An Adversarial Learning Approach for Cross-Patient Electroencephalographic Seizure Classification

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Abstract

Utilizing electroencephalogram (EEG) for epilepsy classification is of significant importance. However, traditional classification methods often struggle to effectively classify EEG signals from unknown patients. Therefore, we propose a graph neural network (GNN)-based method that utilizes EEG representations based on distance and correlation. We employ adversarial training using user IDs through cohomology clustering to enhance the generalization performance of epilepsy classification tasks across different patients. Our study represents the first method to consider epilepsy classification across different patients' scenarios, achieving state-of-the-art results on large-scale publicly available datasets. This significantly enhances the accuracy of seizure classification tasks. With the improvement in performance of our study on cross-patient epilepsy classification tasks, a foundation is laid for personalized medicine, while also facilitating the rational allocation and optimal utilization of societal healthcare resources.

1 Introduction

Epilepsy is a chronic neurological disorder characterized by recurrent and transient seizures, which can cause suffering and inconvenience to patients and their families, and may even pose a threat to the patient's life [Mormann et al., 2007, Zhang et al., 2024]. Currently, there is an urgent need for a new epilepsy classification method that can achieve several goals. Firstly, personalized treatment for patients is crucial. Due to individual differences such as age and gender, electroencephalogram (EEG) signals collected exhibit variability among individuals, leading to challenges in classifying EEG signals from other patients [McIntosh et al., 2008, Kaushik et al., 2018]. Secondly, due to the imbalance in healthcare resources between rural and urban areas, rapid EEG classification can facilitate the efficient and equitable allocation of medical resources [Siuly et al., 2016, Daccache et al., 2022]. Lastly, incorporating interpretable modules into the classification task can help doctors understand the underlying causes of seizures, thereby advancing the field of medicine in addressing epilepsy [Priyasad et al., 2021, Pinto et al., 2022].

However, previous methods [Abiyev et al., 2020, O'Shea et al., 2020, Ke et al., 2021, Peng et al., 2022b] involved mixing data from all patients, then randomly dividing them into training and test sets. Subsequently, the model was trained on the training set and evaluated on the test set. While this approach may achieve good results on the test set, considering the problem from a more practical perspective across different patients, if a patient is undergoing an inquiry for the first time, this model may not classify the EEG data of the patient effectively. We want to use a detailed example to describe the process mentioned above. Suppose there are a total of 10 patients, each with 5 EEG recordings. The training-to-test set ratio is 4:1. According to traditional epilepsy classification methods, all 50 data points (5 recordings per patient × 10 patients) are mixed together. Then, 40 samples are randomly selected for training, and the remaining 10 samples are used for testing. Currently, our approach

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involves randomly selecting 8 patients for training, utilizing their corresponding 40 EEG recordings, while reserving data from the remaining 2 patients for testing. This methodology effectively measures the performance of model in classifying EEG signals from unseen patients.

This study is the first work to consider cross-patient scenarios for EEG-based epilepsy classification. Specifically, this paper extracts the adjacency weight matrix between different brain channels based on a graph neural network approach to obtain a better feature representation. In addition, this paper proposes a robust adversarial neural network structure that can improve the model's generalization ability for classifying seizure type for unseen patients. Experiments conducted on the largest public EEG seizure database validate the effectiveness of the proposed method.

2 Problem Setup

We consider cross-patient seizure classification based on EEG clips. Specifically, each EEG clip records time series from a pre-determined number of channels/electrodes N within a time window size T (in seconds). To transform the signals in time domain to frequency domain, we follow previous studies to apply fast Fourier transform (FFT) [Covert et al., 2019, Ahmedt-Aristizabal et al., 2020, Asif et al., 2020] and denote the transformed signals as $\mathbf{X} \in \mathbb{R}^{N \times T \times M}$, based on which we aim to classify the type of seizure $y \in \{0, 1, \cdots, C\}$. For each patient, the time length of the collected electrical signals is much longer than the time T in a single EEG clip, so each patient corresponds to multiple EEG clips when training the seizure classifier. To improve the generalization performance in cross-patient scenarios, we use EEG clips corresponding to different patients when dividing the training and test sets, i.e., patients in the training set are disjoint from those in the test set.

