A Domain Adaption Approach for EEG-based Automated Seizure Classification with Temporal-Spatial-Spectral Attention

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Abstract. Electroencephalography (EEG) based automated seizure classification can significantly ameliorate seizure diagnosis and treatment. However, the intra- and inter- subject variability in EEG data make it a challenging task. Especially, a model trained on data from multiple subjects typically degenerates when applied to new subjects. In this study, we propose an attention based deep convolutional neural network with domain adaption to tackle these issues. The model is able to learn domain-invariant temporal-spatial-spectral (TSS) features by jointly optimizing a feature extractor, a seizure classifier and a domain discriminator. The feature extractor extracts multi-level TSS features by an attention module. The domain discriminator is designed to determine which domain, i.e., source or target, the features come from. With a gradient reversal layer, it allows extraction of domain-invariant features. Thus, the classifier is able to give accurate prediction for unseen subjects by leveraging knowledge learned from the source domain. We evaluated our approach using the Temple University Hospital EEG Seizure Corpus (TUSZ) v1.5.2. Results demonstrate that the proposed approach achieves the state-of-the-art performance on seizure classification. The code is available at https://github.com/Dondlut/EEG_DOMAIN.

Keywords: Seizure Classification · Domain Adaptation · Temporal-Spatial-Spectral Attention.

1 Introduction

Seizures are one of the most common neurological emergencies worldwide [24]. Categorizing seizures into fine-grained types is crucial for identifying optimal treatment. Traditionally, assessing EEG signals requires visual inspection by EEG experts. However, this is labor-intensive and time-consuming. Automated seizure classification shows great potential in speeding up seizure diagnosis and improve clinical outcomes.

Different seizure types have subtle distinctions in EEG characteristics. Even highly qualified neurologists find it challenging. Although a number of studies have attempted automated seizure classification, challenges remain largely unsolved. First, EEG signals exhibit highly complex temporal dynamics. Second, different seizure types have distinct rhythms distributed across various brain regions, presenting highly complex spectral distributions over the brain [7]. Third, the inter-subject variability is large such that a model trained on data from multiple subjects typically degenerates when applied to new subjects.

In this paper, we propose a domain adaption approach with temporal-spatial-spectral (TSS) attention (DA-ATSS) for EEG-based automated seizure classification. The model is able to learn domain-invariant TSS features by jointly optimizing a feature extractor, a seizure classifier and a domain discriminator. The main contribution of this paper can be summarized as follows.

- We propose a domain adaptation approach for automated seizure classification, which enables extraction of domain-invariant features.
- We design a feature extractor with TSS attention and one-shot aggregation (OSA) to learn multi-level features from the most discriminating time stamps, sensor locations and frequency bands of EEG data.
- We evaluate our DA-ATSS model on the TUSZ dataset. Cross-subject evaluation shows that it achieves state-of-the-art performance on new subjects, without calibrating it with unlabeled data from these subjects.

2 Related Work

Numerous studies have applied deep learning techniques to seizure classification. A typical approach is to convert EEG signals into images, e.g., spectrograms, and feed them into convolutional neural networks (CNNs) [5]. For instance, Yan et al. used a CNN to detect absence seizures from spectrogram of single-sensor EEG [32]. Some researchers stacked the spectrograms from multi-sensor EEG, which was then fed into pre-trained CNNs with transfer learning [17]. Other studies use 1D CNNs [14, 16, 29] or recurrent neural networks (RNNs) [3, 22, 27]. The input of these networks can be either raw EEG [29] or handcrafted features [16, 33]. Hybrid models integrating CNN and RNN have also been proposed [4, 21]. For example, Albaqami et al. combined bidirectional long short-term memory (LSTM) with CNN to classify seizure types [2]. The CNN and LSTM was fed with wavelet-based features and raw EEG signals, respectively. They emphasize the temporal-spectral features of EEG. However, they either treat EEG sensors equally [17, 20] or utilize single-sensor signal [32]. The spatial aspects are largely neglected. Some studies proposed to model multi-sensor EEG signals as a graph and employ graph neural networks (GNNs) to tackle this issue [9, 25, 26]. Although GNNs allows modeling of spatial dependencies of EEG, how to define graph from EEGs is not trivial.

