Radioactive Direction of Arrival Estimation Using Neural Networks Approach

Yossi Salomon[1,2*], Eran Vax[2], Alon Osowizky[2], Yakir Knafo[2], Nadav Ben David[3], and Dan Vilenchick[1]

[1]Ben Gurion University of the Negev, Israel
[2]Electronics and Control Laboratories, Nuclear Research Center-Negev (NRCN), Israel
[3]Israel Atomic Energy Commission (IAEC), Israel
(*) Yosefsal@post.bgu.ac.il

Abstract—**In this paper, we present a comprehensive investigation into improving Direction of Arrival (DOA) estimation for gamma-emitting isotopes using deep neural networks. The direction of arrival estimation is most valuable for Home Land Security (HLS) applications or increased safety in Decontamination and Decommissioning (D&D). Traditional methods, such as beamforming (BF), have limitations in accuracy and sensitivity to noise and background variations. In recent years, data-driven approaches utilizing deep neural networks, including Convolutional Neural Network (CNN) and Gated Recurrent Unit (GRU) models, have shown promise in enhancing DOA estimation. By considering the full energy spectrum and augmenting recorded data, our neural network models outperform traditional BF methods and exhibit greater resilience in diverse background scenarios. The 2-layer CNN model, in particular, achieves up to 40% improvement in estimation accuracy. Our research provides a reliable and data-driven approach for precise DOA estimation with potential applications in nuclear security and safety in D&D.**

Keywords—**Radiation detection, Direction of Arrival (DOA) estimation, convolution neural network (CNN), Reinforcement neural network (RNN), localization of radiation sources.**

I. Introduction

Direction of Arrival (DOA) estimation plays a critical role in radiation detection across various applications, such as preventing homeland security (HLS), medical imaging, and personnel safety in Decontamination and Decommissioning (D&D). The localization of radiation sources is crucial to identifying potential threats and mitigating their impact. In the context of HLS, DOA estimation anticipates actions against concealed radioactive sources and monitors Special Nuclear Materials (SNM) trafficking, e nhancing s ecurity t hrough improved camera direction for prompt threat responses. In post-event scenarios, like malfunctions or radioactive incidents, DOA estimation becomes a means to minimize personnel radiation exposure by expediting hotspot identification, which is crucial for time-sensitive recovery efforts. For instance, in public areas where radioactive materials are detected, knowing the source direction enables authorities to quickly evacuate people and contain the situation. Furthermore, accurate detailed operational information such as DOA estimation, reduces radiation exposure by allowing individuals to move away from the source or take other protective measures.

DOA estimation using sensors array is an important problem that has been extensively researched in fields such as wireless communications, radar, and sonar [1]–[5]. Traditional DOA estimation techniques rely on signal processing algorithms that extract features from the received signals at multiple sensors and then use these features to estimate the direction of the source. Methods such as multiple signal classification (MUSIC) [6], generalized cross-correlation (GCC) [7], beamforming (BF) [8], [9], and Maximum Likelihood (ML) [10] methods have been commonly used for DOA estimation tasks. However, these techniques have limitations in terms of accuracy, especially in noisy or complex environments. One key challenge is the reliance on a calibration matrix that is either calculated analytically, by simulation, or measured. These methods are sensitive to noise and environmental background, as the calibration matrix needs to precisely match the specific environment in which the estimation is performed. In scenarios with varying environmental conditions, the performance of these traditional techniques may deteriorate, affecting accuracy.

Over the last decade, there has been a substantial shift toward using data-driven methods for DOA estimation, particularly in signal and speech recognition [11]. Recent advances in machine learning, especially neural networks, have yielded promising results in DOA estimation. Neural networks can learn to extract features from raw signals and estimate the DOA more accurately and with a higher Signal-to-Noise Ratio (SNR) than traditional techniques. Various neural network architectures have been explored for DOA estimation, including Convolutional Neural Networks (CNNs) [12]–[14], Feed-forward Neural Networks (FNNs) [15], and Recurrent Neural Networks (RNNs) [16].

