieve enhanced beamforming in millimeter-wave massive multiple-input multiple-output systems, hybrid precoding was examined.

The implementation of successive interference cancellation within a hybrid precoding framework yields a reduction in complexity while simultaneously enhancing outcomes. Furthermore, the discourse highlights the optimization of sum rate maximization through the exploration of non-convex challenges and various additional optimization concerns. Subsequently, the authors in conducted an exploration of a hybrid precoding methodology for multiuser mmWave systems, employing a hybrid analog/digital precoding framework characterized by reduced complexity.

Furthermore, a significant portion of the investigations has concentrated on the advancement of hybrid beamforming within the realm of machine learning applications. Nevertheless, numerous challenges persist in the trajectory toward the development of innovative methodologies and viable solutions aimed at alleviating the burdensome high computational complexity and suboptimal performance of the system. The authors in examine the hybrid precoding scheme within the context of broadcast channel layer security, aiming to fortify the Internet of Things (IoT) against the vulnerabilities posed by an eavesdropper with imperfect channel state information (CSI).Recently, the 5G Public Private Partnership (5G PPP) discussed a white paper on the Service performance measurement methods over 5G experimental networks, which makes brief analysis on use cases of different aspects for their application-specific performance Key Performance Indicators (KPIs) and their relevance to the respective 5G system-specific KPIs.Among different network scenario's, vehicle-to-everything (V2X) networks plays a vital role to unlock the potential of next-generation wireless communication, which promise a low -latency data rate in a highly dense mobility scenario. In particular, vehicle-to-infrastructure (V2I) communication is an crucial component of V2X networks [7].

2. CHANNEL MODEL

For the channel between BS and receive antenna, we adopt a geometric channel model in []. with R paths. In this model $\mathbf{N_r x M_t}$ channel matrix H is written as

$$H[k] = \sqrt{\frac{M_t N_r}{N_{sc}}} \sum_{r=1}^{R} \alpha_r \acute{a}_r(\Theta_{a,r}, \Phi_{a,r}) \acute{a}_t^H(\Theta_{d,r}, \Phi_{d,r}) \quad ....(1)$$

Where α_r denotes the gain of the path with complex values of the rth path (including the path loss). The angles $\Theta_{a,r}$, denotes the elevation and azimuthal angle of arrival (AoA's) at the receiving antennas while $\Theta_{d,r}, \Phi_{d,r}$ denotes the rth path angles from the transmitter side. N_{sc} denotes the clusters of the scattering rays. Additionally, $\acute{a}_r$, $\acute{a}_t$ denotes response vector of the array. The array response vector for uniform linear array (ULA) and uniform planar array (UPA) are discussed in[8]. For mmWave frequencies, the calculation revels that the channels are sparse in nature typically the domain which is angular gives a small number of channel paths R (normally in the range of 3-5 paths) [9-11].

In this paper, we propose a machine learning approach towards hybrid beamforming [49] to address problem (5).

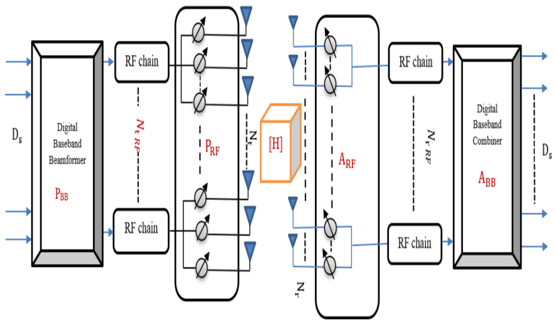

Figure 1: Architecture of Hybrid Beamforming

A channel H is used to discriminate the system between the transmitter and receiver. The data streams D_s is fed to the digital combiner and analog beamformer and digital beamformer. In a conventional digital beamformer, the matrix vector multiplication $\mathbf{s^{BB}} = \mathbf{P_{BB}\, s}$ is processed by the digital beamformer and where both $\mathbf{s^{BB}}$ and s are signals complex in nature having amplitude and phase. Since the conversion from s to $\mathbf{s^{BB}}$ can be assumed as a mapping process of output to input, we can design it in generalized form as $\mathbf{s^{BB}} = \int(s)$.

