Epileptic Signal Classification with Deep Transfer Learning Feature on Mean Amplitude Spectrum

Yaomin Wang, Jiuwen Cao†, Jianzhong Wang, Dinghan Hu, and Muqing Deng

Abstract—**Epilepsy, as a sudden and life-threatening nervous system disease, seriously affected around 6% population in the world. Epileptic classification has attracted wide attention in the past and a number of methods have been developed. But currently studies are mainly on three epileptic states classification (preictal, ictal, interictal) or seizure/non-seizure detection. Among them, the one hour before seizure onset was generally considered as preictal, where the division is actually not fine enough for some practical applications. In this paper, the epileptic signal classification with a more granular time-scale of the preictal stage is studied and a novel deep Electroencephalogram (EEG) feature extraction with the convolutional neural network (CNN) based transfer learning is developed. The subband mean amplitude spectrum map (MAS) of multichannel EEGs is computed for signal representation and three popular deep CNNs are exploited for feature transfer learning, respectively. Experiments on the benchmark CHI-MIT epilepsy EEG database show that the proposed algorithm achieves a highest overall accuracy of 92.77% when the one hour preictal stage is divided into small segments with a fine resolution of 20-minutes scale.**

Index Terms—**Seizure prediction, Preictal prediction, Mean amplitude spectrum, CNN, Transfer learning**

I. Introduction

Epilepsy is one of the most common neurological diseases that affects about 50 million people worldwide [1]. Among these patients, around 10%∼50% are not suitable for medication or surgical treatment [2]. An effective epileptic seizure onset detection algorithm is thus critical to taking precautions so that the injury caused by epilepsy could be prevented or reduced. The scalp electroencephalogram (EEG) signals that contain rich information of the electrical activities in the brain [3], have been comprehensively studied for epileptic signal processing [4][5]. Fruitful EEG features have been studied for epileptic seizure detection, including the Lyapunov index, cumulative energy curve, power spectral, autocorrelation and correlation density, higher order spectra, similarity index, etc. Different popular machine learning algorithms were adopted as the classifiers. For example, Chua et al. applied the Gaussian mixture model (GMM) as the classifier, where the higher order spectra (HOS) and power spectrum are extracted [6]. The classification rates of 93.11% and 88.78% were obtained when using the HOS and spectrum, respectively.

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Although many achievements have been reported, the fine tuned hand-crafted features generally suffered less adaptive capability to different EEG databases. The deep learning methods, which are popular for their good capability of automatic feature learning and large data characterization, have been recently studied for epileptic classification. To name a few, a patient-specified seizure prediction algorithm based on the convolutional neural network (CNN) was developed in [7]. The long-short term memory (LSTM) networks was applied on raw EEG signals for seizure detection in [8]. But the good performance of deep learning algorithms relies on the complex adjustment of millions or even more network parameters. This drawback may make it unsuitable to build a deep neural networks for epileptic signal processing.

As an alternative, the feature transfer learning method based on deep pre-trained networks have recently attracted a lot of research attentions for the advantages of 1) the deep networks pre-trained on huge and complex database are capable of extracting discriminative features and 2) there are no requires of the time-consuming training and feature tunning procedures in transfer learning. Particularly, for the small-size databases, the deep feature transfer learning plays an increasingly important role.

Enlightened by these superiorities, we study the deep transfer feature learning based epileptic classification in this paper. A fine and reasonable preictal stage detection with the time-scale less than one hour is critical to taking precaution and prevention due to the suddenness and repetitiveness of epileptic seizure. The main contributions of the paper are: (1) The one hour preictal EEG signals are divided into several consecutive, equilong and non-overlapped segments and a multi-class classification containing several preictal states with a small time duration scale, seizure, and interictal is formulated. (2) The mean amplitude spectrum map (MAS) derived from subbands of multichannel EEGs is calculated as the input of deep CNNs. It is evident that the MAS is capable of characterizing the δ, θ, α, and β, rhythms of the EEG signals [9], which have long been shown important in epileptic signal characterization. (3) The transfer learning features by three popular deep CNNs, namely, Inception-v3 [10], Resnet152 [11] and Inception-Resnetv2 [12], are studied, respectively, where the deep CNNs are pre-trained on the large ImageNet database. The deep learned features are then fed to a fully-connected network with two layers for classification.

