Deep Learning-based Beamforming Approach Incorporating Linear Antenna Arrays

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Abstract — This research delves into exploring machine learning and deep learning techniques relied upon in antenna design processes. First, the general concepts of machine learning and deep learning are introduced. Then, the focus shifts to various antenna applications, such as those relying on millimeter waves. The feasibility of employing antennas in this band is examined and compared with conventional methods, emphasizing the acceleration of the antenna design process, reduction in the number of simulations, and improved computational efficiency. The proposed method is a low-complexity approach which avoids the need for eigenvalue decomposition, the procedure for computing the entire matrix inversion, as well as incorporating signal and interference correlation matrices in the weight optimization process. The experimental results clearly demonstrate that the proposed method outperforms the compared beamformers by achieving a better signal-to-interference ratio.

Keywords — adaptive beamforming, antenna arrays, convolutional neural network

1. Introduction

Machine learning (ML) has revolutionized various research fields and applications over the past few decades, bringing about significant progress in automating everyday tasks and providing valuable insights across various scientific research and design fields, with design and optimization of antennas and beamforming techniques included. Beamforming is a signal processing method employed to concentrate electromagnetic waves by utilizing an array of aerials aimed at a specific direction. Its application spans diverse engineering fields, including radar, sonar, acoustics, astronomy, seismology, medical imaging, and communications.

The emergence of multi-antenna technologies, particularly in radar and communication systems, has resulted in considerable amounts of research focusing on designing beamformers by utilizing convex or non-convex optimization techniques. For example, in [1], to increase the mean data rate of a multi-antenna wireless system and implement hybrid beamforming in mmWave frequency bands, the reinforcement learning (RL) algorithm was used to speed up the process of selecting spatial beams.

In paper [2], ML techniques were employed to utilize previous beam training data, including receiver locations, nearest vehicles, and receiver sizes, to learn the optimal beam pair index. In order to conduct research on mmWave antennas, a dataset specific to these types of antennas is necessary, and its details are provided in [3]. In the past, numerous approaches were proposed to improve robustness against errors/mismatches. The authors of [4] proposed a hybrid beamforming (BF) design for the downlink connection in multiuser mmWave systems, where the number of adaptive elements (AEs) used at the base station is proportional to the user's distance, thereby optimizing the BF benefits per user. They also developed an ML framework for learning environment-aware beamforming codebooks for large-scale MIMO systems.

Article [5] presents an overview of mmWave channel concepts and discusses the classification of map-based channels. In [6], a system for future body-centric communication is introduced, utilizing commonly available non-wearable devices, such as Wi-Fi routers, network interfaces, and omnidirectional antennas. The authors of [7] provide an overview of mmWave channel models and discuss the classification of map-based channels. Papers [8], [9] describe a terahertz DL computing tomography (CT) system capable of visualizing hidden objects using various material systems. Article [10] presents a DL-based path relied upon to simplify feasible beam hopping (BH) in multibeam satellite systems. It provides a comprehensive description of ML, collector and relay designs. A machine learning-based hybrid framework for propagating both aleatory and epistemic uncertainties in antenna design is proposed in [11].

In paper [12], a neural network based on the delay locked loop (DLL) is established in GPS receivers to reduce multipath interference. In the study conducted in [13], the focus was on addressing the issue of beam squint in reconfigurable intelligent surface (RIS)-aided wideband millimeter wave (mmWave) communications. RIS, being inherently passive, requires uniform phase shifts across all its elements for the entire spectrum. However, in wideband scenarios, distinct path phases induced by beam squint necessitate different phase shifts for different frequencies. This contradiction poses a significant challenge affecting the system's performance, especially considering the large number of elements in RIS and the potentially wide bandwidth of wideband mmWave communications, which can reach several GHz.

To reduce the amount of hardware required and to mitigate cost, power, and area in mmWave massive MIMO systems, hybrid (analog and digital) beamforming has been proposed. Study [14] presents a technique that employs an ML algorithm for offline training to understand the features of mmWave channels. This learning aids in online beam selection, thus resulting in a substantial reduction in overhead without compromising beamforming performance. This framework incorporates codebook-based beam selection and a local learning-based clustering algorithm with feature selection (LLC-fs). Simulation are conducted to validate the performance of the proposed method across three dimensions: scalability, robustness, and compatibility. The authors of [15] introduce a DL approach based on ResNeSt for beamforming in 5G massive multiple-input multiple-output (MIMO) systems. The use of the ResNeSt-based DL method aims to streamline and enhance the beamforming process, thus leading to improved performance and efficiency in 5G and beyond communication networks.

