LETTER *Special Section on Deep Learning Technologies: Architecture, Optimization, Techniques, and Applications*

Epileptic Seizure Prediction Using Convolutional Neural Networks and Fusion Features on Scalp EEG Signals

Qixin LAN[†], **Bin YAO**[†a)], ***and*** **Tao QING**[†], ***Nonmembers***

SUMMARY Epileptic seizure prediction is an important research topic in the clinical epilepsy treatment, which can provide opportunities to take precautionary measures for epilepsy patients and medical staff. EEG is an commonly used tool for studying brain activity, which records the electrical discharge of brain. Many studies based on machine learning algorithms have been proposed to solve the task using EEG signal. In this study, we propose a novel seizure prediction models based on convolutional neural networks and scalp EEG for a binary classification between preictal and interictal states. The short-time Fourier transform has been used to translate raw EEG signals into STFT sepctrums, which is applied as input of the models. The fusion features have been obtained through the side-output constructions and used to train and test our models. The test results show that our models can achieve comparable results in both sensitivity and FPR upon fusion features. The proposed patient-specific model can be used in seizure prediction system for EEG classification.

key words: *epileptic seizure prediction, convolutional neural networks, fusion features*

1. Introduction

A seizure is an unstable situation in epilepsy patients due to excessive electrical discharge by brain cells [1]. There are 60 million people around the globe suffering from epilepsy [2]. Unpredictable epileptic affects the daily lives of sufferers by leading to unexpected accidents and increasing mental stress. The early prediction of these attacks before they occur will be helpful for the patients to take precautionary measures and potentially allow the implementation of preventative therapies [3]. Electroencephalography (EEG) is commonly used to study variations in brain activity and helps to identify normal and abnormal events occurring in the human brain. In addition, scalp EEG signals monitoring is relatively low-cost and convenient for patients [4]. The method of epileptic seizure prediction using EEG signal has attracted extensive attention. The patterns of the EEG signal of epilepsy patients can be classified into four states including ictal, preictal, postical and interictal [5]. Seizure prediction system predicts the onset of a seizure in advance by differentiating between the preictal and the interictal states [4]. The correct identification of the preictal state can be used to generate an alarm for epilepsy patients [1]. Therefore, it is of great significance to design a reliable epileptic seizure prediction system to predict the onset of seizure [6].

In this study, we design a patient-specific epileptic seizure prediction system based on the convolutional neural networks (CNN), that uses the short-time Fourier transform to translate EEG raw signals into time-frequency spectrums, and utilizes these specturms for a binary classification between preictal and interictal states. We introduce the idea of multi-scale fusion features into the seizure prediction task. In our experiments, the fusion features achieve better results than normal features.

2. Related Work

Usman et al. [5] extracted a comprehensive feature set, which consists of handcrafted and automated CNN based features, and fed it into an ensemble classifier that combines the outputs of SVM, CNN and LSTM. Parvez et al. [7] proposed a seizure prediction method based on undulated global and local features using LS-VSM classifier to classify the EEG signals. Aarabi et al. [8] employed a patient-specific method to iEEG data from patients with medically intractable focal hippocampal epilepsy. Preictal periods are characterized with patient-specific changes in univariate and bivariate nonlinear measures. Mirowski et al. [9] compared L1-regularized logistic regression, convolutional networks, and support vector machines based on aggregated features, such as cross-correlation, nonlinear interdependence. Yu et al. [10] developed a two-level sparse multiscale classification model to classify interictal and preictal states from iEEG data. Prathaban et al. [11] proposed a lightweight three-dimensional Optimized Convolutional Neural Network classifier based on Fletcher Reeves algorithms for extracting and classifying the features of seizure. Borhade et al. [12] proposed a Modified Atom Search Optimization-based Deep Recurrent Neural Network to preform seizure prediction.

From the existing studies, it can be observed that convolutional neural network has been widely used in epilepsy prediction approaches, which achieved great results [5], [6], [13]–[15]. On the other hand, the researches also indicate that the current methods is not capable of meeting the needs of clinical application [3], [14]. Therefore, it is necessary to further improve the accuracy and reliability of prediction algorithm based on convolutional neural network.