In this paper, we present a comprehensive investigation into enhancing the accuracy of DOA estimation for radiation isotopes using deep neural networks. Our primary focus is to leverage the power of CNN and Gated Recurrent Unit (GRU) models in capturing spatial features from the full energy spectrum, thereby achieving superior performance compared to traditional BF methods. We train and evaluate our CNN and GRU models to handle various challenging scenarios and background conditions by utilizing recorded data from directional detectors and augmenting it to introduce diversity. This research aims to provide a reliable and data-driven approach for precise DOA estimation under various conditions, in order to enable robust applications in nuclear security, D&D, and beyond. Through a rigorous evaluation of our models and comparisons against existing methods, we aim to demonstrate the efficiency of deep learning techniques in advancing the field of DOA estimation for radiation isotopes.

Our study showcases substantial improvements by utilizing neural networks, with accuracy enhancements ranging from 15% to 20%, and particularly notable improvements of up to 40% observed for ^{60}Co isotopes. This robust enhancement underscores the effectiveness of our proposed approach in overcoming the limitations of traditional algorithms. By exploiting the capabilities of deep learning, we not only confirm the superiority of neural networks over conventional methods but also highlight the potential for precision and accuracy improvements in DOA estimation tasks. These results affirm the promising avenue that data-driven techniques offer in achieving highly accurate and efficient radiation source localization, setting a strong foundation for applications in HLS and D&D.

II. Methodology

In this study, we adopt a data-driven approach, employing deep neural networks to address the challenge of DOA estimation for radiation isotopes. Traditional methods like BF and ML rely on handcrafted features and are sensitive to environmental variations, posing limitations in accuracy and adaptability. To overcome these issues, we harness the power of neural networks, particularly CNN, to automatically learn intricate spatial features from the input spectrum data. Additionally, our directional detector's calibration matrix, obtained from pre-recorded data, provides essential insights into its setup and sensitivity to known signal directions. By synergizing this information with our CNN-based DOA estimation models, we strive to achieve precise and real-time detection and localization of radiation isotopes, unlocking potential applications in nuclear security and personnel safety in D&D.

A. Data-set

The data set used in this study comprises recordings of four distinct radiation isotopes: ^{60}Co, ^{57}Co, ^{137}Cs, and ^{241}Am. Each radiation isotope was recorded for 60 seconds using a directional detector consisting of seven cylindrical detectors made of NaI(Tl) scintillators [17]. The detector arrangement included one central detector positioned higher than the surrounding six detectors, arranged in a non-symmetrical configuration. This design takes advantage of the mutual-shielding effect and offers distinct vantage points, improving the DOA estimation. The NaI(Tl) scintillators used in the detector have $\sim$7% FWHM energy resolution which is well beyond the required for our applications. The high density of the NaI(Tl) (3.67 g/cm^3) gives excellent sensitivity to gamma radiation even for the higher energies, ensuring relatively high count rates for all the radiation isotopes.

During the data acquisition, the directional detector was mounted on a step motor, enabling automated precise rotation of the detector. Each radiation isotope was recorded while being rotated through a complete rotation with a 1° step interval, resulting in 360 labeled samples for each isotope. The data acquisition system utilizes seven Time Over Threshold Multi-Channel Analyzers (MCAs), capturing 50 bins of energy histogram for each of the seven scintillators, these samples of 7 by 50 channels provide insights into the signals' spatial and energy distribution.

As part of our data augmentation strategy, we employed techniques to enhance the variability and quality of the recorded data. Samples with different Signal-to-Noise Ratios (SNRs) and Signal-to-Background Ratios (SNBs) were intentionally captured for each radiation isotope, simulating real-world scenarios and increasing dataset robustness. It is important to note that our testing samples, used for model evaluation, were kept separate from this augmentation process and were recorded with varying SNBs to ensure a comprehensive evaluation of the models' performance. Data augmentation techniques were employed to introduce further variability to each labeled sample by randomly selecting and integrating 20-second segments from the available 60-second spectrum. This approach takes advantage of the stochastic and independent nature of the non-overlapping energy spectrum measurements taken every second. By selecting random segments, we ensure that the neural network models are exposed to diverse combinations of energy patterns within the recorded samples. This augmentation process effectively increases the diversity and coverage of the training dataset, allowing the models to learn a wide range of spatial and temporal characteristics associated with the DOA of different radiation isotopes. Consequently, this data augmentation process significantly expanded the dataset from 500 to 70,000 samples per isotope (as shown in Table I), fostering a rich and diverse training dataset to boost the neural network models.

