# FD-DCNN: A Fourier Domain Denoising Convolutional Neural Network for Cardiac Artifact Removal in Single Channel EEG Signals

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# Outline

- Introduction
- Motivation
- Methods
- Experimental Dataset
- Model Training
- Performance Evaluation
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# Introduction

- Electroencephalography (EEG) is a low-amplitude, non-stationary brain signal that is highly vulnerable to noise, especially in single channel recordings.

- Cardiac (ECG) artifacts appear in EEG due to volume conduction, producing strong, periodic interference that distorts neural features.

- Efficient denoising is critical for real-time, portable single channel EEG systems requiring low-complexity, hardware-friendly solutions.

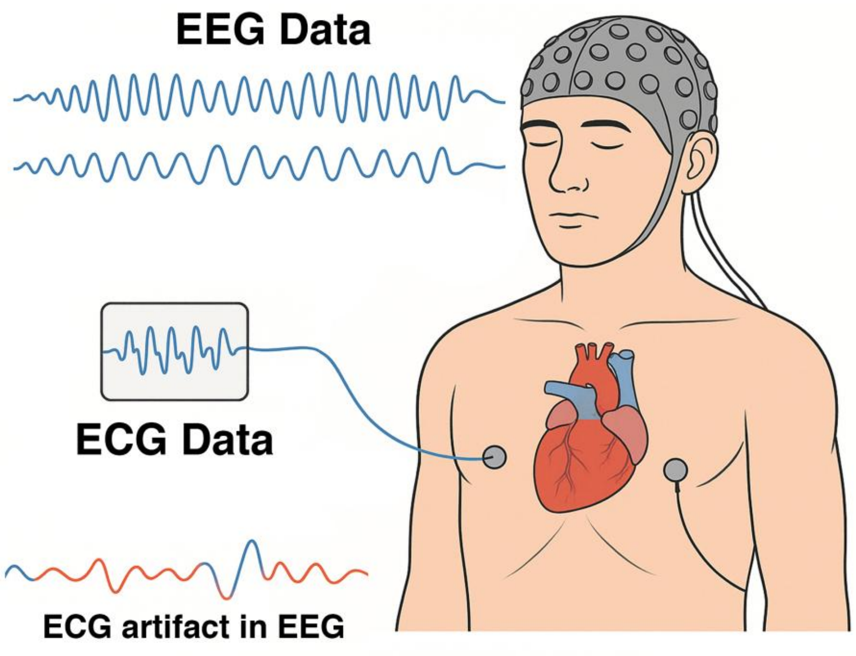


Figure 1. EEG recording and cardiac artifact contamination.

M. Nakamura and H. Shibasaki, “Elimination of EKG artifacts from EEG records: a new method of non-cephalic referential EEG recording,” Electroencephalography and clinical neurophysiology, pp. 89–92, 1987.

# Motivation

- Single channel EEG makes cardiac artifact removal difficult due to limited spatial information.
- Traditional time-domain CNNs are computationally expensive, limiting deployment on portable and low-power EEG devices.
- Existing denoising methods struggle to balance artifact suppression and morphology preservation, leading to signal distortion.
- There is a need for a lightweight, frequency-domain model that can efficiently remove ECG artifacts while preserving neural information.

# Key Contributions

- A lightweight **Fourier domain denoising CNN** is introduced that operates entirely in the spectral domain, reducing computational cost, memory usage, and latency.

- Introduces **PhaseReLU** for complex-phase nonlinear activation to preserve magnitude while enabling non-linear phase transformations for improved cardiac artifact suppression.

- A **morphology preserving loss (MPL) function** is introduced that combines mean squared error and correlation to jointly preserve amplitude fidelity and waveform morphology.

# Methods

- The proposed pipeline mixes ECG with clean EEG, processes it through FD-DCNN, and reconstructs artifact-free EEG.

