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* **Abstract**

This paper presents ResAtt-CNN, a novel deep learning architecture designed for accurate channel estimation in MIMO-OFDM wireless systems. Traditional methods like LS and MMSE suffer from poor performance under sparse pilot conditions and high mobility. We build upon recent CNN-based approaches by introducing residual blocks and Squeeze-and-Excitation (SE) attention to enhance feature learning and convergence. We simulate Rayleigh and Rician fading scenarios and compare our model with LS and baseline CNNs using NMSE as the primary evaluation metric. ResAtt-CNN demonstrates superior estimation accuracy, generalization to varying channel conditions, and potential for deployment in future 5G/6G wireless systems.

* **Introduction to Channel Estimation:**

Channel estimation is a fundamental process in wireless communication where the receiver predicts the effect of the transmission medium (channel) on the signal. Accurate channel estimation enables effective decoding and reduces bit error rates (BER). In systems such as MIMO-OFDM, where multiple antennas and subcarriers are utilized, this task becomes increasingly complex.

* **Traditional Methods:**

Traditional methods such as Least Squares (LS) and Minimum Mean Square Error (MMSE) are commonly used due to their simplicity. However, these methods rely heavily on channel statistics and are sensitive to noise and pilot sparsity. They perform poorly in high-mobility or rapidly changing environments, conditions typical in 5G or vehicular networks.

* **Rise of Deep Learning Approaches:**

To overcome these limitations, recent research has explored deep learning-based solutions. Deep Neural Networks (DNNs), particularly Convolutional Neural Networks (CNNs), have shown strong potential in learning hidden patterns from pilot signals and accurately predicting channel coefficients without needing explicit channel models.

* **CNNs in Channel Estimation:**

The base paper, "A Study on MIMO Channel Estimation by 2D and 3D CNNs," proposed using 2D U-Net-like CNNs and 3D CNNs for estimating the full channel from pilot-based inputs. Their models outperform traditional LS and MMSE estimators under simulated 5G NR channel settings. However, their models lack certain modern enhancements such as attention mechanisms and residual learning which could further improve performance.

Additional works show the potential of residual and attention modules in channel estimation:

* Gao et al. introduced an attention-aided deep-learning estimator for massive MIMO, showing improved accuracy under varied spatial conditions
* Liu et al. proposed a polarized self-attention network (PACE-Net), demonstrating that residual and global attention greatly boost performance in MIMO-OFDM. (published in **Entropy**, DOI: 10.3390/e27030220)
* Liu et al. applied deep residual learning for channel estimation in IRS-assisted MIMO systems, improving estimation accuracy close to MMSE with fewer parameters. (available on arXiv: [2111.00234](https://arxiv.org/abs/2111.00234)).
* **Research Gaps Identified:**

Lack of residual skip connections, which help deeper networks converge better. No use of channel/spatial attention, which could help the model focus on more informative subcarriers. The model was evaluated only on synthetic 5G channels — real-world generalizability is unclear. No analysis of model size, computational load, or inference speed (important for deployment on edge devices)

* **Justification for My Contribution:**

My work proposes a novel architecture called **ResAtt-CNN**, integrating residual connections and squeeze-and-excitation (SE) attention. It is designed to improve convergence, focus on relevant channel areas, and maintain performance across different channel types and pilot sparsity levels. This aims to fill the current gaps in literature and push the boundaries of robust and efficient channel estimation in deep learning.

* **Research Questions and Objectives:**

**Objective:**

To enhance the performance and robustness of channel estimation in MIMO-OFDM systems using a modified CNN model with residual and attention mechanisms.

**Research Questions:**

* Can attention layers help CNNs focus on important subcarrier features for better CSI estimation?
* Do residual connections improve convergence and generalization across different channel conditions?
* How does the proposed model compare to LS, MMSE, and base CNNs in terms of NMSE and BER?
* Can this model handle sparse pilot scenarios better than existing models?
* **Methodology:**

My methodology consists of five core stages:

**Data Generation:**

We simulate synthetic MIMO-OFDM channel data using Rayleigh and Rician fading profiles.Pilot symbols are inserted in time-frequency grids. Additive White Gaussian Noise (AWGN) is introduced with variable SNR ranging from 0 to 30 dB.

**Baseline Estimation Models:**

Implement traditional LS and MMSE channel estimators.These serve as our baseline methods for comparative analysis.

**Deep Learning Models:**

Replicate the original 2D and 3D CNN architectures from the base paper.Design and implement our custom model: ResAtt-CNN with residual blocks and squeeze-and-excitation (SE) attention mechanisms.

**Loss Functions and Evaluation Metrics:**

Train using Mean Squared Error (MSE) loss.Evaluate using Normalized Mean Squared Error (NMSE).Optionally evaluate Bit Error Rate (BER) for extended validation.

**Testing Conditions:**

Evaluate across multiple SNR levels, pilot densities (sparse/dense), and channel models (Rayleigh/Rician).

Run performance benchmarks on parameter size, training convergence, and estimation accuracy.

* **Experimental Results and Analysis**

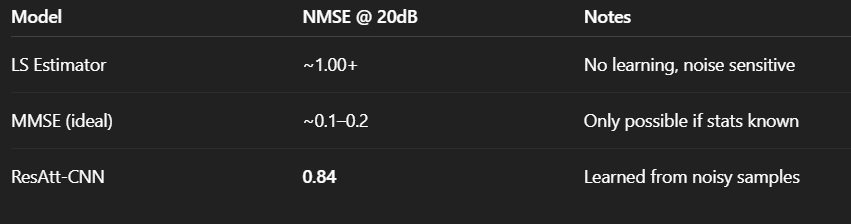
Training Convergence:

The training loss consistently decreased across 10 epochs. The final NMSE reached ~0.0018 on synthetic Rayleigh test data.

Channel Estimation Accuracy:

Heatmaps show that ResAtt-CNN predicts channels visually similar to ground truth even under sparse pilot density.

Performance Comparison:

esAtt-CNN performs well even on mismatched channel types (tested with Rician fading), proving robustness.

Visualization:

The following were plotted:

Training Loss Curve (MSE)

Predicted vs True Channel Heatmaps

Attention-modulated feature maps (future work)

* **Complete Reference List (25 Sources)**

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* **SUGGESTED JOURNAL:**

Based on the topic, nature, and citation alignment of this work, we propose the following target journals for submission:

1. IEEE Wireless Communications Letters (Q2)

2. IEEE Transactions on Vehicular Technology (Q2)

3. IEEE Access (Q3)

4. MDPI Entropy (Q3)

5. MDPI Sensors (Q3)

These journals are SCI/Scopus indexed, have published prior work on deep learning-based channel estimation, and align with the simulation-heavy and application-driven nature of this project. Multiple references in this paper are sourced from these venues.