A Study of Angle of Arrival Estimation of a RF Signal with FPGA Acceleration

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***Abstract*—This paper presents a comprehensive study on angle of arrival (AoA) estimation techniques for wireless communication systems. In particular, signal processing techniques including Multiple Signal Classification (MUSIC) and Estimation of Signal Parameters via Rotational Invariance Techniques (ESPRIT), as well as machine learning (ML) techniques such as artificial neural networks (ANNs) and convolutional neural networks (CNNs), are evaluated. The performance of these techniques is compared using both synthetic and over-the-air (OTA) test scenarios. Additionally, the impact of multipath fading on the performance of these techniques is investigated. Experimental results show that while the MUSIC algorithm exhibits superior accuracy in synthetic scenarios, it suffers from performance degradation in the presence of multipath fading. On the other hand, ML algorithms demonstrate robustness and stability under varying conditions, albeit with a slightly higher error rate compared to simulations. Furthermore, suggestions for improving the ML algorithm in OTA scenarios are discussed, including updates to the synthesis model and the incorporation of OTA samples for training.**

I. Introduction

Angle of Arrival (AoA) estimation is a well-established technique used in various fields to determine the direction from which a signal or wavefront arrives at a receiver or antenna array. It has been extensively applied in wireless communication, radar systems, sonar, navigation, and other areas that require spatial awareness and signal localization. AoA estimation enables the localization of sources, beamforming, direction finding, target tracking, and spatial multiplexing, among other applications.

However, AoA estimation also presents certain challenges and problems. One of the primary issues is the presence of noise and interference in the received signals. Noise can degrade the accuracy of AoA estimation, making it difficult to extract reliable angle measurements. Interference from other sources or multipath effects can further complicate the estimation process by introducing additional signal components that need to be resolved accurately. These factors can result in errors and uncertainties in the estimated angles, affecting the performance of systems that rely on AoA information.

Another challenge in AoA estimation arises from the hardware limitations of antenna arrays. The accuracy of AoA estimation depends on the characteristics and arrangement of the antenna elements. Imperfections in the array, such as mutual coupling between elements, non-ideal radiation patterns, and limited dynamic range, can introduce distortions and inaccuracies in the received signals. These imperfections need to be carefully accounted for and compensated to ensure accurate AoA estimation.

In recent years, efforts have been made to address these challenges and improve the performance of AoA estimation. Advanced signal processing algorithms, machine learning techniques, and adaptive array designs have been developed to mitigate the effects of noise, interference, and hardware limitations. The state-of-the-art signal processing methods for finding the AoA of a wireless transmitter is the MUSIC algorithm [1]–[4]. This is done by finding the covariance matrix of an input antenna array, then performing eigenvalue decomposition on it. The MUSIC algorithm reveals peaks at each angle a signal was received. This method can be used to find the locations of multiple transmitters. MUSIC provides high angular resolution while operating at low SNR levels. However, it comes at the cost of requiring full prior knowledge of the number of sources in the environment.

Many other techniques of estimating AOA, inspired by MUSIC, use the covariance matrix as the input into deep learning models, such as convolutional neural networks (CNNs) [1], [3], artificial neural networks (ANNs) [2], [5], and multilayer perceptrons (MLPs) [6].

In this paper, we tested and implemented various AOA estimation techniques. We examined signal processing methods such as MUSIC and ESPRIT, as well as machine learning techniques like ANN and CNN. The performance of using IQ samples directly versus using the covariance matrix of IQ samples was compared for machine learning.

The rest of the paper is organized as follows: Section II surveys AoA estimation in literature; Section III introduces existing machine learning datasets and our synthetic datasets; Section IV discusses our evaluation processes and results followed by the conclusion in Section V.