At this point, to perform the neural network transformation with training parameters with the help of weights and biases, the function can be written as

$$\Phi = [W; b],\ S^{BB} = f_{\Phi}(s) = \sigma(W.s + b) \quad ....(2)$$

Where b and W are the bias and weights of the neural network (NN) respectively. The σ represents the activation function of NN which gives hyperbolic tangent function $\sigma(x) = \tanh(x)$. The functionality of b and W parameters of fully connected network of digital beamformer / Combiner is discussed [12] in detail.

For our simplicity and without loss of generality, we can consider only one-layer neural network used for representation s^{BB} = f_{Φ} (s). The digital beamformer acts as a ML network and the digital combiner can be designed with the same method in an inverted form, from $\hat{s}^{BB}$ to $\hat{s}$ as $\hat{s}$ = Here, $f_v\left(\hat{s}^{BB}\right)$ s^{BB} is combined signal at receiver side, and v is the set of parameters used for the training of the neural network for combiner section. Thus, techniques used for processing of signal for the digital combiner/ beamformer is achieved in the digital domain, the method used for signal processing of ML is perfectly matched for existing hardware-based beamforming techniques. The DNN architecture does not solve the constant modulus problem of phase shifters due to the adjustment of the phase only. To solve this constraint, we provide a neural network-based method employed a phased shifter for the analog beamformer combiner. where only single hidden layer is used and only the signal phase is only adjustable in beamformer / combiner. The phase shifting operation is done with the help of Euler's operation using multiplication operation. With the use of exponential function and trainable values as index and without the activation function, the analog precoder in fully-connected and sub-connected structure are individually given by [13]

$$S_j^{RF} = \sum_{i=1}^{N_{RF}} S_i^{BB} . e^{j\omega(i-1)M_t+j} \quad ....(3)$$

$$s_j^{RF} = s_i^{BB} . e^{j\omega_j} \quad ....(4)$$

Where $\omega_{(i-1).N_{t+j}}$ and ω_j both are phase shifting angles and can be considered as trainable parameters in analog beamformer neural network. The analog beamformer/ combiner can be designed using phase shifter-based constraint neural network. The training parameters in analog neural network are in matrix form for the case of fully connected architecture. we denote it in a vector form and assumes ω represents the training parameters in analog beamformer. Thus, the NN function can be represented for analog precoder is given by

$$S^{\dagger}RF = g_{\downarrow}\omega\ (S^{\dagger}(BB)) \quad ....(5)$$

Similarly, the expression can be written for analog combiner in fully-connected and sub connected is given by

$$\hat{s}_j^{BB} = \sum_{i=1}^{N_r} y_i . e^{j\bar{\omega}(i-1)N_t+i} \quad ....(6)$$

$$\hat{s}_j^{BB} = \sum_{i=1}^{N_r/N_{RF}} y_i . e^{j\bar{\omega}i} \quad ....(7)$$

the neural network function representation is given by

$$s^{BB} = g_{\bar{\omega}}\ (y) \quad ....(8)$$

where y is the received signal, and $\bar{\omega}$ denotes the trainable parameter for analog combiner. Assuming the transmit power is limited, and the output of NN should be subjected to additional limits.

3. PROOPOSED V2I SEENARIO

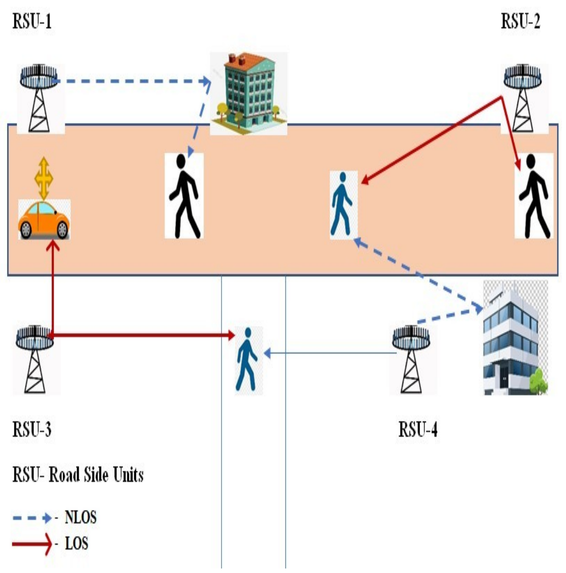

Figure 2 : Vehicle to Infrastructure Scenario

In the proposed vehicular to infrastructure scenario, the road side units (RSU's) are placed along the road serves as a transmitter follows the line of sight (LoS) and non-line of sight (NLoS) properties of incident rays. During the movement of pedestrians and vehicles, the angle ambiguity occurs, which creates the interference degrades signal to interference noise ratio (SINR).

