RANGE-GAN: Residual Architecture Network for Generating EEG-GAN

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Abstract

Generative Adversarial Networks (GANs) offer a promising and powerful method for addressing the issue of scarce data. However, generating realistic, multi-channel Electroencephalography (EEG) signals that preserve complex spectral and temporal features remains a difficult challenge, often hindered by training instability. In this paper, we introduce RANGE-GAN, a novel deep generative architecture that leverages the power of Residual Network (ResNet) architecture within a stable Wasserstein GAN with Gradient penalty (WGAN-GP) framework. We demonstrate that the following architecture achieves the state-of-the-art performance in generating resting state EEG signals, showing exceptional stability throughout training. Through comprehensive quantitative and qualitative evaluations, we show that RANGE-GAN produces the synthetic data with near perfect spectral fidelity, achieving final mean Fréchet Distance (FD) of 0.2542, with a spectral component FD of just 0.0028 - This is a marked improvement over prior benchmarks. Our results indicate that a deep , well regularized convolutional architecture can effectively model the complex dynamics of EEG signals without relying on additional components such as self-attention, establishing RANGE-GAN as a strong and effective baseline for Neurophysiological time-series synthesis.

Keywords: *Generative Adversarial Networks (GANs), Electroencephalography (EEG), Deep Learning, Residual Networks (ResNets), Signal Synthesis, Computational Neuroscience*

1 Introduction

The application of Deep learning to neuroscience offers transformative potential but is frequently constrained by the practical challenges of acquiring huge, diverse and high-quality datasets[1]. Electroencephalography (EEG), a fundamental tool in clinical neurology and cognitive neuroscience, is particularly vulnerable to these limitations. The process of recording clean EEG is resource-intensive and as well as subject to considerable inter individual variability [1].

The Generative Adversarial Networks (GANs) ,which was introduced by Goodfellow et al. [2], provide a powerful unsupervised learning solution to address this data scarcity. By training two neural networks i.e. Generator and a Discriminator in a minmax game, GANs are capable of learning the underlying distribution of a dataset and generate a novel and synthetic samples. For EEG, this capability of GANs is invaluable for tasks such as data augmentation, class balancing for clinical datasets, and generating anonymized data for public sharing [3].

However, the rapid temporal dynamics and non-stationary nature of EEG signals create unique challenges for generative modeling. Early GAN architectures often suffered from training instability, such as mode collapse, where generator produces only a limited variety of samples [2, 4]. While later works such as EEG-GAN [3] and other variants have made impactful progress, achieving both high fidelity and stable training remains an open research problem.

In this paper, we propose RANGE-GAN, a novel architecture designed explicitly for robust and high-fidelity generation of multi-channeled EEG signals. Our primary contributions can be divided in two parts:

*1. **A Novel Deep Residual and Spectral Normalized Architecture:** We leverage the power of deep Residual Networks (ResNets) [5] in the Generator, demonstrating that architectural depth, facilitated by residual connections, is a key factor in capturing the complex features of EEG data. In the Discriminator, we implement spectral-normalized convolutional layers inorder to ensure stability and effective gradient flow..*

*2. **A State-of-the-Art Training Framework:** We integrate this architecture within a stable Conditional Wasserstein GAN with Gradient Penalty (cWGAN-GP) framework [4, 6], which has been enhanced with the Spectral Normalization [7] along with a Mode seeking diversity loss. This combination results in an exceptionally stable training process and state-of-the-art signal quality..*

We present a comprehensive evaluation of RANGE-GAN, showing its superior performance in training stability and as well as in the section of signal fidelity compared to established benchmarks. Highlighting the effectiveness of deep convolutional architectures in capturing intricate neurophysiological time series patterns..

