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EPILEPTIC FOCUS LOCALIZATION BASED ON ENTROPY AND CONVOLUTIONAL NEURAL NETWORK

Xuyang Zhao[1], Lihua Gui[2], Jianting Cao[3], Qibin Zhao[4]

Abstract – Focal location is a necessary step before surgery in epileptic patients and directly affects the outcome of the surgery. However, this is a time-consuming and difficult process for clinical experts. Recent researches have shown that we can use machine learning approaches to reduce the workload of the focal location. In this paper, we proposed a method for extracting features by calculating the entropy of the intracranial electroencephalogram (iEEG) and use a one-dimensional convolutional neural network (1D-CNN) for classification, in this way, we can automatically locate the epileptic foci. More specifically, because epilepsy is caused by abnormal discharge of brain cells, entropy is a very suitable evaluation method. Experimental results show that our approach is effective for epilepsy localization and got an average test accuracy of 85.6%.
Keywords – Epilepsy, Localization, Entropy, Convolutional Neural Network.

1. INTRODUCTION

EPILEPSY is caused by excessive electrical discharges in brain cells and one of the most common neurological diseases globally. According to the World Health Organization (WHO), approximately 50 million people worldwide have epilepsy. Epilepsy can cause a lot of troubles for patients including mental retardation, neurological disorders and safety problems. Up to 70% of patients can be successfully treated with antiepileptic drugs. For patients with drug-resistant, treatment by surgery is an effective method. Before surgery, we first need to confirm the patient's lesion area and localization accuracy is the most important factor affecting the outcome of the surgery. Currently, physical exam, iEEG, magnetoencephalogram (MEG), functional magnetic resonance imaging (fMRI) and other modalities are usually used for the localization of epileptic foci. Compare the advantages and disadvantages of these inspection methods, the iEEG as a fundamental tool in the diagnosis of epilepsy. The iEEG signal recorded form epileptic area are named focal signal, otherwise are named non-focal signal.

In current clinical practice, the iEEG signal is diagnosed by clinical experts through visual judgment, which is a time-consuming process and difficult process. The diagnosis results given by different clinical experts are not completely consistent. Usually, clinical experts need to vote on the final results. All the processes are done manually. Therefore, there is a strong demand for the auxiliary treatment system. The purpose of the system includes improving the accuracy of diagnostic results and reducing the workload of clinical experts.

Recent, some methods for the diagnosis and treatment of epilepsy have been proposed, such as template matching [1] [2], dictionary learning [3], these methods show effectiveness in epileptic focus localization problem. But more and more machine learning methods have been applied to this problem and achieved better performance results. Usually, the machine learning methods are divided into two steps, feature extraction and classification. In feature extraction step, discrete wavelet transform (DWT) [4] [5], entropy [6] [7], Fourier transform (FT) [8] and Empirical mode decomposition (EMD) [9] are usually be used. Considering that the epilepsy seizures are caused by abnormal discharge of brain cells and entropy is a common method of measuring energy, therefore, we use entropy as the feature extraction method. Before calculating the entropy, we divide the iEEG signal into multiple frequency bands, the calculate multiple entropies in each different bands. This inspiration comes from the clinical expert 's diagnostic process, because when clinical experts observe the iEEG signal, they usually first use different bandwidth filters. In the classification process, traditional classifiers such as support vector machines (SVM), decision trees are often be used. This time, we use the CNN model as a classifier. CNN has shown its powerful performance in the computer vision field. For time-series iEEG signals, we use a 1D-CNN model to classify the focal and non-focal signals. In the experimental, we use two kinds of classifiers, fully connected neural network (FCNN) and 1D-CNN model, compare to the FCNN model, 1D-CNN showed the effectiveness of the epileptic focus localization problem.

The rest of the paper is organized as follows: Section II describes the feature extraction method of entropy and the 1D-CNN model. Section III describes the dataset which is used to evaluate our approach. The experimental results are presented in Section IV and the last is the conclusion of this study.