2. Deep Learning-based Beamforming

Smart antennas are arrays of radiators that are able to steer their beams and utilize signal processing algorithms to separate signals coming from multiple sources. One of their key features consists in implementing adaptive beamforming (ABF) techniques [16] which enable them to achieve the highest signal-to-interference-plus-noise ratio (SINR). When dealing with signals with a fixed direction of arrival (DOA), fixed array weights are used (referred to as fixed beamforming). However, in dynamic environments, where the DOAs of incoming signals change over time, the array weights need to be recalculated continuously (these are referred to as ABF). Figure 1 illustrates the general structure of a beamformer, assuming that multiple signals are received by the antenna array from different DOAs.

In the theoretical framework of the beamforming (BF) problem, a linear array composed of m ideal point sources (where $m > N$) is utilized to receive a desired signal (DIS) denoted as s_0 and N undesired interfering signals (UISs) represented as s_n $(n = 1, \ldots, N)$ at a specific frequency f, corresponding to a wavelength λ [1], [2]. Each signal s_n $(n = 0, 1, \ldots, N)$ possesses a DoA characterized by a polar angle θ_n $(n = 0, 1, \ldots, N)$, indicating the angle between the signal's DoA and the z-axis, commonly known as the angle of arrival (AoA). The point sources are uniformly positioned along the z-axis with a separation distance d (Fig. 2). Importantly, each source emits an omnidirectional radiation pattern and there is no interaction or coupling between any two sources. The radiation pattern of such an array is expressed by means of the antenna array factor [17]:

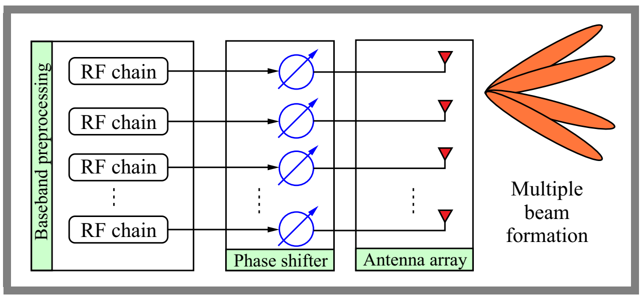

Fig. 1. Beamforming duality techniques using per-antenna power constraints for a fully connected array.

$$AF(\theta) = \sum_{m=0}^{M} W_m^* e^{j\beta Z_m \cos\theta} = W^H a(\theta) \ . \tag{1}$$

In this scenario, I_m $(m = 1, \ldots, M)$ denotes the currents applied to the point sources, β represents the wavenumber in free space $(\beta = 2\pi/\lambda)$, Z_m $(m = 1, \ldots, M)$ indicates the positions of the sources along the z-axis, and θ is the polar angle that determines the direction of observation.

As the array operates in receiving mode, currents I_m act as multipliers of signals x_m generated by the point sources, due to the reception of the desired signal (DIS) and N unwanted interfering signals (UISs). To simplify calculations in the complex frequency domain, it is convenient to use a matrix notation by considering $I_m = W_m^*$, where W_m represents the weight associated with the complex conjugate value of the m-th current. Therefore, Eq. (1) can be transformed into the following form:

$$W = [W_1, W_2, \ldots, W_M]^T \ . \tag{2}$$

Now, steering vector [17], in form of θ, can be written as:

$$a(\theta) = \left[e^{j\beta Z_1 \cos\theta}, \ldots, e^{j\beta Z_m \cos\theta}\right]^T \ . \tag{3}$$

An example of beamforming technique using deep learning is illustrated by Algorithm 1.

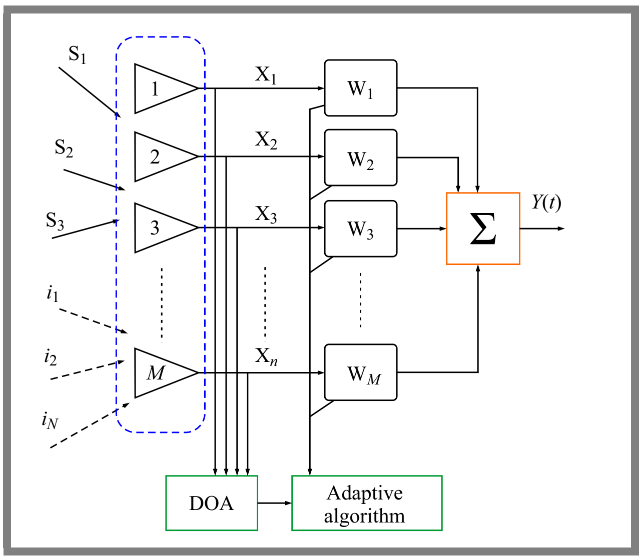

Fig. 2. Antenna system consisting of M radiators, with N separation distances.

