Performance Analysis of Deep Learning-Based Direction Finding in the High-Frequency Band

Suna Choi, Gwangmoon Park and Kanghee Kim
Radio Research Division
Electronics and Telecommunications Research Institute
Daejeon, Korea
sunachoi@etri.re.kr, gmparka@etri.re.kr and kangheekim@etri.re.kr

***Abstract*—This study comparatively analyzes the performance of the traditional MUSIC algorithm and the deep learning-based CNN for direction finding, particularly for multiple HF band signals. Simulations in environments characterized by complex noise, and additionally by frequency variations and multipath effects, reveal that MUSIC's RMSE significantly increases under low SNR conditions, whereas CNN consistently exhibits lower errors. Furthermore, while MUSIC's RMSE rises with increasing separation angles of the input signals, CNN maintains stable performance. These findings indicate that CNN overcomes grid-based resolution limitations, achieving optimal estimation performance by closely approaching the CRLB under diverse conditions.**

***Keywords*—HF band, Direction finding, Multiple-Signal Classification, deep learning, Convolutional Neural Network**

I. Introduction

The High-Frequency (HF, 3-30MHz) band is crucial for various wireless services, including international communications, military operations, aeronautical and maritime links, shortwave broadcasting, and amateur radio. Consequently, robust direction finding in the HF band is essential for rapid detection and identification of interfering signals. The Multiple-Signal Classification (MUSIC) algorithm is widely used for its high resolution and accuracy in direction-of-arrival (DOA) estimation. However, its performance can degrade in complex real-world environments due to various factors such as array imperfections, mutual coupling, phase and amplitude errors. To overcome these limitations, deep learning-based direction finding techniques warrant consideration. This study conducts a comparative analysis of the direction-finding performance of the MUSIC algorithm and a learning-based technique using Convolutional Neural Network (CNN) in multi-signal HF scenarios.

II. Simulation Environment Setup

A. Antenna Array and Signal Model

Two independent signal sources are assumed at a center frequency of 15 MHz within the HF band. The receiver utilizes a 12-element Uniform Linear Array (ULA) with λ/2 spacing. The two source signals have arbitrary DOAs, with a separation angle ranging from 5° to 40°. The received signal from each experiment is collected over 5,000 snapshots, and is then mathematically modeled as follows:

$$\boldsymbol{x}(n) = \sum_{k=1}^{K}\sum_{m=1}^{M_k} \alpha_{k,m}\, \boldsymbol{a}(\theta_{k,m})\, s_k(n)\, e^{j2\pi\Delta f_k n T_s}\, e^{-j2\pi\tau_{k,m} n/N} + \boldsymbol{w}(n)$$

where K is the number of signal sources, M_k is the number of propagation paths for the k-th signal source, $\alpha_{k,m}$ is the complex gain of the m-th path associated with the k-th source, $\theta_{k,m}$ is the angle of arrival, $\boldsymbol{a}(\theta_{k,m})$ denotes the steering vector corresponding to $\theta_{k,m}$, $s_k(n)$ is the transmitted signal at time n, Δf_k is the frequency offset, T_s is the sampling period, $\tau_{k,m}$ is the relative time delay, and N is the number of snapshots ($n = 1, 2, \ldots, N$). Finally, $\boldsymbol{w}(n)$ denotes the complex Gaussian noise vector at time n.

The covariance matrix R is used identically for both MUSIC and CNN methods, defined as:

$$R = \frac{1}{N}\sum_{n=1}^{N} x(n)\, x^H(n)$$

B. Direction Finding Algorithm

The MUSIC algorithm performs an eigen-decomposition of the covariance matrix R to separate the signal and noise subspaces. It then exploits the orthogonality between the noise subspace and the array steering vectors to locate high-resolution DOA peaks. For performance analysis, a grid with 0.1° spacing is constructed in the range of -90° to 90°, and spatial smoothing technique is applied to the traditional MUSIC algorithm to mitigate the coherent signal problem.

The CNN directly predicts DOA by transforming the antenna array signal covariance matrix R into a 2-channel image (real and imaginary parts). This image is processed through convolution, batch normalization and rectified linear unit blocks to extract spatial correlations, with the resulting feature vector fed into a fully connected layer for regression output. The network is trained using a dataset of simulated covariance samples generated by combining various signal to noise ratio (SNR) levels, separation angles, and random arrival angles.

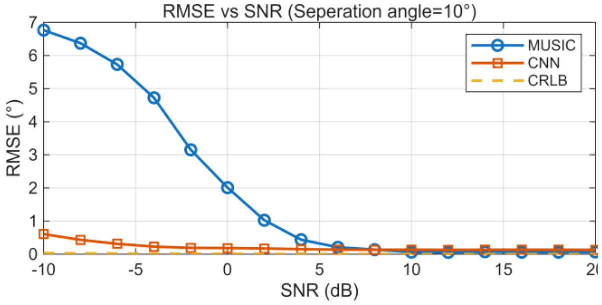
C. Analysis Method

The performance of MUSIC and CNN is analyzed using the following methods under two environments: one with a complex Gaussian noise, and a second environment that includes an additional frequency offset and multipath propagation paths.