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II. The proposed Algorithm

A. Preictal Partition

The preictal state prediction is as important as the seizure onset detection because an accurate locate of the preictal can help to take precautions to prevent injuries caused by the seizure onset. The conventional partition of the preictal state is too general to adopt as an early warning to patients. A preictal warning around 10 minutes before the seizure onset is reasonable as a too early prediction may cause the patient anxiety, resultant an opposite effect, and a too late detection may lose the prime time for prevention. To this end, we divide the one hour preictal EEG signals into three non-overlapped equalong segments, each with a duration of twenty minutes. For the convenience of presentation, we name the three preictal states as PreI, PreII and PreIII, respectively, which denotes the EEG signals belonging to 40∼60 minutes, 20∼40 minutes, and 0∼20 minutes before the seizure onset correspondingly. A five-category classification problem, including the seizure, interictal, and three preictal states, is thus studied in this paper.

B. MAS

The low frequency range of EEG signal within 0.3∼70 Hz contains most of the important information related to epilepsy. Popular EEG signal rhythms, including the δ (less than 4Hz), θ (4∼8 Hz), α (8∼13 Hz), β (13∼30 Hz), and low γ (30∼70 Hz) rhythms, were widely used in epileptic signal processing. The mean amplitude spectrum (MAS) of the subbands of these rhythms was extracted for EEG representation in [9], where the frequency ranges of δ, θ, α rhythms are divided into three subbands, and the rest two rhythms are separated to five subbands, respectively. The MAS map derived from multi-channel EEGs combining with a CNN is used for the preictal and seizure detection [9], where a convincing classification performance was obtained.

To further explored the feature extraction capability of the transfer learning model, the MAS image is also adopted in this paper as it is easy to be calculated and is also effective in characterizing the representative rhythms associated to epilepsy. For each channel, the MAS of 19 subbands will be calculated. Then, for an EEG database with M channels, an M×19 MAS feature map for each frame will be computed, where a brief description of the calculation of MAS is shown below. The amplitude spectrum of a frame of EEG signal and the MAS of each subband are respectively denoted as

$$P(K) = |X_k| \tag{1}$$

$$\text{MAS}_i = \text{mean}\{P(k), k\epsilon K_i\} \tag{2}$$

where $X_k = \sum_{n=0}^{N-1} x(n)e^{\frac{-2\pi j}{N}kn}$ is the short-time Fourier transform (STFT) of the signal $x(n)$, $i (i = 1, 2, 3, \ldots, 19)$ and K_i represents the set of values in the i-th subband. A detailed description on the calculation of MAS can be referred to [9]. For all the M channels of EEG signal, an M×19 MAS map is obtained with each row corresponding to the MAS vector obtained from each channel, respectively.

C. Deep Feature Transfer Learning

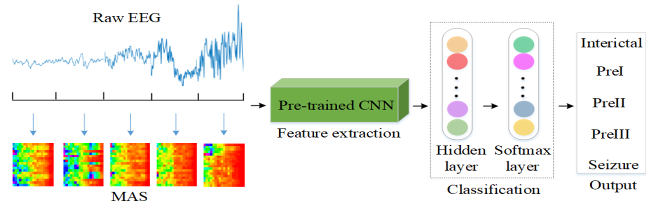

Fig. 1: The deep transfer learning based epileptic classification.

Deep feature transfer learning explores the reused capability of deep models pre-trained on rich and general databases to another task. It has shown the advantages of rapid learning and good generalization performance if a related task is applied [14]. To exploit the MAS map image feature of the EEG signals, we studied the deep transfer feature learning with three popular CNNs, Inception-v3 [10], Resnet152 [11] and Inception-Resnet-v2 [12], respectively. All the CNNs are pre-trained using the large ImageNet database [15] as extensive researches have shown that it is effective in extracting discriminative features for most of the image classification applications. A primary study exploring the transfer learning capabilities of these three CNNs has been presented in [16] for microscope image classification. The detailed structures of the three networks are shown in Table I.

