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Estimation of Direction of Signals using Wavenet in Wireless Communication Systems

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***Abstract*— The project "Estimation of Direction of Signals using Wavenet in Wireless Communication Systems" proposes a novel signal processing method, particularly under suboptimal antenna conditions. The new technique combines convolutional neural networks (CNNs) and wavelet transforms to improve signal direction estimation accuracy even in noisy conditions or when there are equipment defects. CNNs detect intricate signal patterns, while wavelet transforms enable precise time-frequency analysis. All this together forms a strong model that can accommodate real-world problems such as improper antenna placement, signal overlap, and hardware distortions—outperforming existing techniques in terms of accuracy and reliability. The data-driven approach provides excellent training and test outcomes, substantiating the strength of the model to perform well in adverse signal conditions. It estimates vital parameters such as signal delays, frequency shifts, and array distortion, allowing for consistent performance even under dynamic scenarios. Since the system continues to improve with new data, the flexibility of the system makes it very suitable for use in wireless communication, radar, and audio signal processing. By blending deep learning and signal processing know-how, the project creates a new standard in direction-of-arrival estimation, adding substantially to the development of advanced communication systems today.**

***Keywords*— Arrival Direction Detection, AI-Based Learning Models, CNN Architectures, Time-Frequency Signal Decomposition, Non-Ideal Antenna Arrays, Signal Prediction Techniques, Inter-Antenna Interference, Structural Array Irregularities, Self-Improving Algorithms.**

I. INTRODUCTION

The direction of Arrival (DOA) Direction of Arrival (DOA) is the process of finding the direction from which a signal, such as a sound or electromagnetic wave, comes with respect to a reference point like an antenna or microphone array. DOA estimation is crucial in systems such as radar, sonar, wireless communication, and navigation, where precise positioning of the signal source improves performance.
From the figure 1, we are able to identify two targets sending signals to a linear antenna array. The signals reach at varying angles, and the array elements record these differences. This is what constitutes the input for the Wavenet model employed in the DOA estimation process.
Conventional DOA techniques tend to address only finite imperfections of antenna arrays because of complexity in modeling. Most deep learning solutions are based on statistical inputs such as covariance matrices, which limit estimation performance and cannot produce spatial spectra directly. Additionally, the networks tend to need architectural modification when the number of signal sources changes, thus limiting their practicality.

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To address these challenges, we introduce a Wavenet-based deep neural network (SDOA-Net) that can manage imperfect array conditions such as position perturbations, gain/phase mismatches, mutual coupling, and nonlinearities. In contrast to existing approaches, SDOA-Net takes raw sampled signals as input and provides a vector output for spatial spectrum estimation. It employs convolution layers for feature extraction and incorporates a spatial spectrum-based loss function, utilizing Gaussian approximations to enhance estimation accuracy.

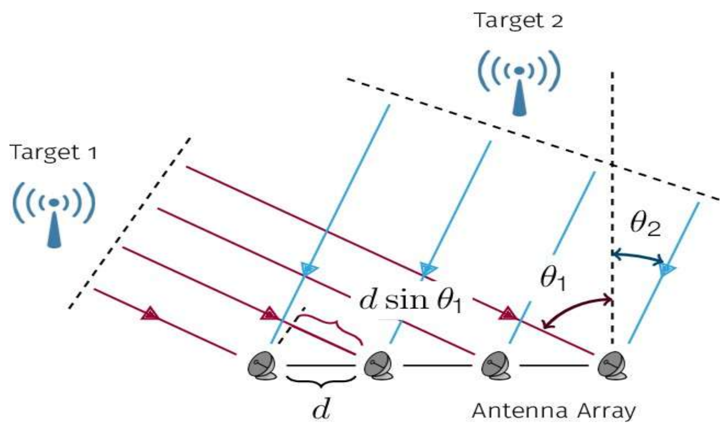

Figure-1 Antenna Array with two targets

Source: https://www.researchgate.net/publication/32c854S27_A_Review_of_Distributed_Algorithms_for_Principal_Component_Analysis

II. PROPOSED MODEL

Simplified system model with primary flaws (position error, uneven gains/phases, nonlinearities). Simplified mathematical-model to identify the primary equation for received signals. Summary of how raw input is passed through WaveNet and CNN for DOA estimation via spatial spectrum peaks.