2 Related Work

The application of Generative Adversarial Networks (GANs) [2] in the field of medical imaging and time-series data has become an active area of research. Particularly *in neurophysiological domain, GANs have be explored chiefly for data augmentation tasks to address common issue of limited as well as imbalanced datasets, which is especially prevalent in clinical applications like seizure detection [3] and brain-computer interfaces[3]. Early efforts in this field , such as EEG-GAN by Hartmann et al. [3], was successfull in adapting Deep Convolutional GAN (DCGAN) architecture [8] to the one-dimensional, multi-channel structure of EEG data, which demonstrates the feasibility of generating realistic-looking brain signals..*

Succeedig research has focused on improving the training stability and generation quality. The introduction of the Wasserstein GAN (WGAN)[4] and its refinement, WGAN with Gradient Penalty (WGAN-GP)[6], provided a more stable training objective by using the Earth-Mover's distance as a metric. This particularly has been instruental in generating high fidelity signals and has been implemented in many modern approaches for EEG synthesis.

However recently, architectural trends have been influenced by the success of Transformer model in natural language processing [9]. The core component i.e., the self-attention mechanism, has been introduced as a method to explicitly model long-range temporal dependencies inherent in complex signals like EEG. This paved path for the development of hybrid models that combine convolutional layers with self attention modules. A prominent example is YARE-GAN[10], which incorporates self-attention into both its generator and discriminator, arguing for its necessity in capturing the full dynamics of the signal and learning useful feature representations. Although these models have pushed the performance boundaries, they often introduce significant computational complexity. .

Our work is positioned at the intersection of these developments. We utilize the stable WGAN-GP training framework questioning the prerequisite of self-attention. We hypothesize that a deep , well-regularized Residual convolutional network, inspired by the success of ResNets in the field of Computer Vision[5], would provide a more efficient and equally , if not more, but a powerful alternative for learning the complex spatio-temporal distributions of EEG data..

3 Materials and Methods

3.1 Dataset and Preprocessing

For training and evaluation purpose we utilized the publicly available MPI-LEMON (Leipzig Mind-Brain-Body) dataset[1], which contains resting-state EEG recordings from a large cohort of Healthy adults..

Our preprocessing pipeline was designed to produceclean and normalized data segments which are suitable for RANGE-GAN training. The steps, applied to each participant's recording are as follows:.

1. **Channel Selection:** *We selected a standard 8-channel montage comprising frontal, central, parietal, and occipital sites: F1, F2, C1, C2, P1, P2, O1, O2.*

2. **Resampling:** *The raw signals were converted to a sampling rate of 98 Hz. This was consciously chosen to effectively eliminate 50 Hz power-line noise via the Nyquist theorem without requiring a specific notch filter.*
3. **Filtering:** *A high-pass filter at 0.5 Hz was applied using a FIR (Finite Impulse Response) filter to remove low-frequency physiological drifts.*
4. **Baseline Correction:** *The average value of the initial 0.5 seconds of each channel was subtracted from the entire channel to center the signal.*
5. **Normalization and Outlier Clamping:** *Inorder to handle variations in amplitude across all subjects and channels, a two-step normalization process was applied. First, a **RobustScaler** was used to mitigate the effect presented by outliars, followed by a **StandardScaler** to achieve Zero mean and Unit Variance. Subsequently, any values exceeding 20 standard deviations were also clamped to prevent extreme artifacts from skewing out the entire training process.*
6. **Segmentation:** *The following coninuous time-series data was segmented into non-overlapping 512 time points each.*

The following pipeline yielded a final dataset of 35,503 epochs, each with a dimension of (512 , 8) . Finally, inorder to align the data distribution with the Generator's `tanh` output layer, the entire dataset was scaled by a single global factor. The maximum absolute value across all data points was calculated ($scale_factor = 20.0$) and the dataset was divided by this value, this resulted in the effective mapping of the input EEG signals to the range `[-1,1]`. This final dataset was then used for model training.

3.2 RANGE-GAN Architecture

RANGE-GAN has been built upon the Conditional Wasserstein GAN with Gradient Penalty (cWGAN-GP) paradigm, chosen for its demonstrated stability and effective conditional EEG generation over traditional GAN formulations. The core of our research and contribution lies in the specific deep residual architectures of the Generator (`G`) and Discriminator (`D`).