The Inception-v3 is an extension of the popular

TABLE I: Architectures of the three CNNs.

Inception-v3	Resnet152	Inception-Resnet-v2
input: MAS Image		
conv-3	conv-7	stem
conv-3	pool	5×Inception-Resnet
conv padded	3×Residual	Reduction
pool		
conv-3	8×Residual	10×Inception-Resnet
conv-3		
conv-3	36×Residual	Reduction
3×Inception		
5×Inception	3×Residual	5×Inception-Resnet
2×Inception		
Max-pool		
linear	fc-1000	dropout
soft-max		

GoogLeNet, that modifies the convolutional layers to small-scaled convolutions to improve the computational efficiency. It combines different convolution layers in parallel. After the convolution kernel decomposition, Inception-v3 reduces the parameter quantity and computational complexity, and increases the deepness and nonlinearity of the network [10]. The Resnet152 is an special structure of Resnet, which was developed to address the degradation issue existed in CNNs. The Resnet minimizes the network residual to replace the conventional approximation of target mapping. The Resnet with 152 layers were referred as the Resnet152 and were examined to have the best performance in [11]. Inception-resnet-v2 is an extended CNN combining the Inception structure and the

Resnet. The use of residual connections in Inception-resnet-v2 avoids the degradation of deep network and reduces the training time. The Inception-resnet-v2 compresses repeated the residuals of inception model thus reducing the number of parallel towers. It was shown that the Inception-ResNet-v2 has a remarkable effect on image recognition [12].

The MAS image calculated from multichannel EEGs are fed to the pre-trained CNNs for feature learning. A two fully-connected classification layers are adopted for feature learning and classification. Fig. 1 shows the flowchart of the proposed deep transfer learning feature based epileptic signal classification. In this paper, the transfer learning by each single deep CNN is exploited independently. The feature dimensions obtained by the Inception-v3, Resnet152, and Inception-resnet-v2 are 2048, 2048, and 1536, respectively.

III. Experiments and Discussions

A. Experiments Set-ups

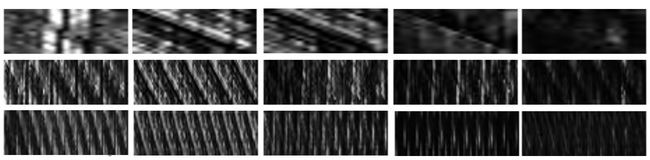

Fig. 2: The MAS images under three different frame numbers. From the top to bottom are 2 seconds, 10 seconds and 20 seconds, respectively and for each row from the left to right are inter, PreI, PreII, PreIII and seizure, respectively.

We evaluated the proposed deep CNN transfer feature learning epileptic signal classification algorithm using the benchmark CHB-MIT dataset in this paper. The CHB-MIT dataset includes the scalp EEG signals of 23 pediatric patients with intractable epilepsy. The amount of channels is 23 and the sampling frequency is 256 Hz. In this experiment, we only use the EEG signals of the first 18 channels. The database contains 178 minutes of seizure onset EEG signals, 180 minutes of the preictal state and interictal state, respectively. For the STFT, the frame length is set to be 2 seconds and the overlap of consecutive frames is set to be 1 second.

The experiment is conducted on the TensorFlow platform, where each MAS feature maps is converted to an image. We test the performance of the MAS image using one, five, and ten frames, respectively, where the obtained MAP image sizes are 18×19, 18×95 and 18×190, respectively. The signal lengths associated to the above three MAS image sizes are 2 seconds, 10 seconds and 20 seconds, respectively. Meanwhile, the derived datasets of these three MAS image sizes contain 50, 000, 10, 000 and 5, 000 samples, respectively. Fig. 2 shows examples of the MAS images under different numbers of frames. To adapt to the input requirement of three used CNNs, each MAS image is converted into a size of $299\times299\times3$, $224\times224\times3$ and $299\times299\times3$ for inception-v3, resnet152 and inception-resnet-v2, respectively. It is also noted that although the input to each CNN consists of three images of three channels, we use the same MAS image to all three channels in our experiments.