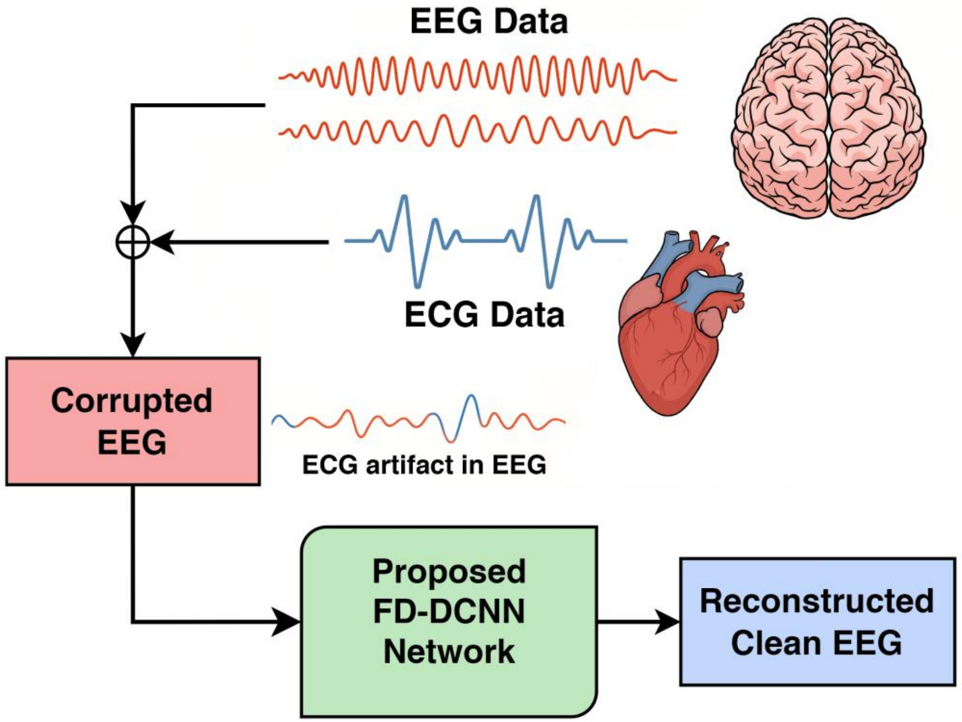


Figure 2. Flowchart of the proposed method.