II. Survey of AoA

Estimating the AoA has been extensively studied in the literature, with a focus on acoustic signals rather than Radio Frequency (RF) signals [7] [8]. Acoustic AoA estimation has garnered more attention, similar to the prevalence of literature on image-based tasks in the field of CNNs. In this review, we explore two main surveys on acoustic AoA estimation: the first survey [7] provides comprehensive information on AoA or Sound Source Localization (SSL), while the second survey [8] focuses on AoA or Acoustic Direction Finding (ADF). Both surveys emphasize the application of deep learning techniques, specifically deep neural networks, for

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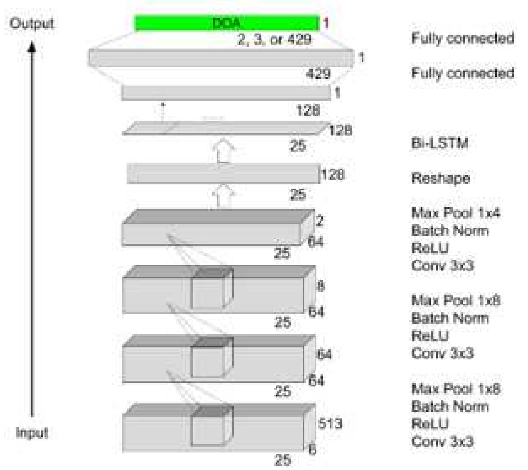
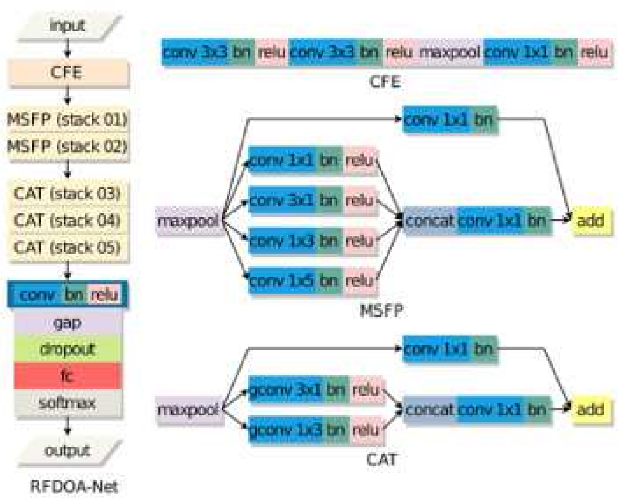
AoA estimation. Notably, the input and output of these deep neural networks consist of a covariance square matrix, where the matrix dimensions are determined by the number of receivers. The output represents either a continuous angle or a class-discrete angle. It is important to note that the same input and output configurations apply to both RF and acoustic signals, enabling a review of AoA methods for both types of signals. In terms of antenna configurations, the surveys predominantly feature linear arrays, although circular arrays are also considered.

Several machine learning architectures have been employed for AoA estimation, including the Convolutional Recurrent Neural Network (CRNN) [9] (see Fig. 1a), the inception-style network RFDOA-Net [10] (see Fig. 1b), the Fully Connected Network (FC net) [11] (see Fig. 2a), and the CNN [5] (see Fig. 2b).



(a)



(b)

Fig. 1: Network Architecture Visual Layers: (a) CRNN; (b) RFDOA-Net.

The CRNN architecture combines Long Short-Term Memory (LSTM) layers and CNN layers for AoA estimation of acoustic signals. The network input consists of a covariance matrix with a frame size, and frames are grouped into sets of 25 for the LSTM layer. The performance evaluation of this architecture employed the LOCATA dataset, with the root mean square error (RMSE) calculated across three recordings.

The RFDOA-Net architecture utilizes an inception network for AoA estimation in Unmanned Aerial Vehicle (UAV) direction finding. The network input comprises the I/Q data multiplied by the frame length and the number of receivers, specifically $2 \times 1024 \times 5$. The authors of this approach employed a linear array configuration and compared the results to the MUSIC algorithm. The performance evaluation includes RMSE and accuracy metrics.