3 Proposed Method

3.1 An Extended GNN Method Combining Distance-Based and Correlation-Based Matrices

An EEG clip can be represented as a graph $\mathcal{G} = \{\mathcal{V}, \mathcal{E}, \mathbf{W}\}$, where the set of nodes $\mathcal{V}$ consists of electrodes, the set of edges is denoted as $\mathcal{E} \in \mathbb{R}^{N \times N}$, and $\mathbf{W}$ stands for adjacency matrix. In this paper, we consider computing the adjacency matrix from both distance-based and correlation-based perspectives. In particular, the distance-based computation [Shuman et al., 2013] exploits the distances between two electrodes placements with Gaussian kernel smoothing

$$\mathbf{W}_{i,j} = I(\mathrm{dist}(v_i, v_j) \le \kappa) \exp\left(-\frac{\mathrm{dist}(v_i, v_j)^2}{\sigma^2}\right), \tag{1}$$

where $I(\cdot)$ is characteristic function and $\mathrm{dist}(v_i, v_j)$ stands for the Euclidean distance between electrodes placements v_i and v_j. An alternative way to compute $\mathbf{W}_{i,j}$ is based on cross-correlation

$$\mathbf{W}_{i,j} = I(v_j \in \mathcal{N}(v_i)) |\mathrm{Cor}(\mathbf{X}_{i,:,:}, \mathbf{X}_{j,:,:})|, \tag{2}$$

where $\mathcal{N}(v_i)$ is the set of top-τ neighbors for v_i, $\mathrm{Cor}(\cdot, \cdot)$ stands for the cross-correlation function, $\mathbf{X}_{i,:,:}$ and $\mathbf{X}_{j,:,:}$ are pre-processed data corresponding to v_i and v_j respectively.

Given EEG clips with both distance-based and correlation-based adjacency matrices, we propose to extend the diffusion convolutional recurrent neural network (DCRNN) [Li et al., 2018, Tang et al., 2022] to exploit both distance-based and correlation-based adjacency matrices. Formally, let $Z^{\mathrm{dist}} \in \mathbb{R}^{N \times T \times M}$ be the output of DCRNN with distance-based weights and $Z^{\mathrm{corr}} \in \mathbb{R}^{N \times T \times M}$ be the output of DCRNN with correlation-based weights. We introduce a learnable weight tensor $\Psi \in \mathbb{R}^{N \times T \times M}$ to combine both Z^{dist} and Z^{corr} with personalized attention weights

$$\Phi(X) = \Psi \odot Z^{\mathrm{dist}} + (\mathbf{1} - \Psi) \odot Z^{\mathrm{corr}}, \tag{3}$$

where $\odot$ stands for Hadamard product and $\mathbf{1} \in \mathbb{R}^{N \times T \times M}$ is an all-one tensor. Finally, a fully connected network is adopted with the cross-entropy loss $\mathcal{L}^{\mathrm{task}}$ to train the seizure classifier.

3.2 Robust Adversarial Neural Network

A naive adversarial learning approach, Patient-Adversarial Neural Networks (PANN) has been proposed to obtain patient-invariant representations Zhang et al. [2024]. They believe that patient identity numbers ids are independent of their health status, thus a cross-patient invariant representation $\Phi(\mathbf{X})$ for seizure analysis should not be able to classify id. Another head for id classification is

Table 1: Experimental results of 4-type seizure classification with five repeated runs.

	12-s			60-s		
Method	F1	Recall	Precision	F1	Recall	Precision
Dense-CNN	0.609 ± 0.022	0.681 ± 0.014	0.663 ± 0.050	0.473 ± 0.052	0.602 ± 0.031	0.436 ± 0.111
TIE-EEGNet	0.525 ± 0.047	0.639 ± 0.028	0.524 ± 0.075	0.572 ± 0.027	0.647 ± 0.008	0.599 ± 0.047
LSTM	0.630 ± 0.041	0.681 ± 0.029	0.630 ± 0.040	0.579 ± 0.026	0.645 ± 0.014	0.567 ± 0.035
CNN-LSTM	0.620 ± 0.046	0.681 ± 0.032	0.638 ± 0.052	0.633 ± 0.027	0.696 ± 0.033	0.642 ± 0.044
GraphS4mer	0.461 ± 0.040	0.508 ± 0.123	0.494 ± 0.033	0.543 ± 0.069	0.687 ± 0.157	0.561 ± 0.051
Corr-DCRNN	0.692 ± 0.051	0.745 ± 0.037	0.721 ± 0.050	0.673 ± 0.066	0.719 ± 0.037	0.705 ± 0.055
Dist-DCRNN	0.693 ± 0.069	0.736 ± 0.047	0.735 ± 0.043	0.660 ± 0.026	0.712 ± 0.027	0.708 ± 0.048
PANN	0.699 ± 0.035	0.743 ± 0.031	0.713 ± 0.040	0.657 ± 0.033	0.715 ± 0.029	0.701 ± 0.041
RANN (ours)	$\mathbf{0.723 \pm 0.044}^*$	$\mathbf{0.764 \pm 0.030}^*$	$\mathbf{0.745 \pm 0.046}$	$\mathbf{0.707 \pm 0.034}^*$	$\mathbf{0.739 \pm 0.024}^*$	$\mathbf{0.740 \pm 0.038}^*$

Note: * means statistically significant results ($p - value \leq 0.05$) using the paired-t-test compared with the best baseline.