TABLE I:
Effect of Data Augmentation on Database Size

Isotope:	Recorded Samples:	After Augmentation Training:	Validation:	Testing:
^{60}Co	743	57,000	14,250	470
^{57}Co	473	53,550	13,400	520
^{137}Cs	464	53,450	13,370	460
^{241}Am	489	56,330	14,090	480

Each input sample in our data set is labeled with the true DOA and the corresponding isotope. The input sample is a 20-second spectrum, comprising 7 measurement channels (from each detector) and 50 energy bins. To prepare the input for the neural network, we aggregate the counts for each energy bin across all channels and reorder the matrix into a 7x50 input matrix. This reprocessing step enables the network to effectively learn spatial and energy features across the detectors and energy bins. As for the beam-forming benchmark, we utilize the total count for each detector over the 20-second duration and all 50 energy bins, resulting in a vector of size 7. This vector captures the total count for each detector, facilitating a performance comparison between the neural network models and the traditional BF approach.

B. DOA Estimation by BF Method

BF is a widely used technique in array signal processing for estimating a signal source's DOA. Its primary objective is to enhance the signal coming from a specific direction while suppressing the noise and interference from other directions. In the context of DOA estimation, BF leverages an array of sensors or antennas to spatially process the incoming signals and estimate the angle of arrival of a signal source. By adjusting the weights and summing the weighted signals received at each sensor, the BF output signal power is largest toward the direction of the incoming signal. This process enables to search over the entire DOA space by steering the signal amplification using the weights effectively localizing the source's direction. One can look at the weights as a matched filter with the signals from the correct direction.

In this study, we employ conventional BF as a benchmark method to evaluate the performance of our DOA estimation models based on Deep Neural Networks architectures for DOA. Our Conventional BF relies on a calibration matrix derived from pre-recorded data to determine the fixed weights for the directional detector array. This calibration matrix is crucial in characterizing the directional detector's setup, providing insights into its sensitivity to known signal directions and the resulting patterns. By utilizing this calibration matrix, conventional BF can effectively estimate the DOA of radiation isotopes based on the signals received by the array of sensors. The calibration matrix serves as a reference for the BF method, enabling it to precisely map incoming radiation signals to their corresponding DOA angles.

Pseudo Code Beam-Forming

1. Obtain Calibration Matrix A
2. Measure Total Counts Vector
3. Calculate the sample covariance Matrix:
   $\mathrm{R}_x = \sum_{t_i} V_{t_i} \cdot V_{t_i}^T$
4. **for** each $\theta \in [0, 360]$ **calc** the BF output:
   $likelihoodPerAngle(\theta_i) = \frac{\overline{a}(\theta_i)^T \cdot R_x \cdot \overline{a}(\theta_i)}{\overline{a}(\theta_i)^T \cdot \overline{a}(\theta_i)}$
5. $estimateDOA = \mathrm{argmax}_{\theta_i}(likelihoodPerAngle)$

C. CNN-based architecture

DOA estimation can be formulated as a classification task [18], aiming to classify incoming data into one of the 360 possible degrees representing the angle of arrival. An effective solution to this classification task is leveraging CNNs to achieve 1° accuracy, making it suitable for leveraging CNNs as an effective solution. CNNs have demonstrated remarkable success in image classification tasks, primarily due to their ability to capture spatial features and learn hierarchical representations from input data. Although our data is not in the form of traditional images, the correlation features that need to be extracted bear similarities to image processing tasks. By utilizing CNNs, we can exploit their capacity to analyze spatial patterns and dependencies within the input signals. This enables the network to learn and extract the essential features necessary for accurate classification, even in non-image data scenarios.