In EEG classification, a model trained on a group of subjects from one domain typically degenerates on new subjects from another domain due to large inter-subject variability. A few studies have explored domain adaptation (DA) to address this issue. In the context of EEG classification, the domain with annotated data from multiple subjects is referred to as the source domain, while the one with limited or no annotations from the target subject is known as the target domain. Some methods attempt to eliminate domain discrepancy between the source and the target domain [6, 13]. For instance, Peng et al. [13] employed autoencoder to embed the input in a latent space and minimized the domain discrepancy in that space. Liang et al. [12] proposed a semi-supervised DA approach where extra unlabeled data from the target domain was used to calibrate the model. Wang et al. [30] proposed multi-source unsupervised DA for cross-subject EEG-based seizure classification. They aligned the overall distributions of the selected source domains. These studies require labeled or unlabeled data from the target subject and mainly focus on seizure prediction and detection. The effectiveness of DA approach on seizure type classification remain to be explored.

3 Methodology

3.1 3D EEG Representation

To fully exploit the temporal, spatial, and spectral EEG features simultaneously, the 3D EEG representation was first constructed. We employed short-time Fourier transform (STFT) to single-sensor signal and stacked the normalized STFTs as the 3D representation of an EEG clip. Specifically, the modulus of each STFT matrix was first scaled in decibel and then min-max normalized. Each EEG clip E can then be represented as $X \in \mathbb{R}^{N \times F \times T}$, where N, F, T is the number of EEG sensors (spatial), frequency bands (spectral) and time stamps (temporal), respectively.

3.2 The Proposed Model

The overview of the model is illustrated in Fig. 1. The model is composed of a feature extractor and a seizure classifier. Unsupervised DA is achieved by adding a domain discriminator connected to the feature extractor via a gradient reversal layer (GRL) [8]. The GRL multiplies the gradient by a negative constant, thereby pushing the feature extractor to learn domain-invariant features.

Feature Extractor The structure of the feature extractor is illustrated in Fig. 2. It learns multi-level TSS features from the 3D representation of EEG through an TSS attention and OSA. Seizures exhibit highly complex temporal dynamics, and vary in temporal evolution. Therefore, we designed a TA block to focus on

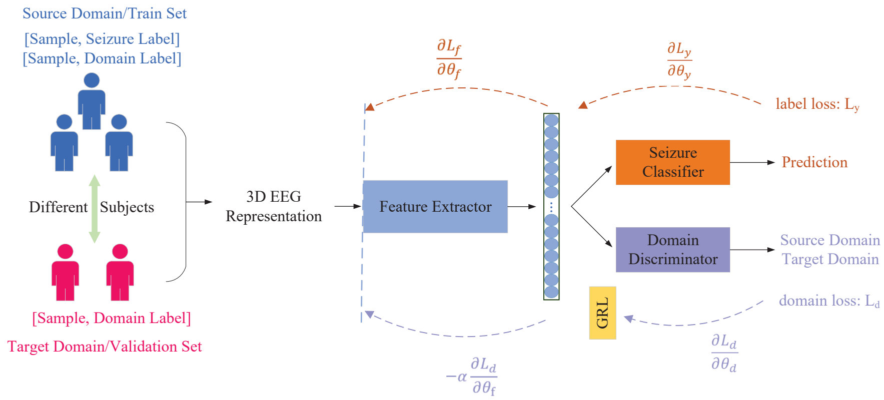


Fig. 1. The proposed DA-ATSS model. Subjects from train and validation set are source and target subjects, respectively. Our test set constitutes another group of subjects.

the discriminative time stamps. Different seizure types present highly complex spectral distributions over brain. This motivates us to design a SSA block that enables the model to pay attention to the most informative frequency bands and electrode sensors. By combining the TA and SSA blocks, the model concurrently extracts TSS features from 3D EEG representation. The OSA module allows aggregation of features from previous layers, facilitating the deep fusion of multi-level features.