Table 2: Ablation Studies of 4-type seizure classification with five repeated runs.

	12-s			60-s		
Method	F1	Recall	Precision	F1	Recall	Precision
PANN	0.699 ± 0.035	0.743 ± 0.031	0.713 ± 0.040	0.657 ± 0.033	0.715 ± 0.029	0.701 ± 0.041
RANN w/o Z^{corr}	0.713 ± 0.025	0.750 ± 0.024	0.736 ± 0.040	0.693 ± 0.015	0.732 ± 0.013	0.713 ± 0.022
RANN w/o Z^{dist}	0.715 ± 0.018	0.755 ± 0.035	0.738 ± 0.031	0.696 ± 0.029	0.727 ± 0.016	0.724 ± 0.024
RANN w/o $\mathcal{L}^{\text{id}}$	0.706 ± 0.039	0.743 ± 0.020	0.731 ± 0.033	0.680 ± 0.020	0.723 ± 0.025	0.710 ± 0.034
RANN	$\mathbf{0.723 \pm 0.044}$	$\mathbf{0.764 \pm 0.030}$	$\mathbf{0.745 \pm 0.046}$	$\mathbf{0.707 \pm 0.034}$	$\mathbf{0.739 \pm 0.024}$	$\mathbf{0.740 \pm 0.038}$

added to the network, which gives the softmax outputs $\hat{id}$. Cross-entropy is still adopted as the id classification loss, i.e. $\mathcal{L}^{\text{id}}(id_i, \hat{id}_i) = -\sum_{j=1}^{D} id_{i,j} \cdot \ln \hat{id}_{i,j}$, where id_i indicates the identity number of the i-th EEG clip, D is the cardinality of the identity number set. Then the final loss is $\mathcal{L} = \mathcal{L}^{\text{task}}_{Naive} - \lambda \mathcal{L}^{\text{id}}_{Naive}$, where $\lambda > 0$ is a tunable hyper-parameter.

However, as the class number (i.e. patient number in this case) increases, the classification performance may be severely degraded, which challenges the effectiveness of adversarial learning for PANN. Instead of using pure id as the cluster label, our approach uses congruence classes modulo a prime number p as classification labels for adversarial learning. Specifically, we introduce $f_p : id \to c$ if $id \equiv c \mod (p)$, which project id to cluster label, where $c \in \{0, 1, ..., p\}$. For each choice of p, we add a head to the model with the prediction $\hat{c}_p$ based on the learn representation $\Phi(\mathbf{X})$, and get a corresponding cross-entropy loss $\mathcal{L}^{\text{id}}_p(f_p(id), \hat{c}_p)$. We choose the first K primes $p_1 = 2, p_2 = 3, p_3 = 5, \cdots, p_K$, where K is a hyper-parameter. If $p_K < D$, we include another prime $p_* \geq D$. Denoting the set of all the chosen primes as P, then we can get the adversarial loss $\mathcal{L}^{\text{id}} = (\sum_{p \in P} \mathcal{L}^{\text{id}}_p)/(|P|)$. And the final loss of our method is $\mathcal{L} = \mathcal{L}^{\text{task}} - \lambda \mathcal{L}^{\text{id}}$. We use the learned representation $\Phi(\mathbf{X})$ to predict both the seizure class label y and the clustering label c. Note that combining the losses produced by different prime numbers (such as $p = 2$ and $p = 3$) equivalent to using the losses when $p = 6$ to perform adversarial learning.

4 Experiment

Dataset. We use the Temple University Hospital Seizure Corpus (TUSZ) dataset v 1.5.2 [Obeid and Picone, 2016, Shah et al., 2018], which contains 3,050 seizure events from 632 patients. Following the previous study [Tang et al., 2022], we include 19 EEG channels in our experiments and evaluate our model on the refined four seizure types, which are combined focal seizure (CF) with 194 patients, generalized non-specific seizure (GN) with 81 patients, combined tonic seizure (CT) witth 17 patients and absence seizure (AB) with 12 patients.

Data preprocessing. Because the EEG signals are sampled at different frequencies in the TUSZ dataset, we first resample them to the same frequency 200 Hz. Meanwhile, following the previous studies [Ahmedt-Aristizabal et al., 2020, Asif et al., 2020, Tang et al., 2022], we perform data preprocessing using FFT to transfer the resampled EEG signals from time domain to frequency domain due to seizures are known to be associated with brain electrical activity in certain frequency bands [Tzallas et al., 2009]. In addition, we consider $T = 12$ second and $T = 60$ second EEG clip signal in our experiment [Tang et al., 2022].