# Proposed Method: FD-DCNN

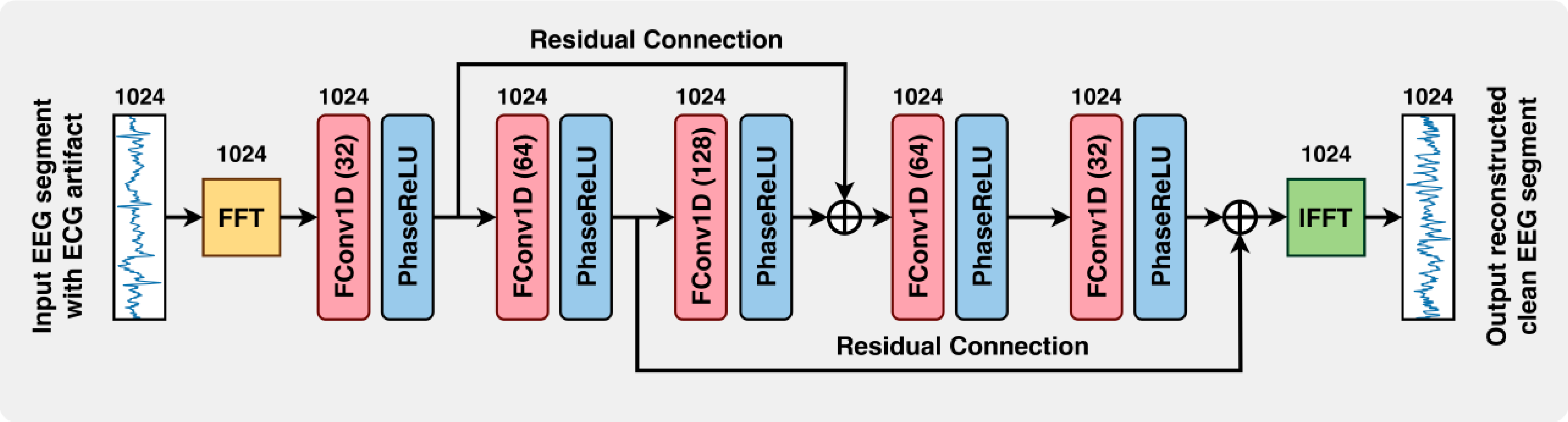


Figure 3. The architecture of the proposed FD-DCNN.

# Proposed Method: FD-DCNN (contd.)

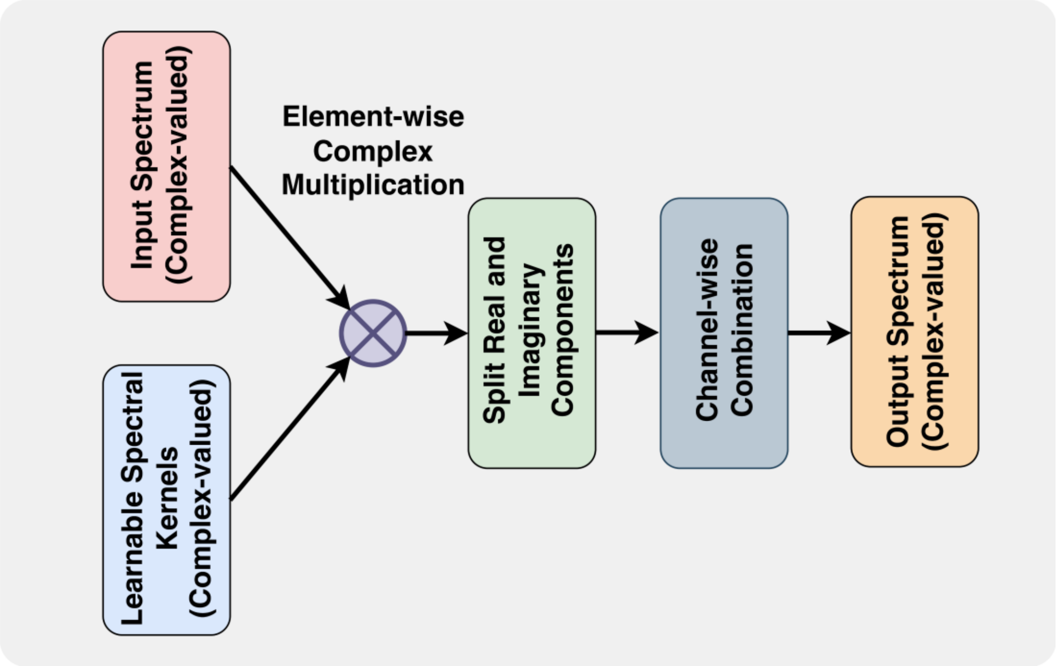


Figure 4. Block diagram of the FConv1D layer.

- According to convolution theorem:

$$y(n) = (x(n) * h(n)) \overset{\mathcal{F}}{\longleftrightarrow} Y(\omega) = X(\omega) \odot H(\omega)$$

- Filter output after element-wise complex multiplication:

$$U_k(\omega) = Z_{\text{in}}(\omega) \odot W_k(\omega)$$

$$U_{k,R}(\omega) = \Re\{U_k(\omega)\}, \quad U_{k,I}(\omega) = \Im\{U_k(\omega)\}$$

- Channel-wise combination:

$$Y_R(\omega) = \sum_{k=1}^{F} \alpha_{k,R} U_{k,R}(\omega) \quad Y_I(\omega) = \sum_{k=1}^{F} \alpha_{k,I} U_{k,I}(\omega)$$

- Output complex-valued spectrum:

$$Y(\omega) = Y_R(\omega) + jY_I(\omega)$$

L. Chi, B. Jiang, and Y. Mu, “Fast fourier convolution,” Advances in Neural Information Processing Systems, vol. 33, pp. 4479–4488, 2020.