3.2.1 Generator

*The Generator's role is to map a point **z**from a simple prior distribution (e.g., Gaussian) and a conditional class vector `c` to the complex data space of EEG signals. The presented Generator is a deep convolutional decoder that progressively upsamples the signal through four specialized **Residual Blocks (ResBlocks)**.*
A single ResBlock [5], performs an upsampling operation followed by a series of 1D convolutions. A "shortcut" or an "identity" connection will add the block's input to its output, allowing the network to learn the residual mapping. This structure is very critical as this mitigates the problem of vanishing gradient and enables the stable training of a very deep network. The output of a ResBlock can be formulated as follows:

$$\mathbf{y} = \mathcal{F}(\mathbf{x}, \{\mathbf{W}_i\}) + \mathbf{W}_s\mathbf{x} \tag{1}$$

where $\mathbf{x}$ and $\mathbf{y}$ are the input and output vectors of the layers considered, $\mathcal{F}(\mathbf{x}, \{\mathbf{W}_i\})$ represents the residual mapping learned by the convolutional stack with weights $\{\mathbf{W}_i\}$, *and* $\mathbf{W}_s$ *is a linear projection (often implemented as a 1x1 convolution) used by the shortcut connection to align with the channel dimensions of* $\mathbf{x}$ *and* $\mathcal{F}$*..*

The final layer of the generator utilizes a ***`tanh`*** *activation function, this bounds the output signals to the range of* *`[-1,1]`*, *this ensures a well defined output space. The function is defined as:.*

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{2}$$

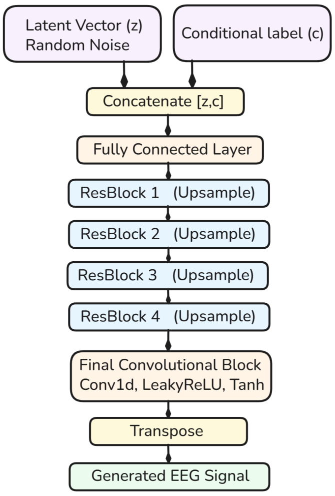


Fig. 1 The architecture of the RANGE-GAN Generator. A latent vector **z** is concatenated with a conditional embedding `c` and projected by a fully connected layer into an initial seed tensor. This tensor is then passed through a stack of four upsampling residual blocks, which progressively increase the temporal resolution while refining features, before a final convolutional layer generates the multi-channel EEG signal.

3.2.2 Discriminator

The Discriminator , also called as Critic, is a deep convolutional encoder which is designed to differentiate between the real and the generated (fake) EEG signals. Its architecture consists of a series of 1D convolutions that downsample the input signal at each layer, thereby building a hierarchical feature representation..

Inorder to adhere to the 1-Lipschitz constraint required by the Wasserstein distance, we have employed ***Spectral Normalization*** *on all convolutional and the linear layers of Discriminator, as proposed by Miyato et al.[7]. Spectral Normalization enhances the training stability by limiting the spectral norm of each layer's weight matrix* $\mathbf{W}$*. The spectrally normalized weight* $\bar{\mathbf{W}}_{SN}$ *is computed as: .*

$$\bar{\mathbf{W}}_{SN}(\mathbf{W}) = \frac{\mathbf{W}}{\sigma(\mathbf{W})} \tag{3}$$

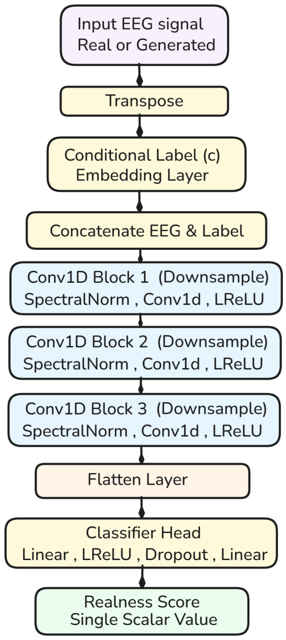


Fig. 2 The architecture of the RANGE-GAN Discriminator (Critic). An Input EEG signal is concatenated with a conditional embedding and is passed through a series of spectrally normalized, strided convolutional layers. This process extracts a high-level feature vector, which is then passed to a classifier head to produce a single scalar "realness" score.