Layer Name	Units	Output Size
Input	n/a	$[B, M^2 \cdot C]$
FC1	1024	$[B, 1024]$
Dropout1	$rate = 0.2$	$[B, 1024]$
FC2	2048	$[B, 2048]$
Dropout2	$rate = 0.2$	$[B, 2048]$
FC3	1024	$[B, 1024]$
Dropout3	$rate = 0.2$	$[B, 1024]$
FC4	512	$[B, 512]$
Dropout4	$rate = 0.2$	$[B, 512]$
Classification Head	Activation='sigmoid'	$[B, 1]$
Regression1 Head	Activation='sigmoid'	$[B, 1]$
Regression2 Head	Activation='sigmoid'	$[B, 1]$

(a)

Layer Name	Units	Output Size
Input	n/a	$[B, M, M, C]$
CNN1	512, kernel=3×3	$[B, 2, 2, 512]$
BN	n/a	$[B, 2, 2, 512]$
Activation	Activation='ReLU'	$[B, 2, 2, 512]$
MaxPool	pool size=2×2	$[B, 1, 1, 512]$
FC2	1024	$[B, 1024]$
Dropout2	$rate = 0.2$	$[B, 1024]$
FC3	1024	$[B, 1024]$
Dropout3	$rate = 0.2$	$[B, 1024]$
FC4	512	$[B, 512]$
Dropout4	$rate = 0.2$	$[B, 512]$
Classification Head	Activation='sigmoid'	$[B, 1]$
Regression1 Head	Activation='sigmoid'	$[B, 1]$
Regression2 Head	Activation='sigmoid'	$[B, 1]$

(b)

Fig. 2: Network Architecture Layers: (a) FC Net; (b) CNN.

In the same paper, the FC net and CNN architectures were utilized on a self-created dataset, consisting of real signals received from a linear array with four receivers on a Software-Defined Radio (SDR). Both networks take the covariance matrix as input and perform regression for AoA estimation. The performance of these architectures was compared to the MUSIC algorithm, with the performance metric being RMSE as a function of Signal-to-Noise Ratio (SNR).

In Khan et al [2], the authors fed the covariance matrix into an ANN, which performed regression to find the AoA. Their approach outperformed MUSIC, with a mean absolute error (MAE) of 16° at 0 dB SNR and an MAE of 8° at 10 dB

SNR. In Alteneiji et al [1], the authors borrow further steps from MUSIC, by performing eigenvalue decomposition on the covariance matrix and feeding the results into a CNN. They test their system using OFDM signals, impaired by AWGN and multipath fading. They find their model to greatly outperform MUSIC, with a RMSE of 3° at 10 dB SNR, and 12° at -10 dB SNR. Comparatively, MUSIC has an RMSE of approximately 42° at -10 dB SNR and 26° at 10 dB SNR. The channel appears to have a very large effect on performance. Specifically, multipath fading can be a difficult challenge. From the literature, it appears that using eigenvalue decomposition on a covariance matrix is an effective way of finding the AoA, in both traditional methods and using ML for regression.

III. Machine Learning Datasets

One of the real datasets used in the literature for acoustic AoA estimation is the LOCATA dataset [12]. This dataset comprises six different tasks, each consisting of 26 recordings of spoken words. For instance, Task 1 focuses on a single sound source with spoken words, while the AoA changes throughout the recording. The receiver array used in LOCATA consists of 15 receivers arranged on a plane. Consequently, each recording includes 15 distinct received signals, one for each receiver. To evaluate their proposed methods, researchers in the acoustic AoA papers compare their results to LOCATA by calculating MAE across a single recording using their respective methods. The correct AoA labels are available at specific timestamps within each recording, enabling the calculation of errors. The DeepAoAnet dataset [11] comprises real signals received from an array with four receivers using SDRs. This dataset contains five folders, consisting of a total of 766 recordings and 57,000 frames. The recordings cover 15 different angles ranging from -70 to 70 degrees. The five folders correspond to different types of data, namely line of sight, line of sight with reflector, not line of sight office, not line of sight corridor, and not line of sight indoor to outdoor. When comparing results to the DeepAoAnet dataset, researchers employ either classification accuracy or RMSE for the tested frames, considering one or more types of data.

