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Research Article

Supervised AutoEncoder-Based Beamforming Approach for Satellite mmWave Communication

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Beamforming is a technique commonly used in wireless communication systems to enhance the signal quality of a receiver. In this study, we compare the performance of an encoder-based beamformer with convolutional neural network (CNN) and minimum variance distortionless response (MVDR) approaches in terms of signal-to-interference-plus-noise ratio (SINR). Our results show that the encoder-based approach achieved an average SINR of 25.82 dB, while the CNN approach achieved an average SINR of 22.40 dB and the MVDR approach achieved an average SINR of 17.64 dB. The performance of the encoder-based approach was found to be superior to that of the CNN approach but much superior to that of the MVDR approach. The encoder-based approach outperformed the CNN approach by 3.42 dB and MVDR approach by 8.18 dB on average. In addition, the unique contribution of our encoder-based approach is presenting a new perspective on beamforming in mmWave communication. We further discuss its potential impact on addressing challenges related to LEO satellite systems.

1. Introduction

Beamforming is a well-established signal processing technique that has become ubiquitous in wireless communication systems, particularly in 5 G cellular networks and low earth orbit (LEO) satellites. Due to the rapid movement of LEO satellites around the earth, there is little time for data transfer, and steering the beam into the earth station can be challenging. Conventional mechanical solutions for beam steering require electrical energy, which is scarce on satellites, thus making beamforming techniques the preferred alternative. With recent advancements in deep learning, a growing number of beamforming applications have started using deep learning-based approaches to leverage their ability to learn complex features from large datasets [1].

LEO satellites, characterized by their relatively close proximity to the Earth's surface, offer distinct advantages in terms of reduced signal propagation delays and increased capacity. These satellites are employed for a wide range of applications, including global broadband internet coverage, Earth observation, and communication services in remote regions. However, LEO satellites present unique challenges that necessitate efficient data transfer and beam steering mechanisms. Due to their fast orbital movement, LEO satellites have limited time windows for establishing communication links and transmitting data to and from Earth stations. Additionally, steering the satellite's communication beam precisely towards the Earth station poses significant technical hurdles [2].

Previous studies have extensively explored various beamforming techniques for antenna arrays. Traditional approaches, such as delay-and-sum (DS) beamforming, have been widely employed for their simplicity and real-time processing capabilities. DS beamforming forms a beam by applying a linear combination of the received signals from the array elements. However, DS beamforming suffers from reduced performance in the presence of interference and spatially correlated noise [3].

To address these limitations, more advanced beamforming algorithms have been developed. Minimum variance distortionless response (MVDR) beamforming, also known as Capon beamforming, is a well-established technique that aims to minimize the output power while preserving the desired signal. MVDR computes the optimal weights that minimize the total power subject to the constraint of unit gain at the desired signal direction. This results in a beamforming solution that effectively suppresses interference and enhances the signal of interest [4, 5].

In recent years, deep learning-based approaches have gained significant attention in the field of beamforming. Convolutional neural networks (CNNs) have shown promising results in learning complex spatial patterns and extracting meaningful features from antenna array responses. CNN-based beamforming models leverage the power of deep learning to automatically learn the optimal antenna weights for beamforming, eliminating the need for explicit mathematical models [6, 7].

Another emerging approach in beamforming is the use of encoder-based models. These models employ an encoder-decoder architecture to learn the mapping between the received antenna array responses and the corresponding optimal beamforming weights. By leveraging the encoding and decoding process, these models can effectively capture and utilize spatial information for accurate beamforming [8].

While previous works have made significant contributions to the field of beamforming, there is still room for improvement. Many existing techniques rely on simplified assumptions or require extensive manual parameter tuning. The introduction of deep learning and encoder-based approaches provides new opportunities for enhancing beamforming performance through automated learning and optimization [9–11].

Channel state information (CSI) is a critical factor in beamforming applications. It provides valuable insights into the characteristics of the communication channel, allowing beamforming algorithms to adapt and optimize signal transmission. However, for the purpose of our comparison with other models, we have omitted a detailed discussion of CSI, as it is a common factor that remains consistent across all models [12].