The Temporal Attention Block The TA block captures the temporal dependencies within EEG data through a squeezing and excitation mechanism [10] as the channel attention proposed in [28]. Here, the temporal dimension of 3D EEG representation is considered as channel. The 3D EEG representation is firstly aggregated within the spatial-spectral feature maps with a global average pooling and a global maximum pooling in parallel, respectively. Subsequently, a 1D convolution with size 3 is used to capture local cross-time interactions of each

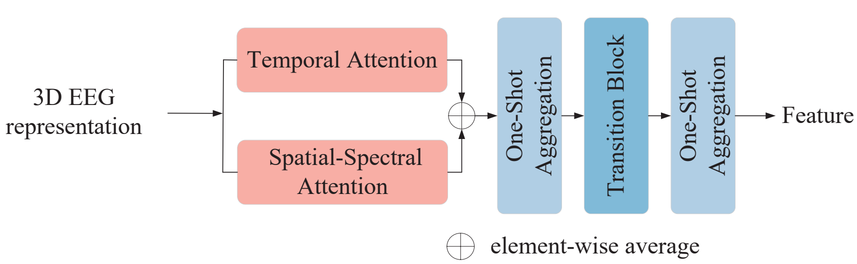


Fig. 2. The diagram of the feature extractor. It allows extraction of multi-level EEG features with temporal-spatial-spectral attention and one-shot aggregation.

branch. The outputs are then concatenated and fed into a 1D convolutional layer of size 1 and a sigmoid to obtain the weights corresponding to each time stamp. Finally, an element-wise product is applied between the weights and the input features with a broadcast mechanism.

The Spatial-Spectral Attention Block The SSA block was designed to capture the spatial-spectral dependencies in EEGs. The spatial here refers to sensor dimension of 3D EEG representation. The SSA block follows the spatial attention design in [31]. The 3D EEG representation is first aggregated within the temporal dimension by parallel average pooling and maximum pooling. The outputs are then concatenated along the first dimension. With a 2D convolution of size 3 and a sigmoid, the weights for each element in the spatial-spectral feature maps can be obtained. Finally, element-wise product is applied between the weights and the input features with a broadcast mechanism.

The One-Shot Aggregation and Transition Block The OSA module was designed to fuse multi-level features [11]. It comprises 4 convolution blocks, each containing a batch normalization (BN), a ReLU, and a 3D convolution of 16 kernels with a size of 3. The feature maps produced by these convolution blocks are then aggregated in the final layer by channel-wise concatenation. Subsequently, the concatenated feature maps are processed by a transition block to further fuse multi-level features and reduce dimensionality, which is composed of a BN, a ReLU, a 3D convolution of size 1, and an average pooling of size 2. The number of feature maps of the transition block reduce to half of its input.

Seizure Classifier and Domain Discriminator The seizure classifier and domain discriminator share the same structure, with a 3D adaptive average pooling, a 3D convolution with kernel size and step size of 1. The 3D adaptive average pooing reduces the dimension of the input features from $C \times T \times N \times F$ to $C \times 1 \times 1 \times 1$ (C is the number of feature maps). To increase nonlinearity and reduce parameters, we use convolution other than fully connected layer, the output channels of which equals to the number of classes. The resulting features are then flattened and a softmax is used to give the model prediction.

4 Experiments and Results

4.1 Dataset and Data Preprocessing

We use the Temporal University Hospital EEG Seizure Corpus (TUSZ) [19] v1.5.2, which contains multi-sensor EEG recordings from 637 subjects, with 3050 annotated seizures. It covers 8 types of seizures, i.e., focal non-specific seizures (FNSZ), generalized non-specific seizures (GNSZ), simple partial seizures (SPSZ), complex partial seizures (CPSZ), absence seizures (ABSZ), tonic seizures (TCSZ), and myoclonic seizures (MYSZ). We follow the classification scheme in [25] and [26]. Specifically, MYSZ is discarded due to its low occurrence. FNSZ, SPSZ,

Table 1: Summary of data in train, validation and test sets used in our study.

split \ class	CFSZ	GNSZ	ABSZ	CTSZ	total
train	16513	7753	97	956	25319
validation	5609	2160	27	180	7976
test	2479	1107	16	91	3693

and CPSZ are combined into a new category called combined focal seizures (CFSZ), since they are indistinguishable from EEG signals alone according to the annotation guidelines. We also combine TCSZ and TNSZ to create a combined tonic seizure (CTSZ) class. As a result, there are four classes in total: CFSZ, GNSZ, ABSZ, and CTSZ.