where $\sigma(\mathbf{W})$ *is the spectral norm of* $\mathbf{W}$ *(its largest singular value), defined as* $\sigma(\mathbf{W}) = \max_{\mathbf{h}:\mathbf{h}\neq 0} \frac{\|\mathbf{Wh}\|_2}{\|\mathbf{h}\|_2}$. *This ensures that the Lispschitz constant of the layer is bounded by 1..*

4 Training Procedure and Loss Functions

The Training procedure of RANGE-GAN follows the adversarial process of WGAN-GP. The Discriminator `D` *is trained to maximize the following objective function, which estimates the Wasserstein-1 distance:.*

$$\mathcal{L}_D = \mathop{\mathbb{E}}_{\tilde{\mathbf{x}}\sim\mathbb{P}_g}[D(\tilde{\mathbf{x}})] - \mathop{\mathbb{E}}_{\mathbf{x}\sim\mathbb{P}_{\hat{\mathbf{x}}}}[(\|\nabla_{\hat{\mathbf{x}}} D(\hat{\mathbf{x}})\|_2 - 1)^2] \tag{4}$$

In this objective: .

- $\mathbb{P}_r$ *is the real data distribution, and* $\mathbb{P}_g$ *is the generator's distribution, which has been defined by* $\tilde{\mathbf{x}} = G(\mathbf{z})$ *where* $\mathbf{z}$ *is drawn from a standard normal distribution.*
- *The first two terms approximate the Wasserstein distance by pushing the critic's score for real samples* $D(\mathbf{x})$ *to be higher than it is for fake samples* $D(\tilde{\mathbf{x}})$.
- *The third term which is known as* ***Gradient Penalty (GP)*** *, with weight* λ *. Its work is to penalize the critic if the L2 norm of its gradient deviates from 1. The*

samples $\hat{\mathbf{x}}$ *are drawn uniformly along straight lines between pairs of real and fake samples, i.e.,* $\hat{\mathbf{x}} = \epsilon\mathbf{x} + (1-\epsilon)\tilde{\mathbf{x}}$ for $\epsilon \sim U[0,1]$.

Similarly, the generator G *is trained to minimize the following objective* $\mathcal{L}_G$*, which aims to produce samples that the discriminator scores as highly realistic while also promoting output diversity:.*

$$\mathcal{L}_G = -\mathop{\mathbf{E}}_{\mathbf{z}\sim p(\mathbf{z})}[D(G(\mathbf{z}))] + \eta \cdot \frac{\mathbb{E}[\|\mathbf{z}_1 - \mathbf{z}_2\|_1]}{\mathbb{E}[\|G(\mathbf{z}_1) - G(\mathbf{z}_2)\|_1] + \epsilon_{ms}} \tag{5}$$

Here:

- *The first term ,* $-\mathbb{E}[D(G(\mathbf{z}))]$*, constitutes of primary adverarial loss, which encourages the generator to procude outputs that are capable of achieving a high score from the discriminator.*
- *The second term is* ***Mode-seeking diversity loss*** *with weight* η *. It maximizes the ratio of the distance between the following two latent vectors* $(\mathbf{z}_1, \mathbf{z}_2)$ *to teh distance between their corresponsing outputs* $(G(\mathbf{z}_1), G(\mathbf{z}_2))$*, measured using the L1 norm. This explicitly penalizes the mode collapse by encouraging unique latent codes to map to distinct outputs. A small constant* ϵ_{ms} *is added for numerical stability.*

5 Results and Discussion

RANGE-GAN was trained for 200 epochs. The model demonstrated an exceptional training stability and generation fidelity, establishing a new benchmark for this task.