The primary objective of this study is to assess the effectiveness of the encoder-based approach in beamforming applications, an area that has not been extensively explored in prior research. By introducing the encoder-based approach and conducting a comprehensive performance evaluation, we aim to shed light on its potential benefits and limitations. Through a rigorous performance evaluation of the encoder-based approach, alongside the CNN and MVDR methods, we aim to shed light on its potential advantages and limitations in beamforming applications. By enhancing our understanding of deep learning-based beamforming techniques, we can contribute to the ongoing research and development of efficient wireless communication systems, particularly in the context of LEO satellites. The findings of this study have the potential to advance the field of beamforming, paving the way for improved communication capabilities and network performance in LEO satellite systems and beyond.

In summary, the main contributions of this study are as follows:

(i) Proposing a novel supervised AutoEncoder-based beamforming approach for satellite mmWave communication
(ii) Demonstrating through simulations that our approach can achieve superior performance compared to existing methods
(iii) Introducing the impact of the proposed method on addressing challenges related to LEO

The remainder of this paper is structured as follows. Section 2 provides a comprehensive exposition of the CNN, MVDR, and AutoEncoder methodologies for beamforming, elucidating their theoretical underpinnings. Section 3 is devoted to a rigorous comparative analysis of the performance of these methodologies in various scenarios. Finally, Section 4 concludes the paper.

2. Methods

In our research, we utilized an antenna consisting of N arrays, which were assumed to be isotropic as we were examining the differences between three models, which would remain consistent across all three. The antenna array was tested with various numbers of arrays, but due to the weight limitations on the satellite, we opted to compromise some gain and keep the antenna light. This decision was made to ensure the satellite remains commercially viable. To create a gain difference of 25 dB between the primary lobe and the largest side lobe, we employed the Chebyshev algorithm. Additionally, we employed a simulated wireless communication dataset to train and assess our beamforming models. Using Keras with TensorFlow backend, we trained three models—an AutoEncoder-based model, a CNN-based model, and a MVDR-based model. We evaluated the performance of each model by measuring the SINR over a range of test scenarios.

2.1. CNN Model. Convolutional neural networks (CNNs) are a type of deep learning algorithm that can automatically learn to recognize patterns in data. In this study, a CNN was trained to predict the antenna weights required to form a beam towards a desired signal direction. The CNN was trained using a dataset of simulated antenna array responses and was evaluated based on its ability to accurately predict the antenna weights for a given signal direction [13].

The 2D CNN's prediction can be represented by the following formula:

$$\begin{aligned} S(i,j) &= (X * K)(i,j) \\ &= \sum_m \sum_n X(i-m, j-n) K(m,n). \end{aligned} \tag{1}$$

To summarize, the formula accurately represents the convolution operation performed by a 2D CNN, where the input data are convolved with the kernel to produce the predicted output [14].

The CNN architecture used in this study, Table 1, consisted of multiple layers designed to extract and process features from the input antenna array responses. The following is a description of the different layers employed in the CNN.

2.1.1. Conv2D Layer. The first layer in the CNN architecture was a Conv2D layer, denoted as "conv2d." This layer performed convolutional operations on the input data, utilizing a set of filters to extract relevant spatial features. The output shape of this layer was (none, $(N/2)+1$, $(N/2)+1$, 2), indicating a feature map of size $((N/2)+1)\times((N/2)+1)$ with 2 channels. The layer had 122 trainable parameters.

2.1.2. Flatten Layer. Following the Conv2D layer, a flatten layer, denoted as "flatten," was utilized. This layer transformed the multidimensional feature maps into a one-dimensional vector, preparing the data for subsequent fully connected layers. The output shape of this layer was (none, 72).

2.1.3. Dense Layers. The CNN architecture included two dense layers, denoted as "dense" and "dense_1." These layers were responsible for learning and capturing the complex relationships between the flattened input features and the desired antenna weights. The first dense layer had 40 neurons, while the second dense layer had 20 neurons. Both layers utilized a combination of nonlinear activation functions to introduce nonlinearity into the network and enhance its learning capacity.