# Proposed Method: FD-DCNN (contd.)

- **PhaseReLU activation:**

$$PhaseReLU(z) = |z|(\cos(ReLU(\phi_z)) + i\sin(ReLU(\phi_z)))$$

where $z = |z|e^{j\phi_z}$ is a complex-valued spectral coefficient.

- **Morphology Preserving Loss (MPL):**

$$\mathcal{L} = \mathcal{L}_{\text{MSE}} - \lambda\mathcal{L}_{\text{corr}}$$

where $\mathcal{L}_{\text{MSE}} = \frac{1}{N}\sum_{n=1}^{N}(x_{\text{clean}}(n) - \hat{x}(n))^2$ and $\mathcal{L}_{\text{corr}} = \frac{\langle x_{\text{clean}}, \hat{x}\rangle}{\|x_{\text{clean}}\| \, \|\hat{x}\|}$

Y. Han and B.-W. Hong, "Deep learning based on fourier convolutional neural network incorporating random kernels," Electronics, vol. 10, no. 16, p. 2004, 2021.

# Performance Metrics

To assess the effectiveness of our proposed method, the following performance metrics are employed:

- **Relative Root Mean Square Error (RRMSE): (**(Measures amplitude deviation)

$$RRMSE_t = \frac{RMS(z - \tilde{z})}{RMS(\tilde{z})}$$

$$RRMSE_f = \frac{RMS(PSD(z) - PSD(\tilde{z}))}{RMS(PSD(\tilde{z}))}$$

- **Correlation Coefficient (CC):** (Measures waveform similarity)

$$CC = \frac{cov(z, \tilde{z})}{\sigma_{zz}\sigma_{\tilde{z}\tilde{z}}}$$

- **Average Power Ratio (APR):** (Preserves EEG frequency bands)

$$APR = \frac{Power\ in\ a\ specific\ frequency\ band}{Total\ power\ across\ all\ frequencies}$$

R. Acharjee and S. R. Ahamed, "Efficient muscle artifact removal from single channel EEG signals using deep long short-term memory network," 2024 IEEE 21st India Council International Conference (INDICON), 2024

# Experimental Dataset

- **EEGdenoiseNet** and **MIT-BIH Polysomnographic** datasets are used to generate simulated data.

Table 1. Summary of the experimental dataset.

| Type | EEGdenoiseNet | MIT-BIH |
|---|---|---|
| Data | Single channel EEG | Single-lead ECG |
| Bandpass filtering | 1-80 Hz | 1-80 Hz |
| Resampling | 256 Hz | 256 Hz |
| Segment length | 4 sec | 4 sec |