Algorithm 1. Beam index optimization using deep learning

Input: Eigen-beam set A, pre-defined codebook W, and parameters of search: $\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4, \alpha, \beta, \gamma$
Output: Optimal beam index Z
Start

1: Create a beam space map based on codebook W to define the operating region of the Rosenbrock search
2: Capture the received power by utilizing beams from the eigen-beam set and record it onto the beam space map
3: Perform a search for local optima in the map ($clocal$)
4: Use the location indices of the clocal optima as the initial solutions $s(c) = [h(c), v(c)]$, for $c \in 1, 2, \ldots, clocal$
5: **for** each local optimal c from 1 to $clocal$ **do**
6: Set the start point $y(1) = s(c)$ and initialize the Rosenbrock search
7: Perform the Rosenbrock search to obtain temporary solution s_c
8: **end for**
9: Determine the solution with the maximum value of the objective function $f(s_c)$, denoted as s_{opt}, among all the temporary solutions s_c for $c \in 1, 2, \ldots, clocal$. Operation $f(\cdot)$ maps the location indices to the received power collected by the corresponding beams
10: Optimal beam index p_{opt} corresponds to the location index of s_{opt} in the beam space map
11: Return the optimal beam index p_{opt}

End

2.1. Deep Mask-based Beamforming

In such applications as automatic speech recognizers (ASRs) [16], where the signal-to-noise ratio (SNR) is low, conventional adaptive beamforming (ABF) algorithms fall short in terms of their effectiveness when compared with a deep neural network-based mask estimator. Although ABF is commonly used as a preprocessor for speech recognition [18], it cannot match the capabilities of a DNN-based mask estimator.

To address this, a solution is presented in [19] which combines a deep feedforward neural network (FNN) with the MVDR beamforming algorithm. This approach utilizes the ideal ratio mask (IRM) followed by the ideal binary mask (IBM). Thanks to this, the performance of the MVDR beamformer is improved. Effectiveness of the proposed algorithm is evaluated using the sentence error rate (SER) metric, which demonstrates its usefulness in low SNR scenarios.

2.2. Massive MIMO Beamforming Using Deep Neural Networks

Integration of deep neural networks (DNNs) with massive MIMO systems has shown significant advantages. For example, in [8], a deep adversarial reinforcement learning model is introduced which greatly enhances the performance and capacity of massive MIMO beamforming. This is achieved by determining the amplitude and phase shift of each antenna element through a small set of training data. However, as the number of antennas increases and the potential number of users becomes variable, the training complexity in massive MIMO beamforming grows as well. This limits the ability of DNNs to achieve optimal performance.

To address this challenge, paper [19] introduces a combined supervised and unsupervised learning-based convolutional multilayer neural network (CMBNN). This approach minimizes training complexity and achieves systematic risk minimization (SRM) with high speed and efficiency, accommodating varying user numbers. Additionally, convolutional neural networks (CNNs) have made significant contributions to massive MIMO. A deep CNN is utilized for beam space separation (BSS), effectively classifying narrow and highly focused beams with high reliability and low complexity characteristics.

The two CNNs enable accurate and efficient specification of transceiver locations, outperforming deterministic methods in terms of time and accuracy, as shown in Fig. 2. CNNs have also proved to be successful in power allocation, uplink beam forming prediction, and SRM, offering performance comparable to that of conventional methods. Moreover, DL-assisted calibration state diagnosis of massive antenna arrays is conducted to prevent potential deviations and enhance the downlink pilot matrix. Then, the deep residual learning approach is adopted to implicitly learn the residual noise for recovering channel coefficients from the noisy pilot-based observations.