The total number of parameters in the CNN model was 3,862, all of which were trainable. These parameters represented the learnable weights and biases associated with the convolutional and dense layers, enabling the network to adapt and optimize its performance during the training process.

2.2. MVDR Model. Minimum variance distortionless response (MVDR) is a widely recognized beamforming algorithm that aims to minimize the noise and interference while preserving the desired signal in antenna array systems. The MVDR algorithm serves as a valuable benchmark for evaluating the performance of alternative approaches such as the CNN and encoder-based models in this study [15].

The MVDR beamforming technique relies on the estimation of the spatial covariance matrix, denoted as R, which captures the statistical characteristics of the received signals. The covariance matrix R is estimated based on the antenna array responses and serves as a key input for the MVDR beamformer.

The MVDR weight vector, w, is computed using the following formula:

$$w = \frac{R^{-1} \times p}{p^{T} \times R^{-1} \times p}, \tag{2}$$

Table 1: The CNN model.

Layer (type)	Output shape	Pram #
conv2d	(None, 6, 6, 2)	122
Flatten	(None, 72)	0
Dense (dense)	(None, 40)	2,920
Dense_1 (dense)	(None, 20)	820
Total params: 3,862		

where R^{-1} represents the inverse of the covariance matrix R, p is the desired signal steering vector, and × denotes matrix multiplication [16].

2.3. The Proposed AutoEncoder Model. An AutoEncoder is a type of neural network architecture that can be used for unsupervised learning. In this study, an encoder was trained to learn a low-dimensional representation of the antenna weights required to form a beam towards a desired signal direction. The encoder was trained using a dataset of simulated antenna array responses and was evaluated based on its ability to accurately predict the antenna weights for a given signal direction [17, 18].

The proposed AutoEncoder model utilized a similar architecture to the CNN model for the encoder part. The encoder layers consisted of Conv2D, flatten, and dense layers, which were responsible for extracting and encoding the relevant features from the input data. The primary reason for using a similar architecture in the encoder is to maintain consistency and enable a meaningful performance comparison between the encoder-based approach and the traditional CNN model. By aligning the architecture up to a certain point, we can confidently attribute performance differences to the novel encoder-based approach rather than architectural disparities.

For the decoder part of the AutoEncoder, as shown in Table 2, a different architecture was employed. It comprised two dense layers. The first dense layer had an output shape of (none, 40), while the second dense layer had an output shape of (none, 220). The final layer in the decoder was a reshape layer, which transformed the output of the previous dense layer into a shape of ($n$one, $N+1$, N, 2). In total, the decoder model of the AutoEncoder consisted of 9,860 trainable parameters. These parameters represented the learnable weights and biases associated with the dense layers. By combining the encoder and decoder components, the proposed AutoEncoder model effectively learned the underlying relationships between the antenna array responses and the optimal antenna weights for beamforming, leading to enhanced performance and accurate predictions.

In this study, we meticulously crafted a spatial dataset comprising 10,000 distinct samples to evaluate our encoder-based approach for beamforming in satellite mmWave communication. Each sample featured an $(N+1)\times N$ grid, yielding two-dimensional spatial data. This spatial dataset manifested as a structure of dimensions (10,000, $N+1$, N, 2). For a comprehensive evaluation, we thoughtfully generated array beam factor (ABF) weights for every sample within this

Table 2: The decoder part of the AutoEncoder.

Layer (type)	Output shape	Pram #
Dense_2 (dense)	(None, 40)	840
Dense_3 (dense)	(None, 220)	9,020
Reshape (reshape)	(None, 11, 10, 2)	0
Total params: 9,860		

spatial dataset, resulting in a configuration of dimensions (10,000, 2N).