- $$EEG_{noisy} = EEG_{clean} + \theta \cdot ECG$$

$$SNR = 10 \log \frac{RMS(EEG_{clean})}{RMS(\theta \cdot ECG)}$$

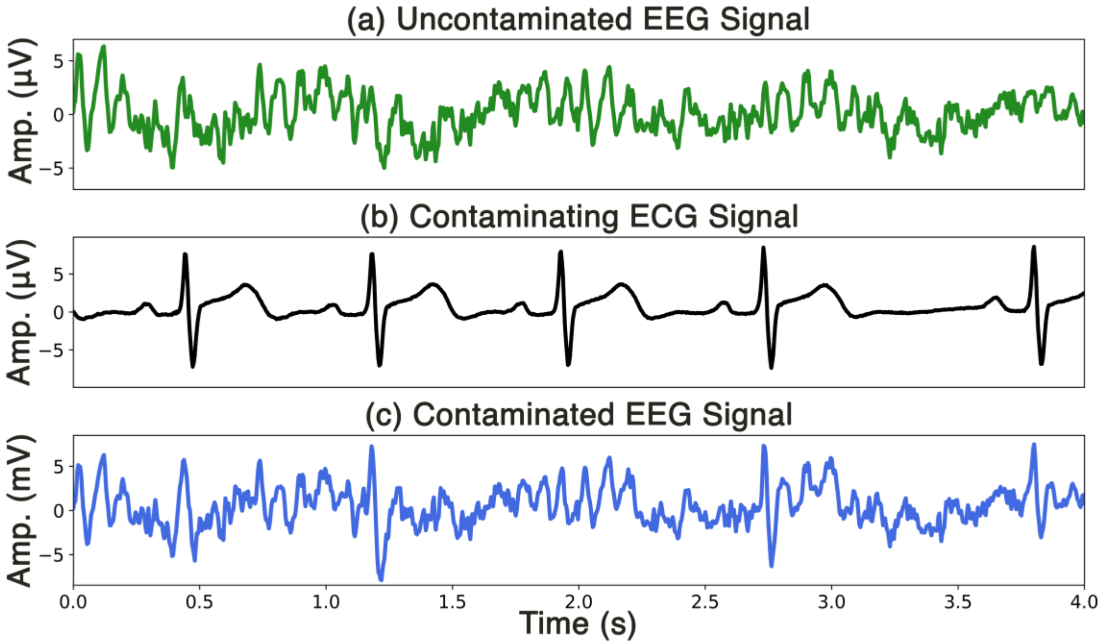


Figure 5. segment of (a) Uncontaminated EEG,
(b) Contaminating ECG, and (c) Contaminated EEG signal

- SNR range: 5-15 dB, epochs: 1128, train-val-test split: 80:10:10


H. Zhang, M. Zhao, C. Wei, D. Mantini, Z. Li, and Q. Liu, “EEGdenoiseNet: a benchmark dataset for deep learning solutions of EEG denoising,” Journal of Neural Engineering, vol. 18, no. 5, p. 056057, 2021.
A. L. Goldberger et al., “PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals,” circulation, vol. 101, no. 23, 2000.

# Model Training

- The FD-DCNN architecture is implemented using TensorFlow 2.0 framework and trained on Xeon Gold-6248 CPU (2.5 GHz) and NVIDIA Tesla V100-PCIe GPU with 32 GB of VRAM.

Table 2. Model training parameters and hyperparameters.

| Parameters/Hyperparameters | Value |
|---|---|
| Activation Function | PhaseReLU |
| Loss Function | MPL ($\lambda = 0.2$) |
| Optimizer | RMSprop |
| Learning Rate | 0.0005 |
| Batch Size | 32 |
| Epochs | 50 |
| Early Stopping | No |
| Weight Initializer | Glorot Uniform |
| Random Seed | 42 |
| Trainable Parameters | $656,010$ |