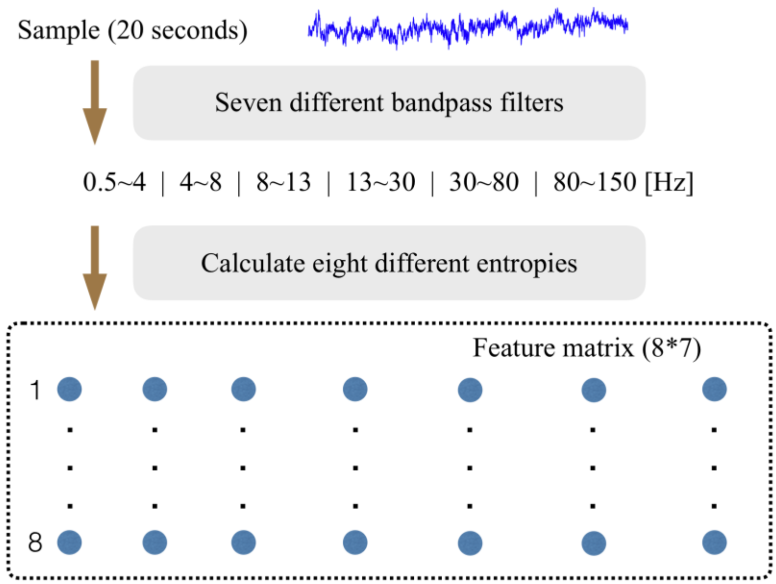
[1] Department of Electronic Engineering, Saitama Institute of Technology, Fukaya, Tensor Learning Unit, RIKEN Center for Advanced Intelligence Project, Tokyo, Japan
[2] Saitama Institute of Technology, Fukaya, Japan
[3] Department of Electronic Engineering, Saitama Institute of Technology, Fukaya, Japan
[4] Tensor Learning Unit, RIKEN Center for Advanced Intelligence Project, Tokyo, Japan, School of Automation, Guangdong University of Technology, Guangzhou, China

2. METHODS

In the article, our main ideas include two parts of feature extraction and classification. We use entropy as the feature extraction method and two kinds of classifiers (FCNN and 1D-CNN). Next, we will introduce them separately.

2.1. Feature extraction

Consider the pathological causes of epilepsy seizures, which is due to abnormal discharge. Entropy is a common indicator for evaluating energy, we extract the features from raw iEEG data by using eight kinds of entropies and six kinds of filters, the flowchart of feature extraction is shown in Fig. 1. The first step is to process the data with different filters (Third-orders Butterworth filter), the bandpass frequency are shown in Table 1, which are the commonly used physiological frequency bands. The second step, for each filtered data, we calculate eight different entropies include Shannon entropy, Renee entropy, Generalized entropy [10] [11], Phase entropy (two types) [12], Approximate entropy [13], Sample entropy [14] and Permutation entropy [15]. Finally, we get a feature matrix with size of 6*8, in the next step of the classification, the matrix will be flattened and entered into the model.



Flowchart of feature extract procedure

Table 1: Frequency Band

Band Name	Frequency [Hz]
Delta	0 ~ 4
Theta	4 ~ 8
Alpha	8 ~ 13
Beta	13 ~ 30
Gamma	30 ~ 80
Ripple	80 ~ 150

2.2. One-dimensional convolutional neural network

CNN models show increasingly important roles in classification, especially in the field of computer vision. Usually, the model has better generalization ability. In order to be able to process a one-dimensional timing signal (iEEG), we use the 1D-CNN model as a classifier. In the model, the input size is set to 1*48 according to the size of the feature matrix, followed by four convolution layers, and the convolution kernel size of each convolution layer is set to be the same. Next is the three fully connected layers, which are finally classified by method softmax. the activation function is relu and optimizer by Adam. The architecture of 1D-CNN model is shown in Table 2.