Our study employed a CNN architecture to estimate the DOA of radiation isotopes consisting of two layers. Our network specifically designed to effectively extract spatial features from the input spectrum data. This architecture is tailored to capture the underlying patterns and correlations present in the data, enabling it to learn and discern the intricate spatial information related to the DOA estimation problem. By leveraging the ability of CNN to analyze and extract meaningful spatial representations, we aim to improve the accuracy and performance of DOA estimation for radiation isotopes. Through our investigation of this CNN architecture, we seek to demonstrate the efficacy of utilizing deep learning approaches in solving the complex and challenging task of DOA estimation.

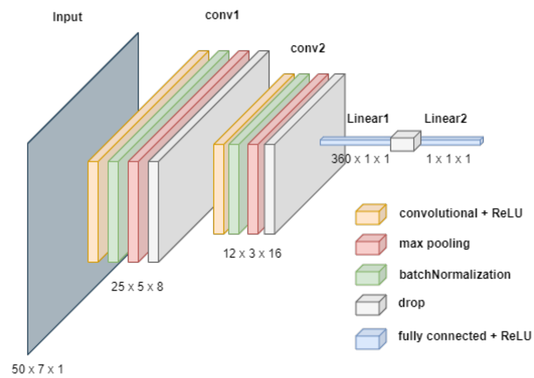


Fig. 1: CNN 2 Layers model Architecture, with 93,000 trainable parameters

For our two-layer CNN architecture (Figure 1), each layer includes a convolution layer with the Rectified Linear Unit (ReLU) activation function, followed by a max pooling layer for downsampling. To promote convergence and mitigate overfitting, batch normalization is applied after each convolution layer. Additionally, a dropout layer [19] with a rate of 0.5 is incorporated to further enhance regularization. These architectural choices facilitate the extraction of informative spatial features from the input spectrum data. Following the convolution layers, two fully connected linear layers with the ReLU activation function process the extracted features. These layers play a crucial role in mapping the learned features to the DOA and isotope classes. During training, the networks utilize an adjusted Mean Squared Error (MSE) loss function, which will be described in detail later. The Adam optimizer [20], a popular gradient-based optimization algorithm, updates the network parameters and facilitates efficient convergence.

D. RNN-based architecture

In addition to the examined CNN architecture, we evaluated the effectiveness of a Gated Recurrent Unit (GRU) network as an independent neural network model for DOA estimation. The GRU network, designed to capture temporal patterns, operates on a distinct input sequence representing the energy bins of 7 detectors over 20 seconds. Comprising a single layer, the GRU network leverages the GRU architecture to effectively model sequential information. It includes two fully connected linear layers, augmented by a dropout layer for regularization. By processing the input data, the GRU network captures temporal dependencies and maps them to the estimated DOA. The inclusion of the GRU network as an alternative model allows for comparison against the CNN architecture, providing insights into the relative performance and advantages of different neural network approaches for DOA estimation.

E. Loss Function

The accurate estimation of DOA is a critical task in various applications. However, this task poses a unique challenge due to the symmetrical and circular nature of the DOA space. Traditional loss functions, such as MSE, are not well-suited to handle this circularity, which can lead to false results and inaccurate estimation metrics.

In a symmetrical scenario, the error between an estimated angle of $10°$ and the true ground angle of $350°$ degrees should not be calculated as a $340°$ error, as MSE would suggest. Instead, the error measurement should reflect the circular nature of the problem, resulting in a $20°$ error. Failing to account for this circularity can lead to misleading results and an inaccurate assessment of the DOA estimation performance.

To address this limitation, we introduce the Symmetrical Mean Squared Error (S-MSE) loss function and ensure that the error metric provides a more precise and reliable measure of the angular difference between the estimated and true ground angles. The S-MSE takes into consideration the absolute circular difference between the angles, resulting in improved estimation metrics that align with the circular nature of the problem.