In addition to the real datasets, we generated a simulated dataset for evaluation purposes. In this simulation, we assumed a receiver with four antennas arranged linearly, with a spacing of $\lambda/2$. A single transmitter with one antenna was positioned at angles between -45° and +45° relative to the receiver. The multipath model followed a Rician distribution, with SNR ranging from -10 dB to +30 dB. We applied a global phase offset equally to each receiver channel and introduced a center frequency offset between the radios, constrained between $\pm$2kHz. The receiver operated at a baseband sample rate of 200kHz, and the samples were organized into frames of size 1024 samples. The modulation type adopted for this simulated dataset was Binary Phase-Shift Keying (BPSK).

IV. Evaluation Results

A. *Signal Processing Method Results*

The performance evaluation of the MUSIC and ESPRIT algorithms was conducted by implementing them in MATLAB and testing them on a synthesized dataset. The objective of these tests was to analyze the impact of different parameters on the estimation performance. In the first set of tests, the parameters under investigation were the number of antenna elements and the spacing between antenna elements. The tests were performed with a received SNR of 20 dB.

Table I presents the results illustrating the effects of antenna spacing and the number of antennas on the estimation performance of both MUSIC and ESPRIT. It is evident from the table that employing a 4-element array yields a significantly improved AoA estimate compared to using only 2 elements. Furthermore, increasing the number of antenna elements in the receiver enhances the performance of both MUSIC and ESPRIT.

The table also highlights the impact of increasing the inter-element spacing in the receiver. When the spacing is increased to λ, we observed multiple peaks in the decomposed eigenvector space, indicating the possibility of spatial aliasing. Subsequently, when the spacing exceeds half the wavelength, the beam pattern of the linear array exhibits additional peaks, aside from the main lobe as observed. Consequently, the receiver lacks the ability to distinguish signals arriving from different directions. Thus, to mitigate spatial aliasing, it is crucial to limit the spacing to $\lambda/2$.

TABLE I: MAE of AoA Estimation by MUSIC & ESPRIT Estimation by Different Array Element and Spacing

Algorithm	2-element, $\frac{\lambda}{2}$	2-element, λ	4-element, $\frac{\lambda}{2}$
MUSIC	0.11	41.6	0.02
ESPRIT	25.4	23.9	0.06

In the second set of tests, the performance of both MUSIC and ESPRIT algorithms was evaluated with respect to varying SNR levels. Figure 3 depicts the MAE for both algorithms when utilizing a 4-element antenna array with spacing at half of the wavelength, λ.The results presented in the figure indicate that MUSIC outperforms ESPRIT at low SNR values. As the SNR increases, the performance gap between the two algorithms gradually diminishes. Notably, both algorithms converge to the same level of performance at high SNR.

In order to assess the performance of the MUSIC algorithm in real-world conditions, we conducted tests using our RF testbed, as shown in Fig. 4, consisting of 4 element antenna array spacing 62.5mm, as shown in Fig. 5, which is $\lambda/2$ distance apart from each other based on our testing frequency. The tests were carried out with the antenna array facing two different angles: 0° and -30°. The results of these tests are presented in Table IV. Fig. 6 displays the estimated AoA over the entire duration of the tests.