5.1 Training Stability

The training process was monitored via several key metrics, shown in Fig. 3

Unlike many other GAN models which exhibit significant oscillations or mode collapse during their training process, RANGE-GAN's loss curves converge smoothly. To quantitatively assess the fidelity of the generated signals, we employed the Fréchet Distance (FD) [11]. The FD measures the distance between two multivariate Gaussian distributions, which are fitted to feature representations extracted from real and generated data, respectively. It is defined as:

$$d^2(\mathbb{P}_r, \mathbb{P}_g) = \|\mu_r - \mu_g\|_2^2 + \mathrm{Tr}(\Sigma_r + \Sigma_g - 2(\Sigma_r\Sigma_g)^{1/2}) \tag{6}$$

where μ_r *and* μ_g *are the means of the features from the real and generated data,* Σ_r *and* Σ_g *are their respective covariance matrices, and Tr denotes the trace of a matrix. A lower FD score indicates a closer match between the two distributions and thus the higher generation quality. The FD drops steeply within the first 30 epochs and remains low for the remaining training period , reaching a best mean FD of* ***0.2542*** *. The spectral component FD was particularly strong , reaching just* ***0.0028****. This demonstrates the model's robustness and its ability to rapidly learn the target data distribution.*

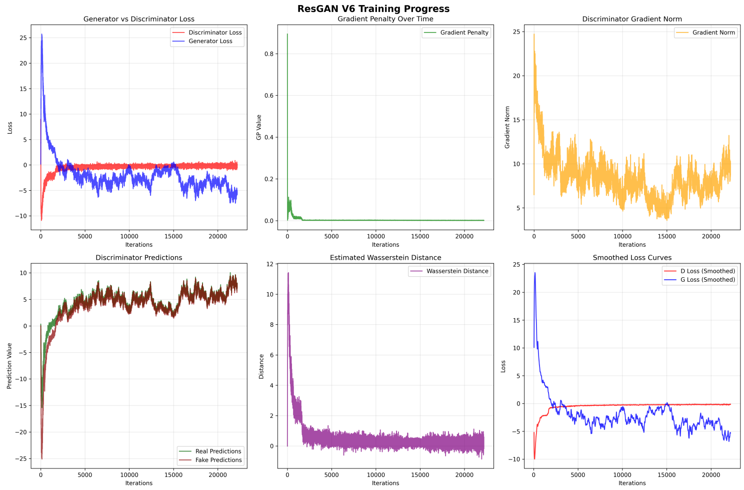


Fig. 3 Training dynamics of RANGE-GAN over 200 epochs (20,000+ iterations) This figure demonstrates the stability of the RANGE-GAN training process. **(Top Row, Left to Right):** (a) Generator vs. Discriminator losses showing a stable adversarial equilibrium; (b) Gradient Penalty (GP) value which is converging rapidly to zero, indicates that the 1-Lipschitz constraint is successfully enforced; (c) Discriminator Gradient Norm stabilizing after an initial decrease. **(Bottom Row, Left to Right):** (d) Output scores for real and fake samples by Discriminator (critic), demonstrating a clear and sustained separation; (e) The estimated Wasserstein Distance, quickly converges to a low value; (f) Smoothed loss curves (Generator vs Discriminator) confirming the long-term stability of both the networks. Collectively, these plots indicate a healthy, non-saturating, and robust training process.