The modified MSE is given by:

$$\text{S-MSE} = \frac{1}{N}\sum_{i=1}^{N}(((180° + \theta_{\text{est}_i} - \theta_{\text{true}_i}) \mod 360°) - 180°)^2 \quad (1)$$

Here, est_i represents the estimated DOA angle for the ith sample, and $true_i$ represents the true ground angle for the ith sample. By utilizing the S-MSE loss function during the training phase, we ensure that the error metric accurately captures the circular nature of the DOA space, leading to improved accuracy in DOA estimation.

F. Evaluation Metrics

To evaluate the performance of our DOA estimation models, we conduct two sets of testing that encompassed different scenarios and challenges. These testing sets allowed us to comprehensively assess the capabilities and robustness of our models in various conditions.

The first testing set is comprised of recordings obtained from different laboratory environments, for each of the four radiation isotopes. This set provides us with a comprehensive evaluation of the model's ability to handle variations in energy spectra and accurately estimate DOA angles across different isotopes. We calculated the Mean Angular Error (MAE) for each model on this testing set, which measures the average absolute angular difference between the estimated and true DOA angles. Furthermore, we compared the performance of our models against the benchmark BF method on this set, providing a baseline for performance comparison.

It is important to note that traditional loss functions, such as MSE, are not suitable for our task due to their lack of tolerance to the symmetrical and circular properties of the DOA angles. Therefore, we employ the MAE and use it for two informative metrics: the loss metric and the accuracy metric.

The loss metric is given by:

$$180° - \frac{1}{N}\sum_{i=1}^{N}|((\theta_{\text{est}_i} - \theta_{\text{true}_i}) \mod 360°) - 180°| \quad (2)$$

while the Accuracy metric is given by:

$$\frac{1}{N}\sum_{i=1}^{N}\frac{|((\theta_{\text{est}_i} - \theta_{\text{true}_i}) \mod 360°) - 180°|}{180} \quad (3)$$

This metric represents the relative angular error normalized to the range of 0 to 1, with 1 indicating perfect accuracy and 0 indicating the wrong and opposite estimation. The normalization of the error to the range of 0 to 1 accounts for the symmetry of the problem, where the maximum possible error is 180 degrees.

Through these testing, we can thoroughly evaluate the performance of our DOA estimation models in diverse scenarios. The MAE evaluation metric allows us to quantify the estimation errors and assess the accuracy of the model's predictions, providing a reliable measure of their performance. The results obtained from these evaluations allow us to compare the performance of our models against each other and the benchmark BF method. This comprehensive evaluation provides valuable insights into the strengths and limitations of our models, guiding their practical application in radiation isotope detection and localization.

III. Results

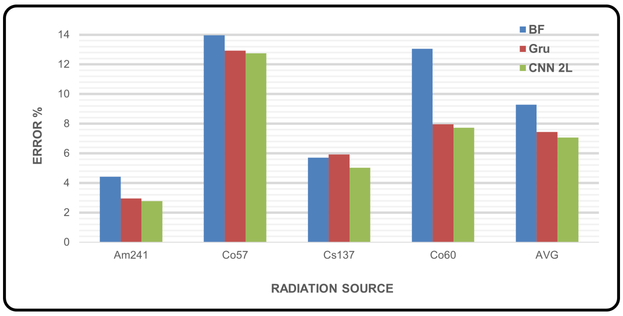
In this section, we present the results of our experiments evaluating the performance of the DOA estimation models based on deep neural networks compared to the traditional DOA estimation method, conventional BF. As described earlier, the evaluation metrics used are the MAE and the Accuracy based one MAE output.

Figure 2 depicts the comparison between different methods for DOA estimation across various isotopes using the MAE as the evaluation metric. We can observe that our convolution neural network model (2-layer CNN) consistently outperformed the BF method and the GRU network for all isotopes, indicating a significant reduction in the estimation error. Our results showcase a remarkable 30-40% improvement in accuracy for ^{60}Co and ^{241}Am isotopes, contributing to an average improvement of 20-25% across all tested isotopes.