Researchers have found that convolutional neural networks with different shallow can extract feature maps with different scale [16], [17]. Inspired by this idea, we propose a

Manuscript received December 8, 2021.
Manuscript revised February 14, 2022.
Manuscript publicized May 27, 2022.
[†]The authors are with the School of Aerospace Engineering, Xiamen University, Xiamen 361005, China.
a) E-mail: yaobin@xmu.edu.cn
DOI: 10.1587/transinf.2022DLL0002

conjecture that feature set consisting of multi-scale features can present more important characteristics of EEG signals, and the use of fusion feature set may achieve better prediction results.

3. Dataset

In this study, the proposed models are trained and tested on the CHB-MIT scalp EEG dataset [18]. The dataset contains 844 hours long continuous scalp EEG data from 23 pediatric patients with intractable epilepsy. We define the 30 minutes recordings before the onset of seizure as the preictal period, and 1 hour recordings between 2 hour before seizure onset and 2 hour after seizure end as the interictal period. We only consider the cases that have at least three seizures and three hours of interictal period in recordings.

4. The Proposed Method

The proposed architecture consists of four parallel paths, as shown in Fig. 1. The three former paths extract features through different shallow convolutional blocks and fully connected block and obtain side output. The last parallel path fuses features extracted by the three former paths with a concatenation layer. In this way, feature maps containing multi-scale information can be generated through the side-output constructions.

In our networks, the convolutional block consists of one convolutions, one max-pooling and one batch-normalization layer. The number of kernels used for the three convolutional layers were set to 16, 32 and 64, respectively. The kernel size were taken as $22 \times 5 \times 5$ with a stride of 2×2, $1 \times 3 \times 3$ with a stride of 1×1 and $1 \times 3 \times 3$ with a stride of 1×1, respectively. The proposed models can not only extract the feature maps, but also automatically optimize the weights of the entire networks to improve the accuracy and generalization through the convolutional blocks.

The fully connected block is connected to the convolutional block containing one flatten layer and several fully-connected layers. A binary classification result of seizure prediction will be obtained by the last fully-connected layer. The rectified linear unit, sigmoid and softmax activation function are used for convolutinal layer, the former fully-connected layer and the last fully-connected layer, respectively. In order to prevent from overfitting during training, the fully-connected layers have a 50% of dropout rate.

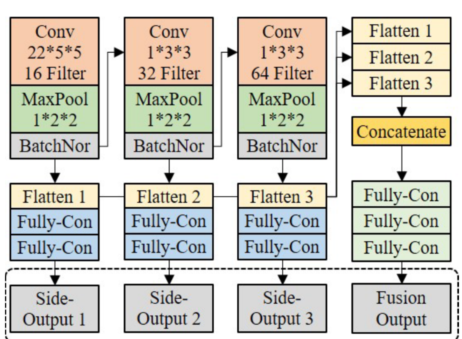

Fig. 1 Architecture of our proposed network.

5. Experiment

5.1 Preprocessing

According to the definition in Sect. 3, six cases from the dataset are selected for our work. We create preictal and interictal signals segments by sliding a 30 s window along the time axis. To overcome the imbalance problem of preictal and interictal signals, the overlapped sampling method is used to get more preictal segments with an overlap of 50%. The butter filter is applied to remove the power line noise at 50-60 Hz. In order to reduce the complexity of the mode, we manually eliminate the recordings with great noise interference. Then, the short-time Fourier transform (STFT) has been used to translate raw EEG signals into two-dimensional spectrums, which composes the normal feature set.

5.2 Model Implementation

The proposed convolutional neural networks is built based on PaddlePaddle deep learning framework [19] with python supported by numpy, scipy, math, pyedflib and random. We performed all our experiments on a workstation driven by Ubuntu system 20.0, equipped with a GPU (GeForce RTX 208) and 30GB random-access memory.