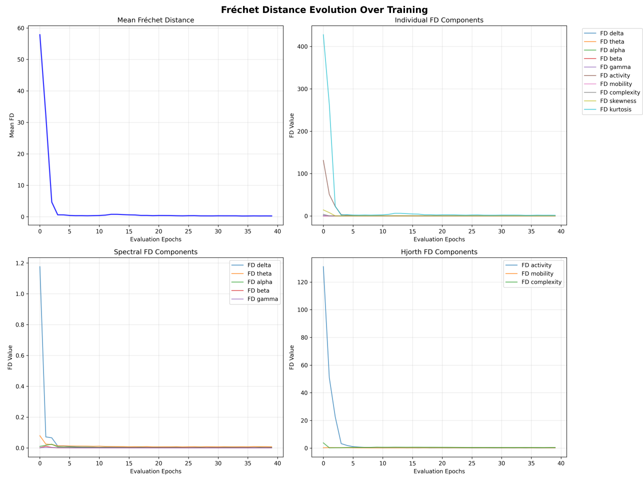
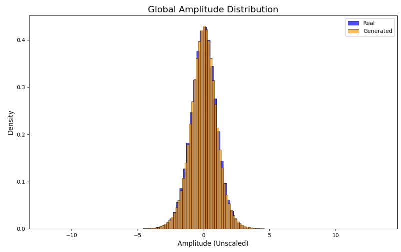
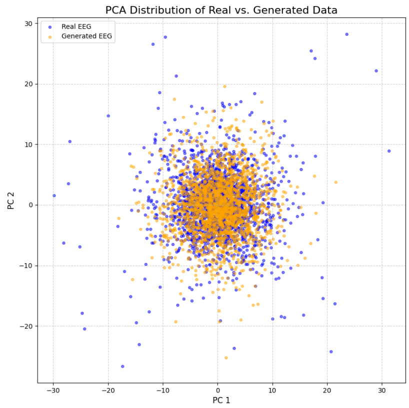


Fig. 4 Fréchet Distance (FD) Evolution Over Training. The figure illustrates the quantitative convergence of ResiEEG-GAN. **(Top-Left)** The Mean FD across all features shows a rapid decrease, stabilizing at a state-of-the-art low value. **(Top-Right & Bottom Row)** The FD for individual, spectral, and temporal (Hjorth) components all demonstrate similar rapid convergence, confirming that the generator successfully learned a wide range of statistical properties from the real data distribution.



(a) The Global amplitude distribution histogram plot.



(b) The final PCA plot (a single snapshot, perhaps from epoch 200

Fig. 5 Comparison of Global and Low-Dimensional Data Distributions. (a) The histogram of signal amplitudes from the generated data (orange) showing a near-perfect overlay with the real data (blue), this demonstrates that first-order statistics are well matched. **(b)** This 2D PCA projection shows a high degree of overlap between the real (blue) and generated (orange) data manifolds, which demonstrates a close match in low-dimensional structure.

5.2 Signal Generation Fidelity

The quality of the generated signals was assessed both qualitatively and quantitatively. Fig. 6 shows a near-perfect match between Power Spectral Display (PSD) of the real and generated data, which is indeed a critical benchmark for EEG synthesis. Our model accurately captures not only the characteristic 1/f spectral decay but also the prominent alpha-band peak (10 Hz).