3. Proposed Approach

An antenna with M elements with N desired signal interference signals architecture with an adaptive algorithm is proposed (Fig. 3). Optimization of a microstrip linear array is performed for the resonant frequency of 60 GHz and an 850 MHz bandwidth, utilizing 16 microstrip rectangular patches ($M = 16$) that are uniformly spaced at a fixed distance of $d = \lambda/2$, where λ represents the wavelength. The microstrip patches are fabricated on the Rogers RT/Duroid 5880 substrate with a thickness of $h = 1.65$ mm and an electric permittivity of $\varepsilon_r = 2.2$. The thickness of the copper cladding employed in the CST simulation for modeling the microstrip patches and the ground plane on both sides of the substrate is assumed to be 40 μm.

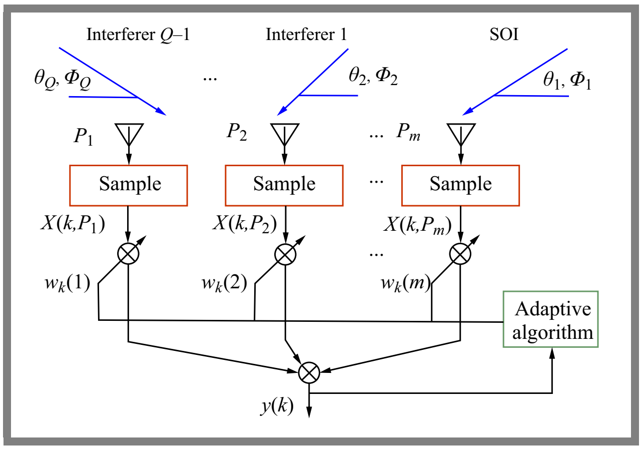

Fig. 3. Antenna elements with desired and interference signals.

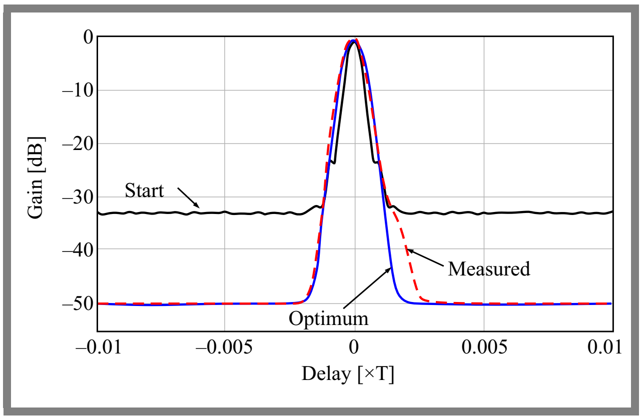

Fig. 4. Reflection coefficient of the proposed antenna featuring CNN-based beamforming with compact size.

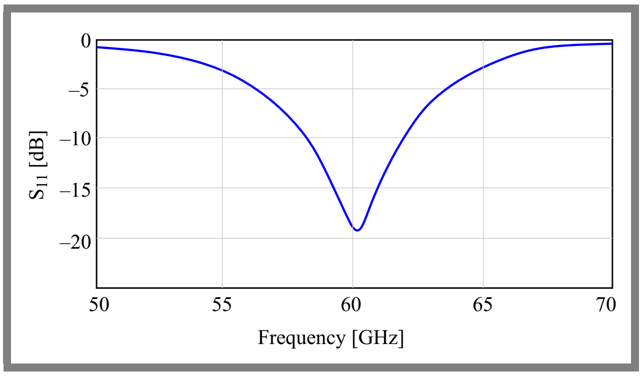

Fig. 5. Benchmark line as a possible SOI steering vector.

Figure 3 shows antenna elements with the desired signal and D interference signals. In practical applications, antenna arrays are often designed to fulfill specific requirements, such as impedance matching. Therefore, it is desirable to design an array with microstrip elements that are matched to 50 Ω – a value similar to that of off-the-shelf microstrip arrays. To achieve this, the inset-feeding technique is applied while designing the microstrip elements. This technique facilitates impedance matching for the array's elements.

In practice, antenna arrays can have more elements, may form different shapes (e.g. planar arrays) and may utilize more complex beamforming techniques. The goal is to optimize the array's performance for specific applications, such as radar or satellite tracking. Visualizing antenna arrays is often done through radiation pattern plots, which show the directionality and gain of the antenna system. The design is specifically tailored to operate at a resonant frequency of 60 GHz, as depicted in Fig. 4, which shows the S_{11} reflection coefficient of the proposed antenna against the frequency band.

The deviation observed in Fig. 5 pertains to an extra lower shoulder lobe which appears in positive delay. This additional lobe is likely a result of the absence of gain flatness within the spectrum analyzer's receive bandwidth.