5.3 Evaluation

For our work, the Seizure Occurrence Period (SOP) is defined as the interval where the seizure is expected to occur. The period between the alarm and the beginning of the SOP is the Seizure Pediction Horizon (SPH) [20]. If the prediction system gives an alarm, a seizure onset should happen after the SPH and within the SOP for a correct prediction. We use sensitivity and False Positive Rate (FPR) to evaluate the performance of our machine learning models. Sensitivity is defined as the percentage of seizures correctly predicted divided by the total number of seizures. The number of false alarms per hour is regarded as the FPR. Regarding clinical use, the SPH should be long enough to allow effective intervention or precautions, and the SOP should be short. In our work, the SPH and SOP are set to 5 minutes, 30 minutes, respectively.

In order to choose the best model, we randomly selected 80% as the training set and 20% as the validation set from feature set. The Adaptive Moment Estimation optimizer is employed with the learning rate of 0.0001. The categorical cross entropy was selected as loss function. It takes 30 minutes to train each subject's model for 400 epochs with a batch size of 50. The leave-one-out cross-validation approach is used for model validation to prevent overfitting.

The trained models are tested on the test dataset and

Table 1 Seizure prediction results obtained from test dataset.

Patient No	Sensitivity(%)			FPR(/h)		
	side2	side3	fusion	side2	side3	fusion
01	0.66	0.71	0.80	0.89	0.75	0.10
02	0.47	0.86	0.89	2.90	1.09	0.16
05	0.47	0.74	0.85	6.37	0.89	0.41
09	0.55	0.86	0.92	2.1	1.92	0.13
19	0.45	0.90	0.86	4.12	0.31	0.17
21	0.76	0.92	0.81	1.16	0.81	0.14
23	0.78	0.62	0.91	2.4	1.0	0.20
Average	0.591	0.801	86.2	2.85	0.97	0.18

Table 2 Comparison of recent seizure prediction methods.

Method	Dataset	Sen(%)	FPR(/h)	SOP	SPH
[15]	MIT	81.2	0.16	30	5
[8]	FB	86.7	0.126	30	10
[6]	MIT	85.7	0.096	30	1
[7]	FB	95.4	0.36	30	0
This work	MIT	86.2	0.18	30	5

the testing results are showed in Table 1. The fusion-output branch obtains the best average sensitivity of 86.2% and the best average FPR of 0.18. The result demonstrates that the fusion features provide better representation of EEG signals. Compared with the state-of-the-art models under similar conditions, our models are capable of achieving comparable results, as shown in Table 2.

6. Conclusion

We propose a novel approach for EEG classification based on CNNs and fusion features. Compared with the state-of-the art models, it achieves comparable results in both sensitivity and FPR. Our test shows that the fusion features can present more important characteristics of EEG signals and achieve better prediction results than the normal features. The models can be used for seizure prediction system to analyse EEG signals and classify seizure states.

Acknowledgments

This work is supported by the National Key Research and Development Program of China (No.2020YFB1713503); the Fundamental Research Funds for the Central Universities (No.20720190009) and 2019 Industry-University-Research Cooperation Project of Aero Engine Corporation of China (No. HFZL2019CXY02).

References

[1] R. Jana and I. Mukherjee, "Deep learning based efficient epileptic seizure prediction with eeg channel optimization," Biomed. Signal Proces., vol.68, July 2021.

[2] M.J. Cook, T.J. O'Brien, S.F. Berkovic, M. Murphy, A. Morokoff, G. Fabinyi, W. D'Souza, R. Yerra, J. Archer, L. Litewka, S. Hosking, P. Lightfoot, V. Ruedebusch, W.D. Sheffield, D. Snyder, K. Leyde, and D. Himes, "Prediction of seizure likelihood with a long-term, implanted seizure advisory system in patients with drug-resistant epilepsy: A first-in-man study," Lancet Neurol., vol.12, no.6, pp.563–571, June 2013.

[3] K. Rasheed, J. Qadir, T.J. O'Brien, L. Kuhlmann, and A. Razi, "A generative model to synthesize eeg data for epileptic seizure prediction," IEEE Trans. Neural Syst. Rehabil. Eng., vol.29, pp.2322–2332, 2021.