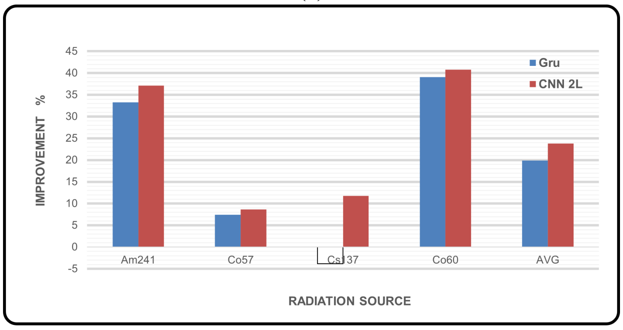
Among the isotopes, the best improvement was achieved with ^{60}Co and ^{241}Am using the 2-layer CNN model, demonstrating their effectiveness in capturing complex spatial features and accurately estimating the DOA angles for both high-energy and low-energy spectrum isotopes.

Furthermore, when comparing the performance of the deep neural network models with the GRU network, we found that the CNN architectures were better suited for the DOA estimation task. The CNN model's ability to capture spatial dependencies and hierarchical features from the input spectrum data contributed to their improved accuracy over the GRU model.

To quantify the improvement achieved by our deep neural network models, we examined the percentage improvement in MAE compared to the BF and GRU methods. Figure 2b displays the percentage improvement for each isotope. Notably, we achieved a substantial 40% improvement in the estimation accuracy for both ^{60}Co and ^{241}Am isotopes. These findings demonstrate that our deep neural network models significantly enhance the DOA estimation accuracy for both high-energy and low-energy spectrum isotopes, making them highly effective for radiation detection and localization tasks across a wide range of isotopic sources.



(a)



(b)

Fig. 2: Comparison of Different Radiation Isotopes (a) Error: DNN models outperform BF method for all isotopes. (b) Improvement: DNN models achieve significant accuracy enhancement.

In this results section, we evaluated the performance of our DOA estimation models based on deep neural networks, comparing them to the conventional BF method. The 2-layer CNN model consistently outperformed both BF and the GRU model across different isotopes. These results highlight the effectiveness of deep learning approaches for precise DOA estimation in radiation isotopes and pave the way for further discussions in the subsequent section.

IV. Conclusion

In conclusion, our study demonstrates the effectiveness of deep neural networks, particularly CNN, in enhancing the accuracy of DOA estimation for radiation isotopes. By considering the full energy spectrum in our neural network models, we achieved improved accuracy compared to traditional BF methods, which rely solely on total counts. Our investigation showcases substantial improvements by utilizing neural networks, with accuracy enhancements ranging from 15% to 20%, and particularly notable improvements of up to 40% observed for ^{60}Co isotopes. This robust enhancement underscores the effectiveness of our proposed approach in overcoming the limitations of traditional algorithms.

The augmentation of our recorded data significantly increased the dataset size and diversity, providing the models with exposure to a broader range of scenarios. This, in turn, enabled our CNN models to better generalize and handle various challenging conditions and variations, resulting in stable and consistent improvements in accuracy compared to the BF and GRU models across different SBR ratios.

To further improve the performance and generalization of our deep neural network models, we propose several avenues for future work. Further enhancement of data augmentation techniques, incorporating more diverse and realistic simulation data to provide the models with exposure to rare or extreme scenarios that may occur infrequently in real-life measurements. Thereby enhancing the accuracy and robustness of the DoA estimation models by increasing the similarity between the recorded and simulated data sets.

Furthermore, we propose extending our evaluation to encompass a broader range of Signal-to-Background (SNB) scenarios. Different background conditions can significantly influence the performance of DoA estimation methods, and testing NN models across a spectrum of SNB ratios would provide valuable insights into their robustness and reliability.

Additionally, exploring advanced and deeper neural network architectures along with model configurations could further boost performance. The continuous advancement in deep learning offers new possibilities for model innovation and optimization. By leveraging state-of-the-art architectures and training techniques, we can potentially achieve even higher accuracy and better performance, bolstering the practical applicability of our deep neural network-based DOA estimation approach.

Overall, our findings underscore the potential of neural networks in enabling precise and real-time detection and localization of radiation isotopes, with applications in nuclear security and environmental monitoring. As the field of deep learning continues to progress, we anticipate continuous improvements in accuracy and performance, unlocking new possibilities for DOA estimation and beyond.