We apply the TCP bipolar montage to reduce signal noise and emphasize the seizures, as neurologists usually do [18]. A zero-phase 4-order Butterworth bandstop filter is used to remove power-line interference after resampling to 200Hz. The seizure events are segmented into 5-second segments. We discard the segments shorter than 5 seconds. Sensor-wise Min-Max normalization is then applied, from which the 3D EEG representation is calculated. The dataset was randomly splitted into train, validation and test sets by roughly 7:2:1 for each class (see Table 1). It is not precise because we have to guarantee that they consist of distinct subjects. We consider the train and validation set as the source and target domain, respectively. Importantly, we do not use any data from the test set, even unlabeled, to calibrate the model.

4.2 Experimental Setup

We compared our DA-ATSS model with 5 representative baselines: (1) Wavelet + LightGBM [1]. (2) CNN [17]: we trained the GoogLeNet using transfer learning, as it outperformed the others. (3) GNN [25]: we used distance-based graph, fast Fourier transform as node features and self-supervised learning. (4) Transformer [23]: a model with a spatial and a temporal self-attention. (5) CNN + Attention [15]: a CNN-based model with attentive fusion of sensor-wise features.

Since the number of samples in each class is highly unbalanced, we used weighted cross entropy as the loss function, accuracy, weighted precision, and weighted F1-score as the evaluation metrics. The weighted precision or F1-score was calculated as the weighted sum of the metric value for each class, with the weights being the proportions of samples in each class. All models were trained/tested on one NVIDIA GeForce RTX 3090 24GB GPU. For hyperparameters, we used 1e-04 initial learning rate with 0.1 weight decay, 100 epochs and 64 batch size.

Table 2: Seizure classification results. Best results are highlighted in bold.

Model	Accuracy(%)	Weighted Pre(%)	Weighted F1
Wavelet+LightGBM [1]	72.0	74.0	0.725
CNN [17]	79.9	80.1	0.787
GNN [25]	79.7	84.0	0.816
Transformer [23]	74.5	73.8	0.743
CNN+Attention [15]	72.1	69.8	0.684
DA-ATSS w/o TA	78.8	78.5	0.786
DA-ATSS w/o SSA	83.9	86.7	0.851
DA-ATSS w/o DA	84.9	84.4	0.851
DA-ATSS(ours)	**85.1**	**88.2**	**0.863**

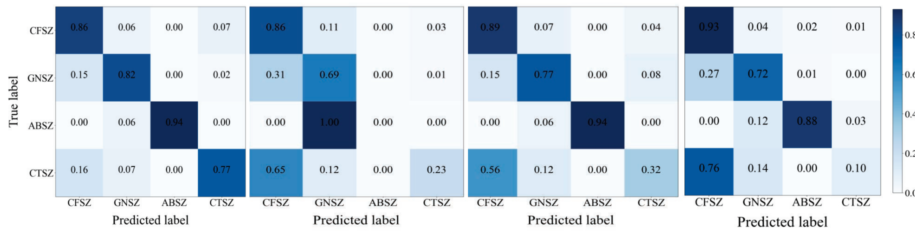
4.3 Experimental results

Our DA-ATSS model achieved 85.1% accuracy, 88.2% weighted precision and 0.863 weighted F1-score (see Table 2), outperforming all baselines in terms of all metrics, with an average increase of 9.46%, 11.86%, 0.112 in accuracy, weighted precision and weighted F1-score, respectively. Grad-CAM visualizations demonstrate consistency between annotated abnormal channels and the channels our model attends to (See supplementary material). In addition, we conducted an ablation experiment to examine the effectiveness of the attention blocks and DA. We can see from Table 2 (7th-10th row) that if either is removed, the model's performance deteriorates.

To give more details, we show the confusion matrices of our DA-ATSS model, DA-ATSS without TA black, DA-ATSS without SSA block and DA-ATSS without DA (see Fig. 3). Our DA-ATSS model achieved a high sensitivity for all classes, i.e., 86%, 82%, 94%, and 77% for CFSZ, GNSZ, ABSZ, and CTSZ, respectively. We assume that the use of weighted cross entropy loss alleviates the data unbalance. However, around 15% of GNSZs and 16% of CTSZs are mistakenly classified as CFSZs (Fig. 3(a)). The model appears to have a slight bias towards CFSZ, which constitutes the largest proportion in the dataset.