While the estimated AoA generally follows the actual AoA, noticeable sudden changes in the estimate can be observed,

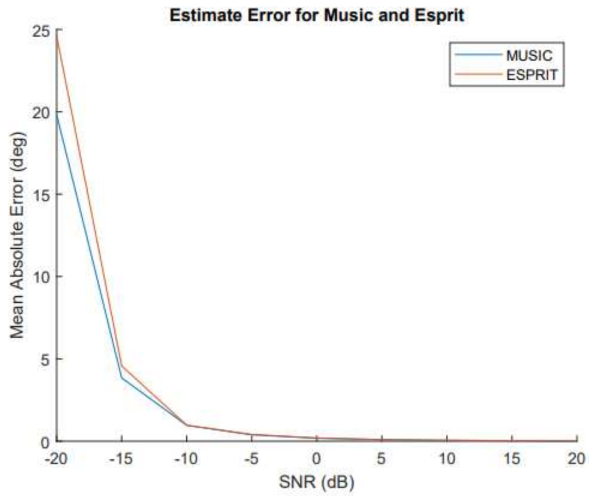


Fig. 3: Performance comparison between MUSIC and ESPRIT with 4-element antenna array

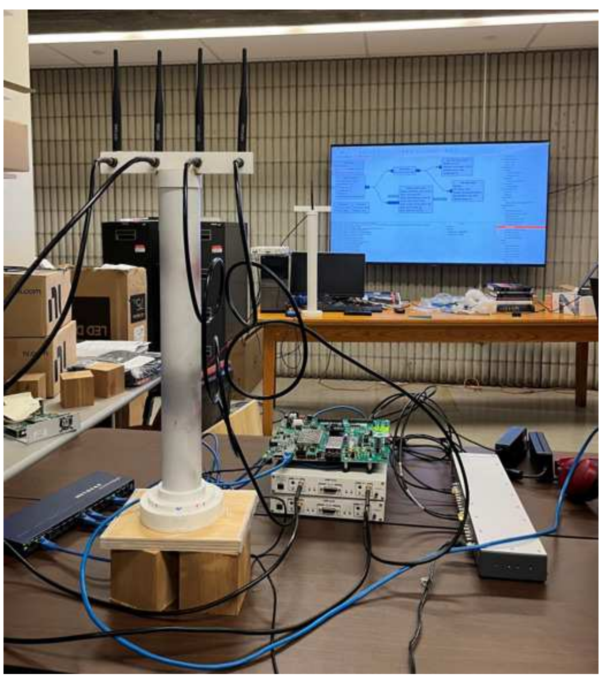


Fig. 4: Our SDR-based AoA Testbed

which significantly affect the overall performance. In a practical setting, most of these perturbations can be mitigated by applying a lowpass filter. It is evident from the results that the performance of the MUSIC algorithm deteriorates for OTA samples, with a best-case MAE of 2.1° compared to nearly zero-degree MAE in simulation under high SNR conditions. Furthermore, when the antenna array faced 0°, the error was considerably high, with an MAE of 7.3. However, when the perturbations are absent, the MUSIC algorithm closely tracks the real AoA.

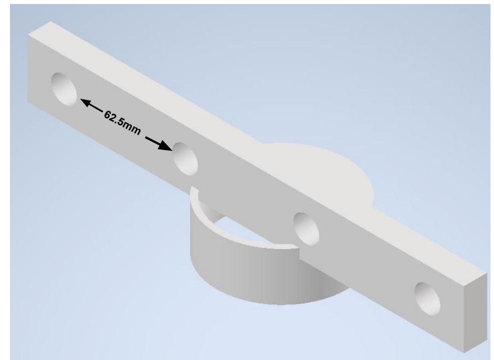


Fig. 5: Details on the antenna holder of Our SDR-based AoA Testbed

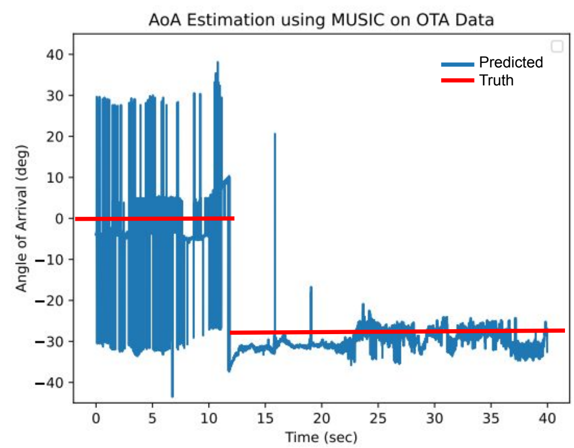


Fig. 6: Estimating OTA AoA using Music (0° to -30°)