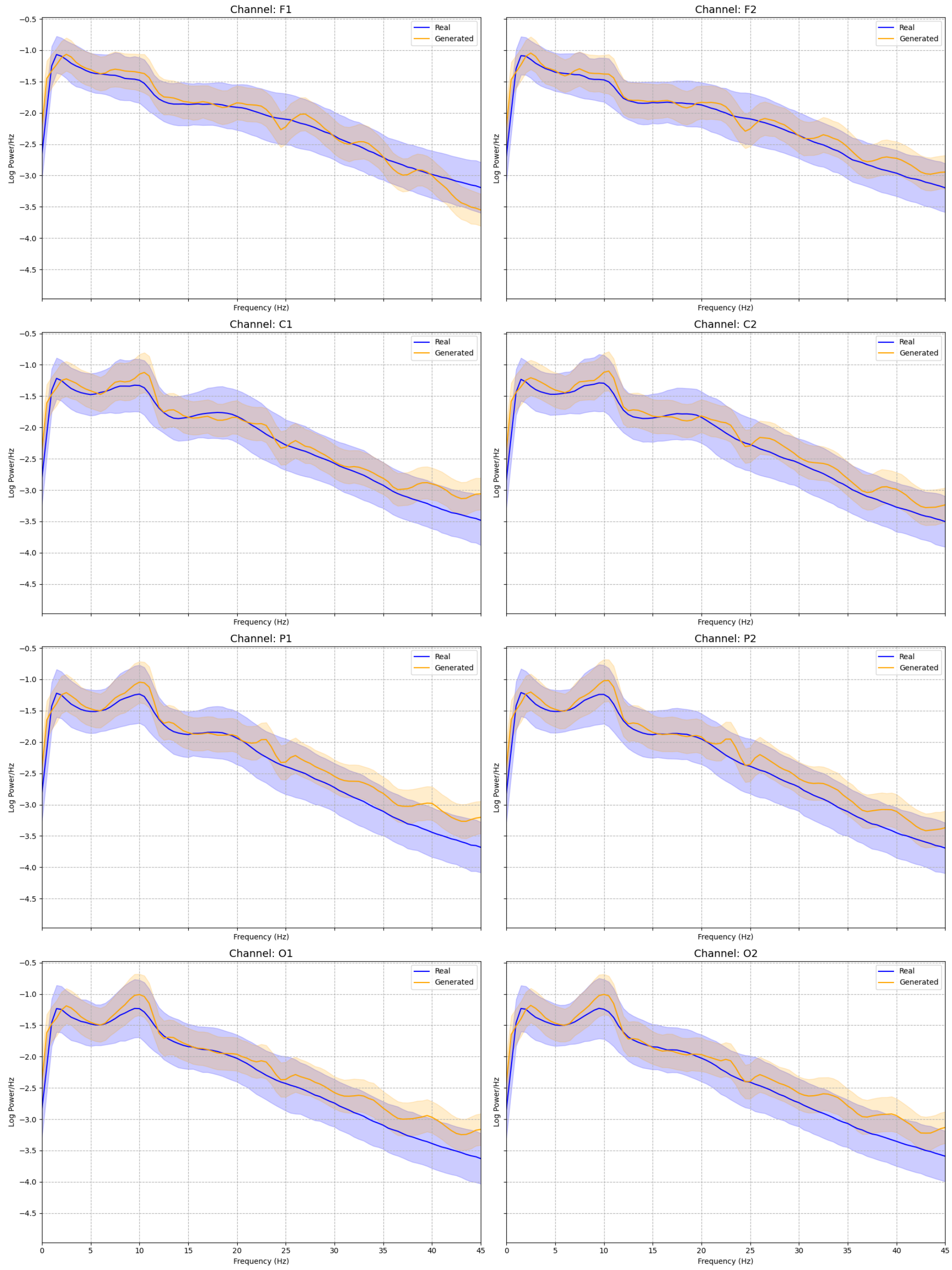
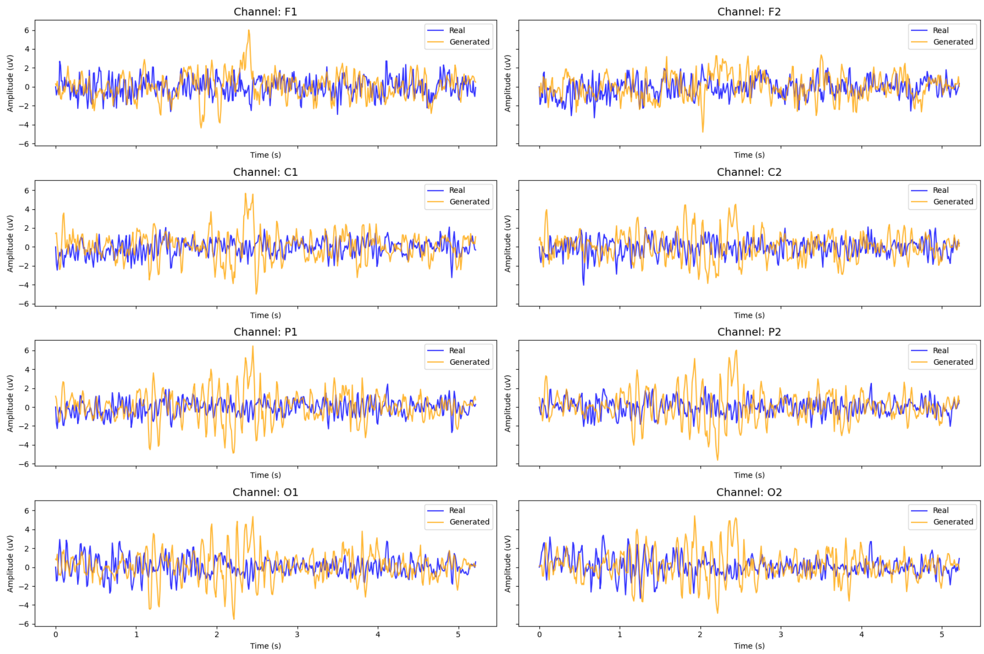
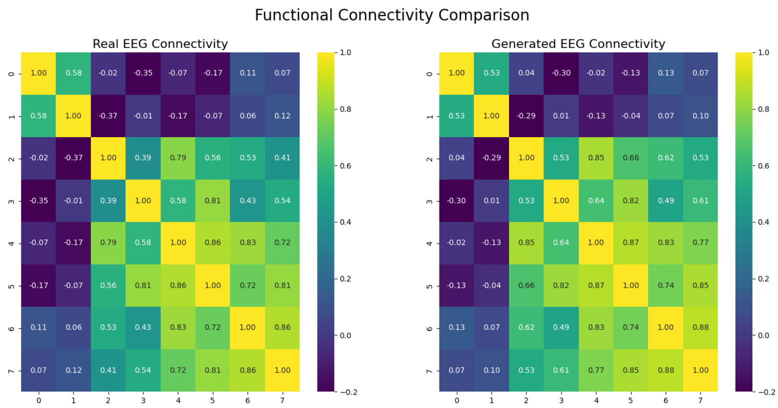