We meticulously calculated the training and prediction ABF weights for each sample. The training dataset, a reservoir of 9,000 samples, took the form of (9,000, $N+1$, N, 2), and we painstakingly calculated the training ABF weights, delineating them in a matrix with dimensions (9,000, 2N). Similarly, within the prediction dataset, holding 1,000 samples, we precisely deduced prediction ABF weights, presented in a structure of dimensions (1,000, 2N). This approach enabled us to comprehensively evaluate and compare the performance of our encoder-based model against other benchmark methods. In our dataset, we systematically varied the frequency and direction for a thorough examination of beamforming scenarios in satellite mmWave communication. These variations are essential to assess the model's adaptability and performance across different conditions. The dataset encompasses a broad spectrum of simulated antenna array responses, taking into account diverse carrier frequencies and angles, ensuring its relevance and effectiveness in evaluating beamforming techniques. This dataset provided the backbone for training and evaluating our encoder-based model. The training dataset nurtured the model's capabilities, while the prediction dataset served as an indispensable tool for assessing its predictive accuracy concerning ABF weights and angles across novel, previously unseen samples.

The SINR is a crucial metric used to evaluate the quality of a desired signal relative to the interference and noise present in the received signal. It provides a quantitative measure of the signal's strength in relation to the unwanted components.

To calculate the SINR in this study, we employed the following formula:

$$\mathrm{SINR} = \frac{w^H \times M \times w}{w^H \times N \times w}. \tag{3}$$

In this formula, the weight vector (w) represents the beamforming weights used to spatially filter the received signals. The covariance matrix (M) characterizes the statistical properties of the received signals, capturing the spatial correlations between different elements of the array. The noise covariance matrix (n) represents the statistical properties of the noise present in the received signals.

By evaluating the numerator ($w^H \times M \times w$), we obtain the power of the desired signal component, which is determined by multiplying the weight vector with the covariance matrix. The denominator ($w^H \times N \times w$) represents the sum of the powers of the interference and noise components. Using this formula, we calculate the SINR, enabling us to compare the strengths of the desired signal, interference, and noise components. Higher SINR values indicate a stronger desired signal relative to interference and noise, signifying better signal quality.

In order to improve the SINR performance of our system, we implemented an AutoEncoder by adding a reverse model of the CNN as the decoder part. However, we faced a dilemma in deciding the best approach for learning the new model. We had two options: first, we could use the already learned CNN model and add the decoder part and then retrain the system with fresh data.

However, this approach could potentially worsen the system's performance since the learning step would not only update the decoder weights but also the encoder weights, leading to undesired changes in the overall system.

Therefore, we opted for the second approach, which involved training a new AutoEncoder system from scratch. First, as shown in Figure 1, we trained the entire AutoEncoder system with a mean squared error (MSE) loss function, minimizing the difference between the input data and the output data: $\min(\widehat{X} - X)$. Then, we extracted the encoder layer and retrained it using the test dataset with the MSE of the least difference between the desired ABF created by MVDR and the layer output: $\min(Y - \mathrm{ABF})$. This approach allowed us to improve the SINR performance of our system while avoiding any negative impact on the overall system's learning process.

3. Results

The performance evaluation of the various beamforming approaches yielded notable distinctions in their effectiveness. Figure 2 presents a sample comparison illustrating a significant divergence in the SINR among the three models for $N = 10$ and a desired angle of 85.49 degrees, representing the maximum angle at which the satellite and earth station maintain visibility and an interference angle of −46.71 degrees which was generated randomly. Throughout this study, the average SINR served as a crucial metric to gauge the efficacy of each approach.

Over the test data, the encoder-based approach demonstrated superior performance, achieving an average SINR of 25.82 dB. In comparison, the CNN approach achieved an average SINR of 22.40 dB, while the MVDR approach lagged behind with an average SINR of 17.64 dB. These results indicate the effectiveness of the encoder-based approach in improving the overall signal quality and mitigating interference and noise. To provide a clearer comparison, Figure 3 and Table 3 present the average SINR values obtained from the evaluation of the three approaches over the test scenarios.