For each trial, the training and testing samples are randomly shuffled with ratio 4:1. Within the training dataset, we used 90% samples for classifier training while the remaining 10% are used for validation. We employ the Gaussian distribution to initialize the weights of the network with the standard deviation of 0.001. Forty independent trials for each algorithm are conducted for in the experiment, and the average results are used for comparison.

B. Results and Discussions

We compare the proposed method with three most recent algorithms in this paper, which are brief described in the following respectively

- MAS+CNN [9]: The MAS map image combining with a fully connected CNN for feature learning and the support vector machine (SVM) is developed in [9] for preictal state classification and seizure detection.
- WPF+RF [16]: The wavelet packet decomposition (W-PD) based subband statistical features (WPF) have been extracted for multichannel EEG representation. The Random forest algorithm has been adopted for preictal state classification.
- WPF+LDA [16]: The same WPFs of [10] are adopted, where the linear discriminant analysis (LDA) is adopted as the classifier.

We first compare the classification performance of the proposed algorithm among using the three deep CNNs in feature transfer learning. The preictal state overall accuracy denoting the average accuracy of PreI, PreII, PreIII states and the overall accuracy denoting the average accuracy of all five epileptic states are presented in Table II for comparison. It is readily found from Table II that using 10 and 20 seconds respectively in constructing the MAS image, the proposed algorithm with all three different CNNs in transfer learning provides significantly better classification accuracies than using the MAS image with 2 seconds, regardless of the preictal state overall accuracy or the overall accuracy. The superiority can attribute to that the MAS images of 10 and 20 seconds EEGs contain more information than the one with 2 seconds. In general, the proposed algorithm using the transfer learning network with Inception-Resnet-v2 achieves the best performance (with the preictal state overall accuracy of 94.21% and the overall accuracy of 92.77%) when adopting the MAS image of 10 seconds.

The effectiveness of the proposed algorithm is demonstrated by comparisons to several up-to-date algorithms, where the accuracy confusion matrices are presented in Fig. 3. The detailed classification accuracy and misclassification of each class are shown, where for all the algorithms, the length of EEG signal used for feature extraction is set to be 10s. As observed from Fig. 3, the proposed CNN transfer learning based methods provide a significant enhancement on the three preictal states. Taking the Inception-Resnet-v2 as an example, it offers 9.69%, 15.21%, and 31.49% increments of classification rate over

(a) MAS+Inception-Resnet-v2 (b) MAS+Inception-v3 (c) MAS+Resnet152

(d) MAS+CNN (e) WPF+RF (f) WPF+LDA

Fig. 3: Confusion matrices comparisons.

MAS+CNN, WPF+RF, and WPF+LDA, on the PreI category. For the PreII and PreIII classes, the improvements are 19.95%, 24.05%, 33.91%, and 17.38%, 13.13%, 26.66%, respectively. Similar observations can be found for the proposed algorithm with the other two CNNs based transfer learning methods.

TABLE II: Performance on using different CNNs in feature transfer learning.

Algorithm	Period	Preictal State	Overall
MAS+ Resnet152	2s	88.34	87.82
	10s	**93.45**	**92.20**
	20s	90.27	90.25
MAS+ Inception-v3	2s	87.38	86.73
	10s	**92.40**	**92.52**
	20s	92.23	92.28
MAS+ Inception-Resnet-v2	2s	85.67	85.82
	10s	**94.21**	**92.77**
	20s	94.14	92.49

IV. CONCLUSIONS

We proposed an effective epileptic state classification method based on the deep network transfer learning algorithm in this paper. Different to conventional epileptic signal classification, that pays most of the attentions on seizure/non-seizure detection, the preictal state classification with a more granular time-scale of 20 minutes duration has been studied in the paper. The feature transfer learning performance with three representative deep CNNs pre-trained on the large ImageNet database has been presented, where the image of mean amplitude spectra of subbands (MAS) is employed for multichannel EEG signal representation. Experiments on the benchmark CHI-MIT database demonstrated that the proposed CNN transfer learning methods outperform several state-of-the-art epileptic classification algorithms with a significant enhancement on the preictal state classification accuracy.

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