Fig. 6 Power Spectral Density Comparison with Variance(Epoch 200). The following figure provides a detailed comparison of the frequency content between real (blue) and generated (orange) EEG signals across all of the 8 channels. The solid line represents the mean Power Spectral Density (PSD), and the shaded area represents one standard deviation, illustrating the variability across samples present. RANGE-GAN demonstrates exceptional spectral fidelity, as the generated PSDs not only match the mean of the real data but also accurately replicate its variance. The model successfully captures the characteristic 1/f power-law decay and the prominent alpha-band peak ($\tilde{1}0$ Hz), confirming its ability to learn the fundamental oscillatory dynamics of resting-state brain activity.



(a) (a) The 8 channel time-series plot



(b) (b) The functional connectivity heatmap.

Fig. 7 Qualitative Assessment of the Temporal and Spatial Fidelity. **(a)** Generated EEG waveforms (Orange) are visually indistinguishable from that of the real signals (Blue), capturing the characteristic texture and oscillatory patterns. **(b)** The functional connectivity matrix (i.e., cosine similarity) of the generated data successfully replicates the spatial correlation patterns present in the real data, This proves that the model learns realistic inter-channel dependencies.

5.3 Unsupervised Feature Representation

However, the primary focus of this work is on signal synthesis, we briefly evaluated the quality of the features learned by the RANGE-GAN critic. Using the trained critic as a frozed feature extractor on a held-out dataset of Healthy controls, a simple logistic regression classifier achieved a gender classification accuracy of ***59.68%*** *. This result, is significantly above chance (50%), this indicates that without even an explicit attention mechanism, the deep convolutional hierarchy learns meaningful and transferable representations from the data..*

6 Conclusion

In this paper, we presented RANGE-GAN, a deep residual GAN , achieving state-of-the-art performance in realistic EEG signal generation. The combination of deep ResNet architecture with a stable WGAN-GP training framework has resulted in the demonstration of exceptional training stability and production of synthetic data that is statistically and spectrally almost indistinguishable from real recordings. .

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