Key steps:

- Simplification of signal model.
- Preprocessing of input via real and imaginary parts.
- WaveNet for temporal feature extraction via dilated convolutions.
- FC and convolution layers to output.
- Gaussian reference model and loss function with spatial spectrum.

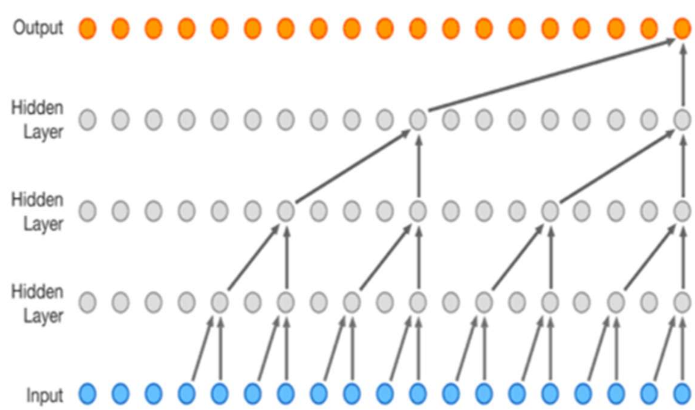

Figure-2 Dilated Convolution

Figure 2 shows the idea of dilated convolution applied in Wavenet architecture. It indicates how the receptive field increases exponentially by skipping some input values at every layer, enabling the network to learn long-range dependencies without significantly raising the computational cost. This architecture allows effective learning from sequential data such as audio or signals.

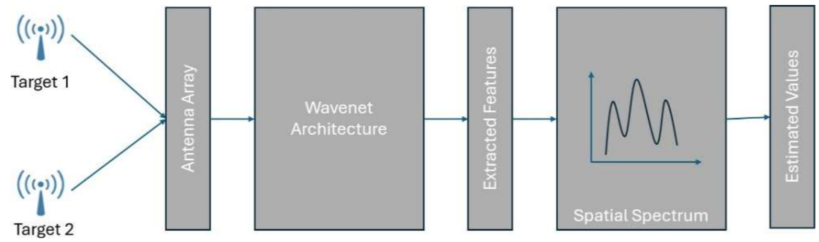

Figure-3 Block Diagram of DOA Estimation Using Wavenet

The figure 3 depicts block flow of DOA estimation employing a Wavenet-based deep learning method. Signals arriving at the antenna array from various targets are processed through a Wavenet structure using dilated convolutions to learn temporal and spatial features. The features are utilized to produce the spatial spectrum, from which direction of arrival is estimated accurately.

III. Simulation Results Observations

I have generated the synthetic data with the parameters mentioned above, considering imperfection factors. From the below graph, at 5 dB SNR, Wavenet is spectrum amplitude is higher than CNN spectrum. This proves that, Wavenet is extracting the feature better than CNN.

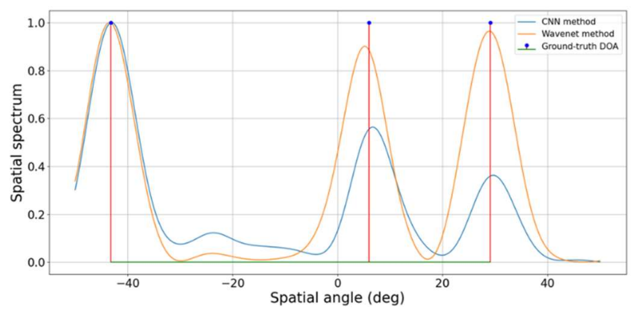

Figure-4 Spatial Spectrum at 5 dB SNR

From the figure 4, we are able to identify that in low SNR, it is observed that Wavenet
Performs better than CNN. This is because,

- Receptive Field Advantages: Dilated convolutions have larger effective receptive fields without increasing parameter count. This wider context helps distinguish true signals from noise when SNR is low.
- Multi-scale Feature Learning: Dilated convolutions can capture multi-scale features more efficiently.
- Noise Resilience: The "gaps" in dilated convolutions can actually help skip over localized noise.