The machine learning based techniques used to predict the interference in advance using regression methods. Vehicular-to-Infrastructure (V2I) communication plays a critical role in intelligent transportation systems, enabling data exchange between vehicles and roadside infrastructure, such as Road Side Units (RSUs), to improve traffic management, safety, and autonomous driving. Hybrid beamforming enhances V2I communication by combining digital and analog beamforming to optimize signal transmission and reception, particularly in dynamic environments with Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) conditions. By enabling precise beam steering, hybrid beamforming directs focused beams towards moving vehicles, dynamically adjusting to their positions and reducing signal degradation caused by obstacles like buildings. This approach improves signal strength, reduces interference, and mitigates Doppler effects, ensuring stable, high-throughput connectivity even at high vehicle speeds. Additionally, hybrid beamforming supports multi-user communication, allowing RSUs to connect with multiple vehicles simultaneously, while enhancing energy efficiency by focusing transmission only where needed. These benefits make hybrid beamforming essential for real-time V2I applications such as autonomous vehicle navigation, traffic control, and safety-critical communications, where reliable and efficient data exchange is paramount [14].

The simulator employs a duo of instruments. Initially, there is SUMO, which emulates the dynamics of vehicles and pedestrians along predetermined trajectories from origin to destination, alongside the Open Street Maps (OSM) Web Wizard, as it accurately represents real-world scenarios. The OSM Web Wizard adeptly extracts real-time data from the OpenStreetMap platform, subsequently generating a scenario[15-17] that delineates node routes. Employing the OpenStreetMap, the Map Processing module utilizes these instruments to generate a static signal-to-noise ratio representation. It facilitates the identification of the optimal line -of-sight area within the cellular network, corresponding to the architectural configuration of the building.

The Map module encompasses the attenuation of the signal as well as the effects of shadow fading. Subsequently, the Node processing module facilitates the assimilation of the collected data, synthesizes User Equipments from the SUMO simulation nodes, and provides their Signal-to-Noise Ratio traces. The network traffic generation modules subsequently acquire a traffic trace for each user equipment. Ultimately, the Dataset aggregation module consolidates the SNR and traffic traces into a singular, comprehensive trace [19-22].

4. RESUSTS AND DISCUSSION

The optimizable Tree is the best-performing model based on key performance metrics. It offers the lowest RMSE (1.42e-09), indicating minimal prediction error, while its high R-Squared value (0.95) demonstrates that it explains a large portion of the data's variance. Furthermore, its low MSE (2.02e-16) and MAE (1.19e-08) confirm its exceptional accuracy. In terms of prediction speed, the Optimizable Tree leads with the ability to process 12,000 observations per second, making it highly suitable for real-time applications. While it has the longest training time at 20.47 seconds, this is a justifiable trade-off for tasks that require both accuracy and rapid predictions. Thus, despite the extended training duration, the Optimizable Tree stands out for its excellent balance of accuracy and prediction speed.

Table 1: Performance Analysis of the Hybrid Scenari

Model	Root Means Square Error (RMSE)	R-Squared	Mean Square Error (MSE)	Mean Absolute Error (MAE)	Prediction Speed (obs/sec)	Training Time (Sec)	Minimum Leaf Size
Fine Tree	1.23e-08	0.96	2e-08	6000	8200	0.84167	4
Coarse Tree	2.27e-08	0.88	5.15e-16	1.83e-08	3800	3.03	36
Medium Tree	1.42e-08	0.95	2.02e-16	1.19e-08	3800	3.23	12
Optimizable Tree	1.42e-09	0.95	2.02e-16	1.19e-08	12000	20.47	12

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