According to the annotation guidelines, the above three seizure types are closely resembled in EEG. The cerebral activities of CTSZs are similar to that of a CFSZ or GNSZ, but are overwhelmed by muscle artifacts because of violent muscle contractions and stiffening of muscles. Therefore, the clinical recognition of CTSZ is almost always made by cross-check of EEG and behavior. Besides, a CFSZ may progress into a GNSZ if the seizure spreads across the brain. They share the same morphology, progression, and frequency descriptors, but GNSZs involve a larger brain coverage. Consequently, distinguishing these two types based on EEG is challenging, even for experienced neurologists.

We observe that the removal of TA leads to heavier confusion among the three (see Fig. 3(b)), e.g., 16% (31% vs. 15%) more GNSZs are misclassified as CFSZs, 49% (65% vs. 16%) more CTSZs are misclassified as CFSZs, and 5%



(a) DA-ATSS (b) DA-ATSS w/o TA (c) DA-ATSS w/o SSA (d) DA-ATSS w/o DA

Fig. 3. The confusion matrices for our DA-ATSS, DA-TASS w/o TA, DA-TASS w/o SSA, and DA-TASS w/o DA

(12% vs. 7%) more CTSZs are misclassified as GNSZs. Therefore, the temporal features are important for distinguishing CTSZ, GNSZ and CFSZ. There may be a subtle difference in temporal evolution of these seizures. Overall, without TA,the sensitivity of GNSZ, ABSZ, and CTSZ deceases largely, with a magnitude of 13%, 94%, and 54%, respectively. Interestingly, all ABSZs are misclassified as GNSZs if the TA block is ablated. The temporal features seem to play a critical role in recognizing ABSZs.

The ablation of SSA also leads to performance decline (see Fig. 3(c)), e.g., heavier confusion among CTSZ, CFSZ, and GNSZA. Specifically, 40% (56% vs. 16%) more CTSZs are misclassified as CFSZs, 5% (12% vs. 7%) more CTSZs are misclassified as GNSZs, and 6% (8% vs. 2%) GNSZs are misclassified as CTSZs. The sensitivity of GNSZ and CTSZ reduced to 77% and 32%, respectively. These results shows the importance of spatial-spectral features in seizure classification.

The removal of DA causes sharp drop of sensitivity for CTSZ, from 77% to 10% (see Fig. 3(d)). Without DA, distinguishing among CTSZ, CFSZ, and GNSZ becomes more challenging. Specifically, 12% (27% vs. 15%) more GNSZs and 60% (76% vs. 16%) more CTSZs are misclassified as CFSZs. Moreover, 6% (12% vs. 6%) more ABSZs and 7% (14% vs. 7%) more CTSZs are misclassified as GNSZs. Therefore, the DA approach increases the generalizability of the model.

5 Conclusion

We propose a domain adaptation approach with temporal-spatial-spectral (TSS) attention (DA-ATSS) for automated EEG-based seizure classification. It allows to learn domain-invariant TSS features by adding a domain discriminator connected to the feature extractor via a gradient reversal layer. With the TSS attention module, the model learns to attend to the most distinguishing time stamps, sensors, and frequency bands of EEG for seizure classification. We test our DA-ATSS in a cross-subject scenario, with a test set that is completely independent from the training process, i.e., even unlabeled data from the test subjects is not used. Therefore, the resulting performance indicates the model's performance on new subjects. In this case, our DA-ATSS achieved 85.1% accuracy, 88.2% weighted precision and 0.863 weighted F1-score on the TUSZ v1.5.2

dataset, outperforming other baselines such as CNN, GNN, transformer, and the state-of-the-art traditional machine learning methods. Our results highlight the effectiveness of the proposed model in extracting domain-invariant TSS EEG features. Moreover, ablation study shows the necessity of the DA approach, the temporal and spatial-spectral dependencies in EEG for seizure classification.

Currently, TUSZ is the only available dataset annotated with seizure types. Validation on other datasets, if available, should be performed to further evaluate the generalizability and robustness of the proposed model.

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