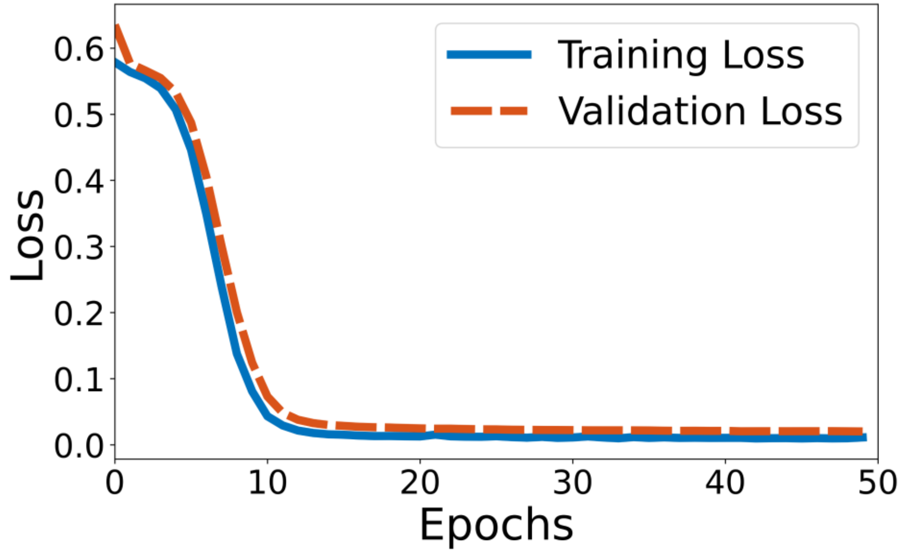


Figure 6. Training and validation loss curve.

- The FD-DCNN obtained training loss of **0.0099** and validation loss of **0.0177**.

# Performance Evaluation

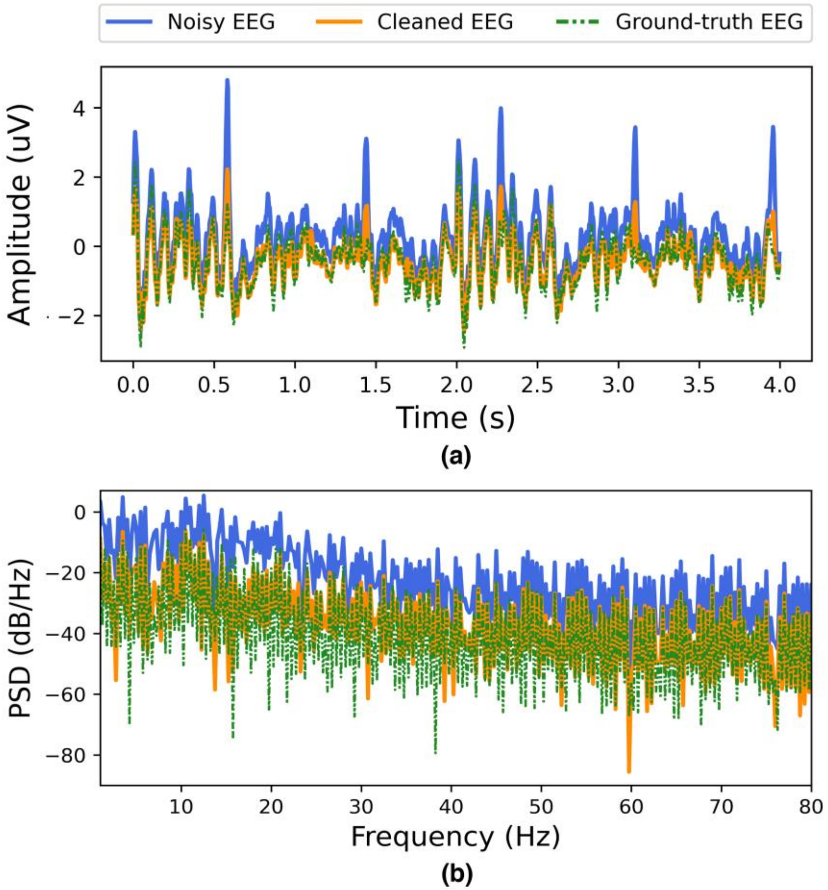


Figure 7. Reconstructed clean EEG by the FD-DCNN model in comparison with the noisy and ground-truth EEG,
(a) Time domain, and (b) Frequency domain representation.