Experiment Protocals and Details. We implement the same data splitting method as [Tang et al., 2022], which includes at least one patient of each seizure type in train, validation and test set.

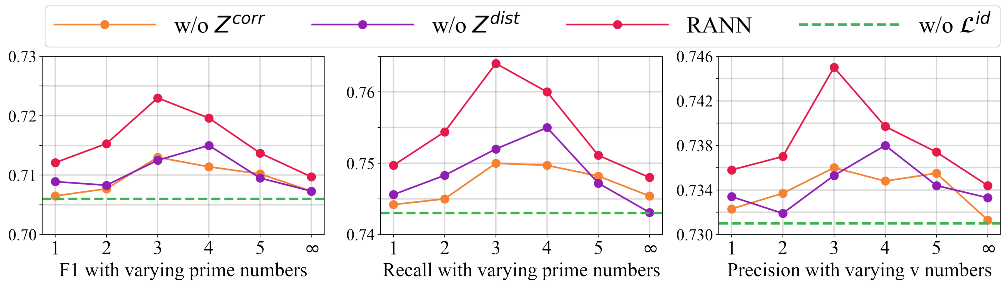

Figure 1: The F1, Recall and Precision under varying prime numbers p with $T = 12$ second.

Meanwhile, there is *no overlap patient* between train, validation and test set. Following recent studies on seizure type classification [Peng et al., 2022a, Tang et al., 2022, Albaqami et al., 2022, 2023], the weighted F1-score, Recall, and Precision are used as the evaluation metrics to measure the performance. The number of recurrent gated graph layers are tuned in $\{2, 3, 4, 5\}$, the number of hidden units are tuned in $\{32, 64, 128\}$, and the λ in $\{1e-4, 5e-4, ..., 1\}$.

Baselines. We compare the proposed method with the following six baselines: two CNN-based methods: Dense-CNN [Saab et al., 2020] and TIE-EEGNet [Peng et al., 2022a], two temporal-based methods: LSTM [Hochreiter and Schmidhuber, 1997], and CNN-LSTM [Ahmedt-Aristizabal et al., 2020], two methods that can capture spatial information: GraphS4mer [Tang et al., 2023] and DCRNN [Tang et al., 2022], and one method based on adversarial learning: PANN [Zhang et al., 2024].

4.1 Performance Comparison

Table 1 shows the performance of the different methods on the TUSZ dataset for 12-s and 60-s scenarios. First, the Corr-DCRNN and Dist-DCRNN methods, which consider the connections between patients' brain electrodes, and the PANN method, which considers adversarial learning based on patients' ids, reach competitive performances in baseline. Second, our proposed methods stably and statistically significantly outperform all baseline methods, demonstrating its effectiveness.

4.2 In-Depth Analysis

In the proposed method, the adversarial loss $\mathcal{L}^{\mathrm{id}}$ and weights tensor (Z^{corr} and Z^{dist}) play an important role. Therefore, it is necessary to design ablation study to explore the effects of each component. The results are shown in Table 2. First, all methods outperform the baseline method PANN. Second, the proposed method with all components achieves the best performance. Meanwhile, due to the absence of the adversarial network, method RANN w/o $\mathcal{L}^{\mathrm{id}}$ does not perform as well as methods RANN w/o Z^{dist} and RANN w/o Z^{corr} in the cross-patient scenario. In addition, we found that the performance of RANN w/o Z^{dist} is slightly better than RANN w/o Z^{corr}, which suggests that the connections between different brain channels can be more fully exploited using the correlation based weight matrix than the physical distances based weight matrix. In addition, Figure 1 shows the performance of proposed methods under varying prime number K. We find that the proposed method performs best when the size of prime number is moderate (e.g., K = 3 or 4). In addition, all methods outperform the RANN w/o $\mathcal{L}^{\mathrm{id}}$ method at all different prime numbers, which also shows the effectiveness of the proposed adversarial network structure.

5 Conclusion

We propose a graph neural network-based approach to enhance the generalization performance of seizure classification tasks in cross-patient scenarios using both distance-based and correlation-based EEG graph representations and adversarial training with congruently clustered user ids. Our study is the first to consider seizure classification in cross-patient scenarios and achieves SOTA on a large public dataset, significantly improving the accuracy of the seizure classification task. The cross-patient property ensures that our method has wide applicability to different patients. Meanwhile, good classification performance can improve the accuracy of seizure diagnosis and treatment and lay the foundation for personalized medicine. It is foreseeable that as the performance of cross-patient seizure classification task initiated by this study continues to improve, seizure patients will be treated more effectively, and the overall burden of seizure disease on society will also be significantly reduced.

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