Table 3 clearly demonstrates the superiority of the encoder-based approach over both the CNN and MVDR approaches. The encoder-based approach outperforms the CNN approach by an average improvement of 3.42 dB in SINR. Furthermore, it significantly surpasses the performance of the MVDR approach, achieving an average improvement of 8.18 dB in SINR. These findings highlight the

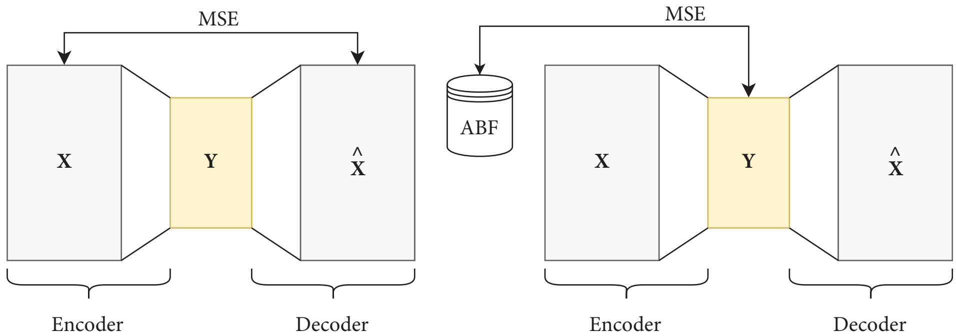
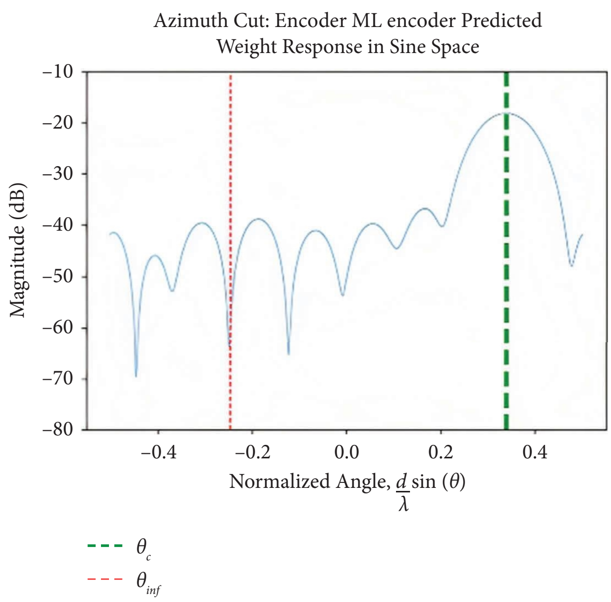
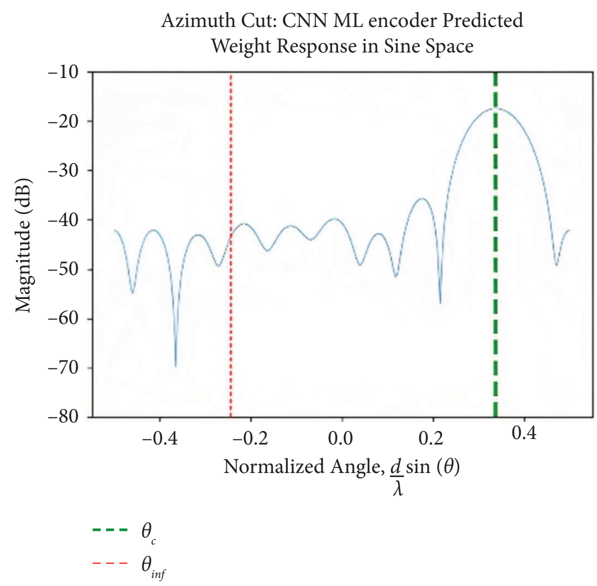