B. Machine Learning Results

In the machine learning performance testing, we initially evaluated multiple potential network types on the LOCATA dataset before the simulated frames were able to be generated. The networks, as detailed in Table II, were tested on the LOCATA dataset, which contains multiple receivers and has similarity to simulated frames due to its formatting, which is achieved by splitting the dataset into small frames as Frame X Samples X IQ.

TABLE II: LOCATA Dataset Machine Learning Results

Network Type	Raw Data Input $1 \times 400 \times 15$ (MAE)	Covariance Input $1 \times 15 \times 15$ (MAE)
ResNet	11.7°	12.8°
ResNet+LSTM	**9.4**°	12.8°
AMC CNN	14.3°	13.7°
MCNET	15.8°	N/A
DeepAoANet	17.3°	14.67°
CRNN	12.46°	**12.54**°

Upon testing, the ResNet with LSTM layers (further referred to as just ResNet) emerged as the best performer for raw data input, while the CRNN was the best performer using covariance matrix input. Considering ResNet's similar performance to CRNN in covariance matrix input and superiority in raw data input, we selected it for further use. Subsequently, more tests were conducted on the simulated dataset using ResNet and additional potential networks listed in Table III. These tests were using a simulated dataset. For the ML methods, we had two major metrics; the RMSE in a test case, as well as the time it takes for the network to produce a result, given one input, also called the inference time. In both cases, each network performs regression, predicting a real-valued number for the AoA. Each network was trained with the Adam optimizer and used mean squared error (MSE) for the loss.

The results revealed a performance similar to the LOCATA dataset, as hypothesized due to the similarity in the datasets' formats. Networks with `Cov` have input using the covariance matrix and networks without cov are using raw data input. ResNet showed the highest performance in terms of MAE and RMSE. However, being a larger network in terms of the number of layers, it also had the highest inference time. In contrast, networks like ANN or CNN with covariance input reported lower inference times but higher MAE and RMSE than ResNet.

TABLE III: Simulated Dataset Machine Learning Results

Network	RMSE	MAE	Inference Time
CNN Cov	0.81°	0.54°	**0.0027s**
CNN	26.40°	22.92°	0.0040s
ResNet Cov	0.76°	0.58°	0.0078s
ResNet	**0.51°**	**0.36°**	0.0145s
ANN Cov	2.28°	1.36°	0.0040s
ANN	25.80°	22.28°	**0.0027s**

Based on these findings, ResNet had the highest performance, and thus was used for OTA tests; We chose to use the IQ architecture as it had absolute lowest RMSE.

We tested the ML architecture on data collected through a 4 antenna array. To perform metric tests, we collected data through the SDRs and antenna array and saved it to a file. For a test case, we started recording when the AoA was zero degrees, then rotated the array to -30°. This is the same test performed for MUSIC results. We measured the RMSE and MAE at 0° and -30°; these results are summarized alongside the MUSIC results in Table IV. Additionally, we measure the AoA throughout the entire recorded session, to observe changes in the estimate as the array is rotated; this could be seen in Fig. 7. The estimated error increases for OTA compared to simulation, increasing from an MAE of 0.58° to 4.4° for the best OTA case.