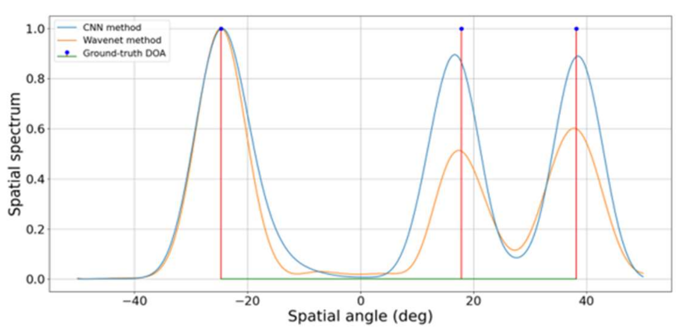

Figure-5 Spatial Spectrum at 25 dB SNR

From the figure 5, we are able to identify that in high SNR, CNN performs better.
This is due to,

- Normal Convolutions Perform Better: Local features are more distinctly visible in high SNR. Standard convolutions excel at capturing these clear, local patterns.

➢ Resolution Benefits: Normal convolutions preserve fine-grained details better. More effective at capturing subtle variations in the signal. Important when signal features are clearly distinguishable from noise.
➢ Feature Detection: Better preservation of phase information. More precise temporal localization of features.

From the above graph, at 25 dB SNR, CNN is spectrum amplitude is higher than Wavenet spectrum. This proves that, CNN is extracting the feature better than Wavenet.

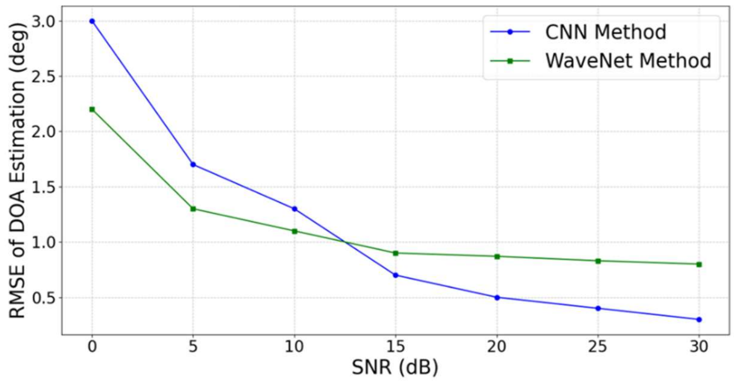

Figure-6 Comparison of CNN and WaveNet Methods

Figure 6 is average of root mean square errors of 100 test cases generated at every 5 dB interval from 0 to 30 dB. It is observed that, Wavenet is outperforming the CNN at SNR range of 0 to 13dB.

IV. Future Work

The performance of the entire system can be greatly enhanced by strategically utilizing both WaveNet and CNN, which are each efficient under different Signal-to-Noise Ratio (SNR) conditions. To obtain best results, a deep learning-based SNR classifier can be implemented to dynamically assess the input signal's SNR. According to this evaluation, the classifier directs the signal to the most appropriate model—WaveNet in low SNR and CNN in high SNR environments—so that every signal is handled by the network that is best capable of handling its noise level. WaveNet, with its capability to model temporal dependencies and learn soft patterns, performs best in noisy, low-SNR environments. On the other hand, CNNs are highly effective under high-SNR scenarios, providing accurate estimations with reduced computational complexity. The dynamic activation scheme enables the system to be adaptive across changing noise conditions, providing better and consistent direction-of-arrival estimations for all SNR values. Coupling classification with dedicated processing, the system is robust, scalable, and extremely efficient for real-world signal processing applications.

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