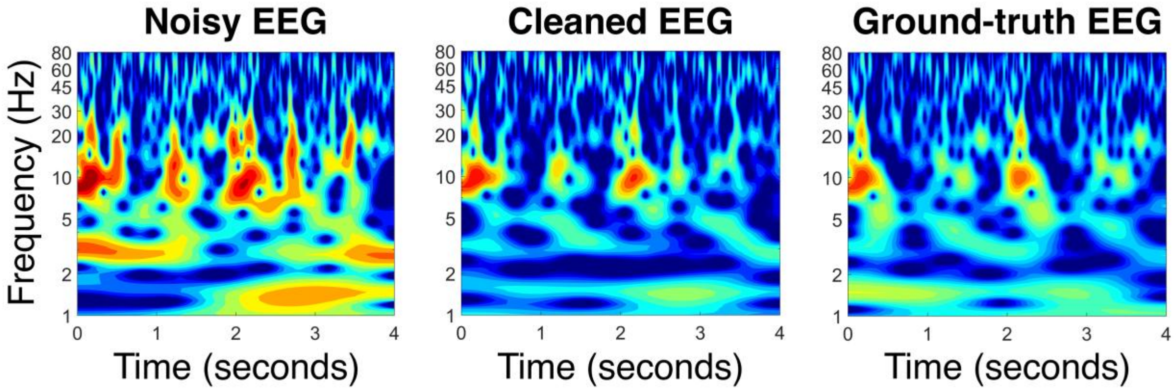


Figure 8. Time-frequency plots of noisy, cleaned, and ground-truth EEG

# Performance Evaluation (contd.)

Table 3. Comparison of the proposed FD-DCNN with the baseline TD-CNN model.

| Metrics | FD-DCNN | TD-CNN |
|---|---|---|
| Total parameters | 0.67M | 33.67M |
| Memory | 2.50MB | 128.42MB |
| FLOPs | 2.31M | 290.39M |
| Inference latency (GPU) | 2.46 ms/seg | 16.12 ms/seg |
| Throughput (GPU) | 406.5 seg/s | 62.03 seg/s |
| $RRMSE_t$ | 0.4301 | 0.5672 |
| $RRMSE_f$ | 0.3548 | 0.3748 |
| Correlation | 0.8879 | 0.7674 |

Table 4. Comparison with related works.

| Method | $RRMSE_t \downarrow$ | $RRMSE_f \downarrow$ | CC $\uparrow$ |
|---|---|---|---|
| FCNN | 0.6832 | 0.6422 | 0.7266 |
| Simple LSTM | 0.5668 | 0.5879 | 0.7951 |
| Simple CNN | 0.5715 | 0.4826 | 0.8133 |
| ResNet | 0.5497 | 0.4728 | 0.8379 |
| 1D-CDAE | 0.4622 | 0.4148 | 0.8442 |
| **FD-DCNN** | **0.4301** | **0.3548** | **0.8879** |

H. Zhang, M. Zhao, C. Wei, D. Mantini, Z. Li, and Q. Liu, “EEGdenoiseNet: a benchmark dataset for deep learning solutions of EEG denoising,” Journal of Neural Engineering, vol. 18, no. 5, p. 056057, 2021.
K. He et al., “Deep residual learning for image recognition,” 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 770–778, 2015.
R. Acharjee and S. R. Ahamed, “Automatic Eyeblink Artifact Removal from Single Channel EEG Signals Using One-Dimensional Convolutional Denoising Autoencoder,” ICCECE, 2024, pp. 1–7.

# Performance Evaluation (contd.)

Table 5. Average power ratios in different frequency bands for noisy EEG, cleaned EEG, and the ground-truth EEG signals.

| Frequency Bands | Noisy EEG | Cleaned EEG | Ground-truth |
|---|---|---|---|
| Delta (1 – 4 Hz) | 0.264 | 0.211 | 0.225 |
| Theta (4 – 8 Hz) | 0.168 | 0.151 | 0.163 |
| Alpha (8 – 13 Hz) | 0.314 | 0.440 | 0.426 |
| Beta (13 – 30 Hz) | 0.231 | 0.155 | 0.171 |
| Gamma (30 – 80 Hz) | 0.045 | 0.094 | 0.072 |