Efficiency of the wireless communication link and overall system quality are significantly influenced by the performance of the sensor/antenna in the front-end stage. Therefore, in the proposed design, a patch antenna with a circular shape and resonant frequency of 60 GHz has been developed.

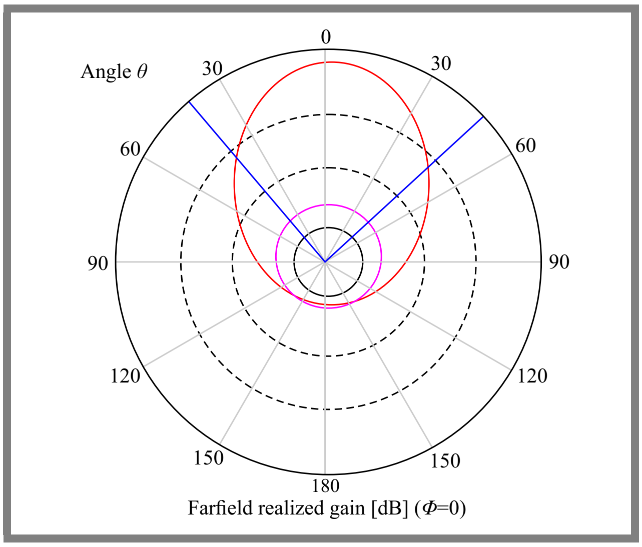

Fig. 6. 2D radiation pattern of the proposed beamforming.

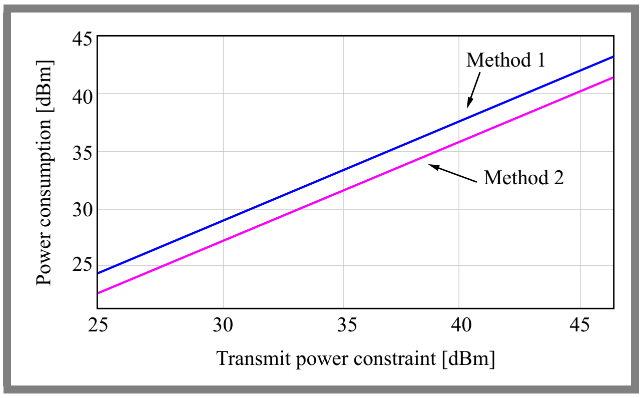

Fig. 7. Average beamformer output transmit power constraint versus consumption power in dB with $\theta = [45°, 57°]$ and $T = 110$.

The simulation of 2D radiation patterns of the proposed antenna is visualized in Fig. 6. The realized gain process good performance of the system. The design features low back lobes and achieves a directivity of 6.82 dBi. Figure 7 illustrates the average beamformer output transmit power constraint versus consumption power for $\theta = [45°, 57°]$ and $T = 110$.

4. Results and Discussion

In order to validate the effectiveness of the proposed method, the weight vectors are calculated using various signal reception scenarios. Each scenario involves a desired signal (DIS) and a predetermined number N of undesired interfering signals (UISs), all simultaneously received by the antenna array from different DoAs. It is worth noting that the N of UISs corresponds to the sequential number of the scenario.

The selection of the AoAs is limited to the angular sector [30°, 150°] as the assumption E_θ , E_ϕ holds true within this sector. To analyze the spatial distribution of the incoming signals, the angular distance Δ_θ between any two adjacent signals, i.e. between UISs or between the DIS and any UIS, is not randomly chosen but is assigned a specific value of 6°, 8°, or 10°. Consequently, in each N-th scenario, a multitude of combinations consisting of $N+1$ AoAs may be generated.

5. Conclusion

By implementing the proposed AI modification outlined in this article, it becomes possible to integrate the distinctive non-isotropic radiation pattern generated by the specific type of elements comprising the antenna array, simultaneously accounting for the mutual coupling between these array elements, into traditional beamformers. AI-based methods are characterized by impressive performance, especially in scenarios where traditional techniques may fall short. An inherent advantage of AI approaches lies in their ability to tackle large-scale, non-linear problems that involve a multitude of variables.

In contrast, traditional signal processing algorithms tend to excel in local contexts with a limited number of variables. Moreover, AI ensures robust performance even in the presence of noise and multipath effects, which may be a source of difficulties for traditional methods, preventing them from achieving satisfactory SNR or bit error rate performance levels.

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