[4] T. Dissanayake, T. Fernando, S. Denman, S. Sridharan, and C. Fookes, "Deep learning for patient-independent epileptic seizure prediction using scalp eeg signals," IEEE Sens. J., vol.21, no.7, pp.9377–9388, April 2021.

[5] S.M. Usman, S. Khalid, and S. Bashir, "A deep learning based ensemble learning method for epileptic seizure prediction," Comput. Biol. Med., vol.136, Sept. 2021.

[6] A.R. Ozcan and S. Erturk, "Seizure prediction in scalp eeg using 3d convolutional neural networks with an image-based approach," IEEE Trans. Neural Syst. Rehabil. Eng., vol.27, no.11, pp.2284–2293, Nov. 2019.

[7] M.Z. Parvez and M. Paul, "Seizure prediction using undulated global and local features," IEEE Trans. Biomed. Eng., vol.64, no.1, pp.208–217, Jan. 2017.

[8] A. Aarabi and B. He, "Seizure prediction in patients with focal hippocampal epilepsy," Clin. Neurophysiol., vol.128, no.7, pp.1299–1307, July 2017.

[9] P.W. Mirowski, Y. LeCun, D. Madhavan, and R. Kuzniecky, "Comparing svm and convolutional networks for epileptic seizure prediction from intracranial eeg," 2008 IEEE Workshop on Machine Learning for Signal Processing, pp.244–249, 2008.

[10] P.-N. Yu, C.Y. Liu, C.N. Heck, T.W. Berger, and D. Song, "A sparse multiscale nonlinear autoregressive model for seizure prediction," J. Neural Eng., vol.18, no.2, April 2021.

[11] B.P. Prathaban and R. Balasubramanian, "Dynamic learning framework for epileptic seizure prediction using sparsity based eeg reconstruction with optimized cnn classifier," Expert. Syst. Appl., vol.170, May 2021.

[12] R.R. Borhade and M.S. Nagmode, "Modified atom search optimization-based deep recurrent neural network for epileptic seizure prediction using electroencephalogram signals," Biocybern. Biomed. Eng., vol.40, no.4, pp.1638–1653, Oct.-Dec. 2020.

[13] R. Hussein, S. Lee, R. Ward, and M.J. McKeown, "Semi-dilated convolutional neural networks for epileptic seizure prediction," Neural Networks, vol.139, pp.212–222, July 2021.

[14] X. Chen, Y. Zheng, C. Dong, and S. Song, "Multi-dimensional enhanced seizure prediction framework based on graph convolutional network," Front. Neuroinform., vol.15, pp.605729, 2021.

[15] N.D. Truong, A.D. Nguyen, L. Kuhlmann, M.R. Bonyadi, J.W. Yang, S. Ippolito, and O. Kavehei, "Convolutional neural networks for seizure prediction using intracranial and scalp electroencephalogram," Neural Networks, vol.105, pp.104–111, Sept. 2018.

[16] W.L. Kuang, B. Tu, W.Q. He, G.Y. Zhang, and Y.S. Peng, "A spectral-spatial attention aggregation network for hyperspectral imagery classification," Int. J. Remote. Sens., vol.42, no.19, pp.7551–7580, Oct. 2021.

[17] H.T. Mustafa, J. Yang, H. Mustafa, and M. Zareapoor, "Infrared and visible image fusion based on dilated residual attention network," Optik, vol.224, Dec. 2020.

[18] A.H. Shoeb, "Application of machine learning to epileptic seizure onset detection and treatment," in Harvard University–MIT Division of Health Sciences and Technology, Harvard University, Cambridge, MA, USA, 2009.

[19] X. Tang, D.K. Du, Z. He, and J. Liu, "Pyramidbox: A context-assisted single shot face detector," Lect. Notes Comput. Sc., vol.11213, pp.812–828, 2018.

[20] T. Maiwald, M. Winterhalder, R. Aschenbrenner-Scheibe, H.U. Voss, A. Schulze-Bonhage and J. Timmer, "Comparison of three nonlinear seizure prediction methods by means of the seizure prediction characteristic," Physica D: Nonlinear Phenomena, vol.194, no.3-4, pp.357–368, July 2004.