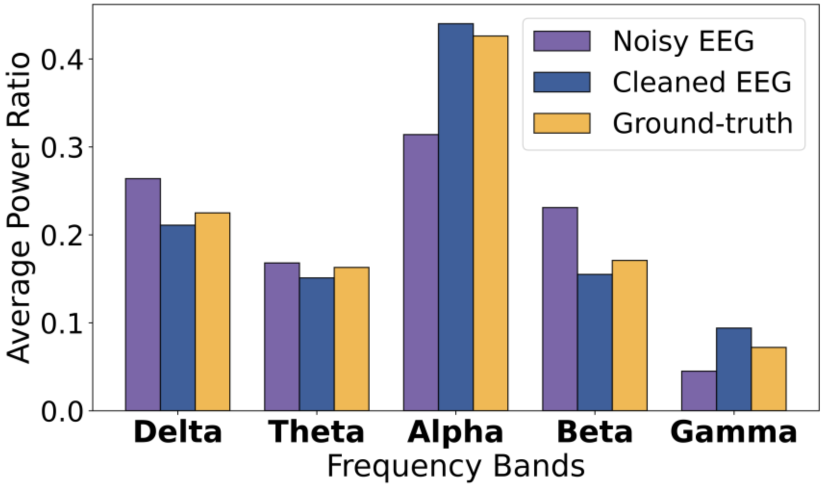


Figure 9. Bar plot for comparison of APR between noisy, cleaned, and ground-truth EEG in different frequency bands.

# Ablation Study

Table 6. Ablation study showing the effect of PhaseReLU, MPL (λ variation), and skip connections on FD-DCNN performance.

| Variant | $\text{RRMSE}_t \downarrow$ | $\text{RRMSE}_f \downarrow$ | Correlation $\uparrow$ | Remarks |
|---|---|---|---|---|
| Baseline (PhaseReLU + MPL, $\lambda = 0.2$, with residuals) | 0.4301 | 0.3548 | 0.8879 | Full model |
| PhaseReLU only, without MPL ($\lambda = 0$, MSE only) | 0.4653 | 0.3813 | 0.8671 | Tests effect of correlation term in MPL |
| ReLU (real and imag), with MPL | 0.5119 | 0.4155 | 0.8267 | Tests effect of PhaseReLU by replacing with standard ReLU |
| $\lambda$ variation $(0 - 1.0)$ | 0.4301 | 0.3548 | 0.8879 | Sensitivity of MPL weight, best at $\lambda = 0.2$ |
| No Residuals | 0.4721 | 0.3853 | 0.8434 | Tests skip-connection effect |

- PhaseReLU, MPL, and skip connections significantly improve morphology preservation.

# Conclusion

- FD-DCNN performs all **convolutions in the Fourier domain**, replacing costly time-domain operations with efficient complex multiplications, resulting in **reduced FLOPs, memory, and parameters.**
- Effectively suppresses **cardiac (ECG) artifacts** in **single channel EEG** while preserving essential temporal and spectral neural information, outperforming existing CNN-based denoising approaches.
- The proposed **MPL loss** and **PhaseReLU** activation enable superior denoising, achieving lower RRMSE and higher correlation than the baseline time-domain CNN while preserving EEG morphology.
- Its **lightweight** and **hardware-friendly** design makes FD-DCNN ideal for **real-time, low-power EEG systems**, outperforming conventional CNNs in both accuracy and efficiency.
- The study uses **synthetically contaminated EEG**, which may limit real-world generalizability. Future work includes testing on naturally contaminated EEG and deploying the model on FPGA/ASIC for real-time portable applications.

# References

[1] M. Nakamura and H. Shibasaki, “Elimination of EKG artifacts from EEG records: a new method of non-cephalic referential EEG recording,” Electroencephalography and clinical neurophysiology, pp. 89–92, 1987.

[2] L. Chi, B. Jiang, and Y. Mu, “Fast fourier convolution,” Advances in Neural Information Processing Systems, pp. 4479–4488, 2020.

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# Thank You

## Any Questions?