References

[1] H. Krim and M. Viberg, "Two decades of array signal processing research: the parametric approach," *IEEE signal processing magazine*, vol. 13, no. 4, pp. 67–94, 1996.

[2] H. L. Van Trees, *Optimum array processing: Part IV of detection, estimation, and modulation theory*. John Wiley & Sons, 2002.

[3] A. Nehorai and E. Paldi, "Vector-sensor array processing for electromagnetic source localization," *IEEE transactions on signal processing*, vol. 42, no. 2, pp. 376–398, 1994.

[4] W. Cash, "Parameter estimation in astronomy through application of the likelihood ratio," *Astrophysical Journal, Part 1, vol. 228, Mar. 15, 1979, p. 939-947.*, vol. 228, pp. 939–947, 1979.

[5] J. Shi, F. Wen, and T. Liu, "Nested mimo radar: coarrays, tensor modeling, and angle estimation," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 57, no. 1, pp. 573–585, 2020.
[6] R. Schmidt, "Multiple emitter location and signal parameter estimation," *IEEE transactions on antennas and propagation*, vol. 34, no. 3, pp. 276–280, 1986.
[7] C. Knapp and G. Carter, "The generalized correlation method for estimation of time delay," *IEEE transactions on acoustics, speech, and signal processing*, vol. 24, no. 4, pp. 320–327, 1976.
[8] B. D. Van Veen and K. M. Buckley, "Beamforming: A versatile approach to spatial filtering," *IEEE assp magazine*, vol. 5, no. 2, pp. 4–24, 1988.
[9] J. Litva and T. K. Lo, *Digital beamforming in wireless communications*. Artech House, Inc., 1996.
[10] P. Stoica and K. C. Sharman, "Maximum likelihood methods for direction-of-arrival estimation," *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. 38, no. 7, pp. 1132–1143, 1990.
[11] A. Barthelme and W. Utschick, "A machine learning approach to doa estimation and model order selection for antenna arrays with subarray sampling," *IEEE Transactions on Signal Processing*, vol. 69, pp. 3075–3087, 2021.
[12] S. Chakrabarty and E. A. Habets, "Broadband doa estimation using convolutional neural networks trained with noise signals," in *2017 IEEE Workshop on Applications of Signal Processing to Audio and Acoustics (WASPAA)*. IEEE, 2017, pp. 136–140.
[13] ——, "Multi-speaker doa estimation using deep convolutional networks trained with noise signals," *IEEE Journal of Selected Topics in Signal Processing*, vol. 13, no. 1, pp. 8–21, 2019.
[14] A. M. Elbir, "Deepmusic: Multiple signal classification via deep learning," *IEEE Sensors Letters*, vol. 4, no. 4, pp. 1–4, 2020.
[15] E. Ozanich, P. Gerstoft, and H. Niu, "A feedforward neural network for direction-of-arrival estimation," *The journal of the acoustical society of America*, vol. 147, no. 3, pp. 2035–2048, 2020.
[16] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, "Empirical evaluation of gated recurrent neural networks on sequence modeling," *arXiv preprint arXiv:1412.3555*, 2014.
[17] Y. Ifergan, E. Vax, Y. Yehuda-zada, B. Sarussi, D. Smadja, S. Dadon, Y. Levin, T. Mazor, Y. Kadmon, Y. Knafo, *et al.*, "Improving the radiation detection level and operational data of pre and post event monitoring systems," in *International Conference on Nuclear Security: Commitments and Actions. Summary of an International Conference. Companion CD-ROM*, 2017.
[18] T. Hastie, R. Tibshirani, J. H. Friedman, and J. H. Friedman, *The elements of statistical learning: data mining, inference, and prediction*. Springer, 2009, vol. 2.
[19] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: a simple way to prevent neural networks from overfitting," *The journal of machine learning research*, vol. 15, no. 1, pp. 1929–1958, 2014.
[20] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," *arXiv preprint arXiv:1412.6980*, 2014.