TABLE IV: Over-the-Air Results

	0°		$-30°$	
Algorithm	MAE	RMSE	MAE	RMSE
MUSIC	7.30	11.4	**1.10**	**2.10**
ResNet ML	**2.22**	**2.23**	**5.87**	**5.88**

From the results table, we can see that the perturbations MUSIC experiences significantly hinder the results, while the ML approach is not subject to these perturbations. When comparing the estimates over time for ML (Fig. 7) and MUSIC (Fig. 6), the ML graph is much smoother, without large perturbations. However, outside of these, the MUSIC algorithm has a lower error, which is reflected between the plots and the results table. When the array is at -30°, the MUSIC estimate is far more stable, and the MAE is lower than for ML at the same angle.

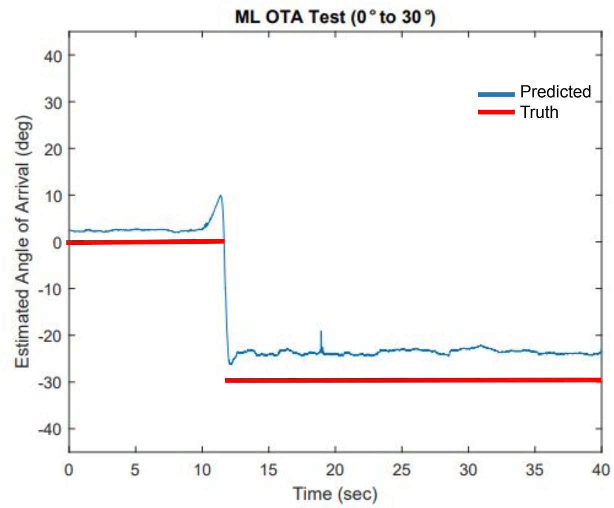


Fig. 7: Estimating OTA AoA using ML (0° to -30°)

For further testing of the ML architecture over the air under the same setup, we have loaded the ML architecture to FPGA ZCU102 for acceleration under the usage of Vitis by using Xilinx's prebuilt OS image. Table V shows the comparison of FPGA to PC side, at which the inference cycle is reduced by 28.2%.

TABLE V: FPGA Acceleration

Device	RMSE(deg)	Power Consumption	Inference Cycle
FPGA	0.51	**22.8W**	**81.9e6**
PC	0.51	150W	114.2e6

V. Conclusion

In this study, we conducted tests and implemented various AoA estimation techniques, including signal processing methods (MUSIC and ESPRIT) and machine learning (ML) approaches utilizing ANNs and CNNs. The performance of ML techniques was compared using direct I/Q samples and covariance matrices as inputs. We employed synthesized samples to assess performance differences.

Our findings revealed that MUSIC outperformed ESPRIT in terms of MAE in synthetic scenarios. Among the ML techniques, a CNN based on the ResNet architecture exhibited the best MAE performance, albeit with slower execution speed. The ML architecture that utilized a basic CNN on the covariance matrix and an ANN on I/Q samples demonstrated the fastest execution time.

To evaluate the robustness of these techniques in real-world scenarios, we conducted over-the-air (OTA) tests using a custom-designed RF testbed. We observed that the performance of the MUSIC algorithm deteriorated in the presence of multipath fading, unlike its performance in synthetic scenarios. However, under favorable conditions, MUSIC displayed the lowest error rate. In contrast, the ML algorithms exhibited stable performance as the antenna array rotated and experienced minimal perturbations compared to MUSIC. Nevertheless, both ML and MUSIC algorithms showed increased error rates in OTA tests compared to simulations, with the ML algorithm aligning better with simulation results.

To enhance the ML algorithm's performance, potential improvements involve diagnosing the differences between OTA and synthetic scenarios and updating the synthesis model accordingly. Alternatively, incorporating OTA samples into the training dataset can enhance the ML algorithm's robustness by increasing sample diversity.

Overall, this study provides valuable insights into the performance of various AoA estimation techniques in different scenarios. Our findings contribute to the understanding of the strengths and limitations of signal processing and ML approaches and offer suggestions for improving their performance in real-world OTA scenarios.

Acknowledgements

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