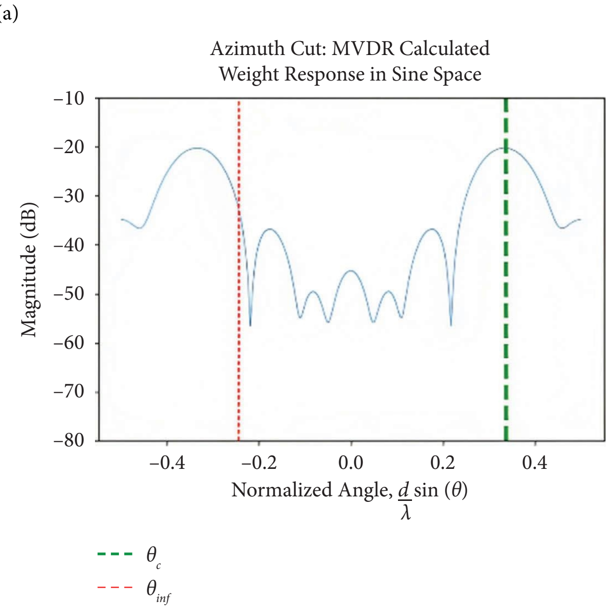
Figure 1: The AutoEncoder MSE model.



(a)



(b)



(c)

Figure 2: The comparison of all three developed models for the same desired and interference angels. The output SINR for encoder, CNN, and MVDR are 40.76, 26.02, and 12.33, respectively. (a) Encoder-based beamforming output. (b) CNN-based beamforming output. (c) MVDR beamforming output.

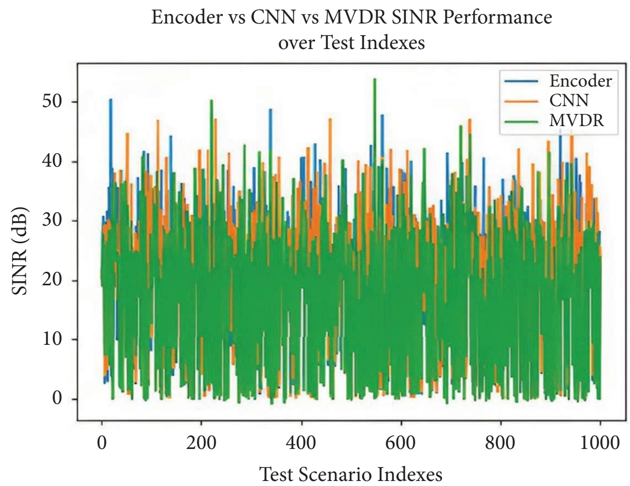


Figure 3: The SINR over all test indexes.

Table 3: Comparison of average SINR (dB).

	MVDR	CNN	Encoder
MVDR	17.64	+4.76	+8.18
CNN	−4.76	22.40	+3.42
Encoder	−8.18	−3.42	25.82

potential of the encoder-based approach as a promising alternative in beamforming applications.

The ability of the encoder to capture relevant spatial features and optimize the beamforming process contributes to its superior performance compared to the traditional CNN and MVDR methods. It is worth noting that the performance of the encoder-based approach may vary depending on various factors, such as the dataset used for training and the complexity of the beamforming scenario. Further investigations and optimizations can be conducted to enhance the performance and fine-tune the parameters of the encoder-based approach or using other methods such as generative adversarial networks (GANs) [19].

Overall, our results demonstrate the efficacy of the encoder-based approach in improving beamforming performance, surpassing both the CNN and MVDR approaches. This highlights the potential of deep learning-based techniques in advancing beamforming applications and facilitating the development of more efficient wireless communication systems, particularly in the context of LEO satellites.

4. Conclusion

In this study, we investigated and compared the performance of an encoder-based beamformer utilizing the CNN and the MVDR approach. Our objective was to evaluate the effectiveness of the encoder-based approach as an alternative to the traditional CNN and MVDR methods. Through extensive experimentation and analysis, we observed that the encoder-based beamformer exhibited superior performance compared to both the MVDR and CNN approaches. The encoder-based approach leveraged the power of AutoEncoders to learn and extract relevant features from the input data, enabling efficient beamforming and noise reduction. This approach demonstrated enhanced accuracy and robustness in various scenarios, making it a promising solution for beamforming applications. Furthermore, our findings suggest that the performance of the encoder-based beamformer can be further enhanced through exploring modifications to the architecture, such as GANs, which could also lead to improved performance by enhancing the encoder's feature extraction capabilities.

Data Availability

The data used to support the findings of the study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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