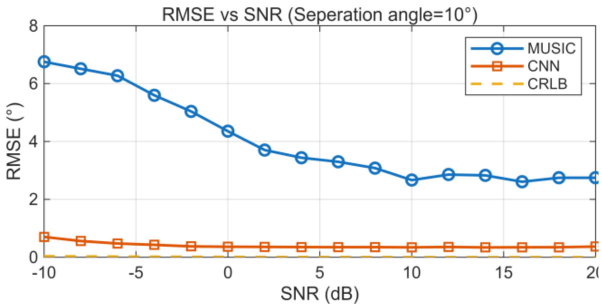
- The RMSE of MUSIC and CNN is examined by fixing the separation angle at 10° and varying the SNR from -10 dB to 20 dB in 2 dB increments.
- The RMSE of MUSIC and CNN is examined by maintaining the SNR at 10 dB and varying the separation angle from 5° to 40° in 5° increments.

To ensure statistical reliability, 1000 Monte Carlo iterations are performed. Additionally, The Cramer-Rao Lower Bound (CRLB), representing the theoretical

This work was supported by Institute of Information & Communications Technology Planning & Evaluation (IITP) grant funded by the Korea government (MSIT) (No. 2018-0-00194, Laboratory for Advanced Spectrum Monitoring).

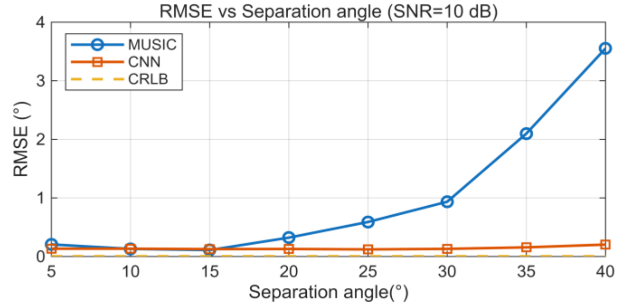


(a) In complex Gaussian noise environment

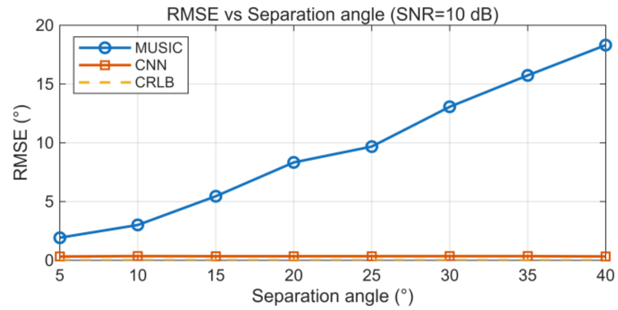


(b) Under additional frequency offset and multipath propagation

Fig. 1. Performance of MUSIC and CNN with varying SNR



(a) In complex Gaussian noise environment



(b) Under additional frequency offset and multipath propagation

Fig. 2. Performance of MUSIC and CNN with varying separation angle

performance limit of direction is presented to evaluate the gap from the lower performance bound.

III. Direction Finding Performance Analysis

Figure 1 shows RMSE results as a function of SNR with fixed separation angle of 10°. The performance in complex Gaussian noise environment is shown in Fig. 1(a). The MUSIC algorithm exhibits high RMSE exceeding 2° in the low SNR range of -10 to 0 dB, however, its performance markedly improves beyond 5 dB SNR, converging to approximately 0.2°. In contrast, the CNN consistently achieves low RMSE values below 1° even at -10 dB and maintains stable performance below 0.3° for SNRs above 0 dB. Notably, for SNRs greater than 0 dB, the CNN's RMSE closely approaches the CRLB, maintaining errors under 0.1°. The results under an environment with additional 1% frequency offset and two multipath propagation paths are shown in Fig. 1(b). The MUSIC algorithm exhibits high RMSE at low SNRs, but its accuracy improves as SNR increases, converging to around 3° at high SNR. In contrast, the CNN consistently maintains low RMSE below 1° across the entire SNR range, closely tracking the CRLB, especially at higher SNRs. This demonstrates the superior robustness of the CNN method to noise, particularly in challenging low SNR conditions.

Figure 2 illustrates the RMSE as a function of separation angle at a fixed SNR of 10dB. In a complex Gaussian noise environment, as shown in Fig. 2(a), both MUSIC and CNN methods achieve RMSE values below 0.3° for small separation angles from 5° to 15°. The CNN, in particular, demonstrates stable results around 0.1° to 0.2°, closely agreeing with the CRLB. However, as the separation angle increases beyond 20°, the RMSE of MUSIC rises rapidly, exceeding 3.5° at 40°. This degradation is attributed to increased off-grid errors and reduced peak localization accuracy, primarily caused by grid resolution limitations and spectral leakage as the separation angle widens. The results under the environment with additional 1% frequency offset and two multipath propagation paths is shown in Fig. 2(b). The RMSE of MUSIC algorithm increases rapidly with larger separation angles, exceeding 15° at a separation of 40°, indicating significant performance degradation. In contrast, the CNN consistently achieves RMSE values under 1°, remaining near the theoretical CRLB across all tested separations. These results highlight the CNN estimator's strong ability to maintain high accuracy and robustness regardless of source separation.

IV. Conclusion

In this study, the direction finding performance of MUSIC and CNN in the HF band was analyzed. The MUSIC algorithm approached the CRLB only in high SNR and small separation angle regions. However, at low SNR or with increasing separation angles, its RMSE sharply increased. In contrast, the deep learning-based method using CNN addressed physical and numerical limitations through training under various SNR and separation angle conditions, maintaining stable and superior estimation accuracy close to the CRLB across all simulated scenarios. This confirms the practicality of a deep learning-based approach for HF direction finding, demonstrating consistent performance even in low SNR and wide separation angle environments.

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