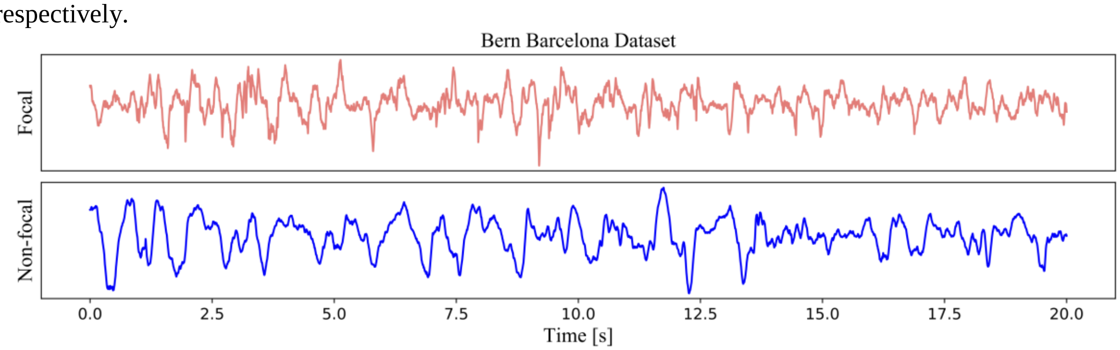
Table 2: Architecture of 1D-CNN Model

Layer	Kernel size	Number	Strides
Conv	1*4	64	1
Conv	1*4	128	1
Conv	1*4	128	1
Conv	1*4	64	1

Fully connected 1	Size 32
Fully connected 2	Size 64
Fully connected 3	Size 32
Softmax	

3. DATASET

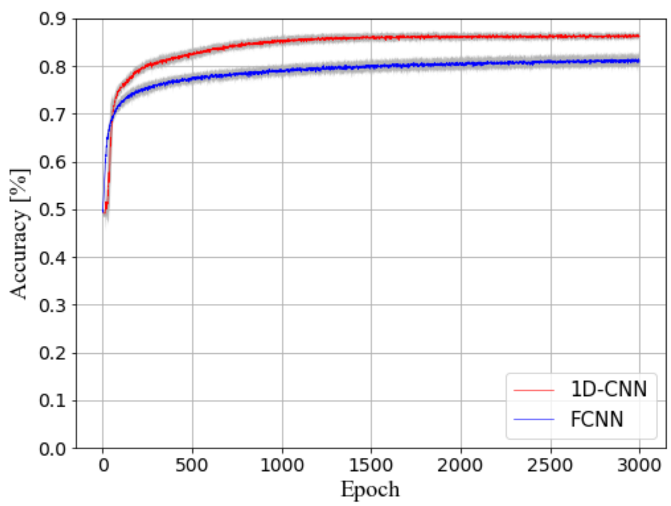
Bern-Barcelona iEEG dataset [16] is used for evaluating our methods. The dataset is recorded from the Department of Neurology, University of Bern, Barcelona, Spain. The dataset collected from five patients suffering from pharmacoresistant focal onset epilepsy. Dataset includes of 7,500 focal signals and 7,500 non-focal signals, each signal is 20 seconds with the sampling frequency of 512 Hz and each signal is bandpass filtered between 0.5 and 150 Hz by using a fourth-order Butterworth filter. Signals recorded form epileptogenic channels are labeled as focal signals, otherwise, labeled as non-focal signals. According to the article [16], the focal signal is more stationary and less random than the non-focal signal. In the visual distinction, the focal signal will contain some spike, sharp wave, slow-wave and spike-and-slow-wave complex. This is also the most important basis for clinical experts to diagnose. An example of the focal and non-focal iEEG signals are shown in Fig. 2, respectively.



Example of the focal and non-focal iEEG signals

4. EXPERIMENT AND RESULTT

Bern Barcelona iEEG dataset is used to evaluate the 1D-CNN model and we also use the FCNN model as a reference indicator. In the experiment, both models are evaluated by 10-folds Cross-validation which is a comprehensive evaluation of model performance. The batch size of the two models is set to 64. The training curve is shown in Fig. 3, the curve in the figure represents the average of 10-folds cross-validations, and the gray area is the corresponding standard deviation. As can be seen from the curve in figure, the 1D-CNN model shows better performance in both the mean value and stability of the results compared to the FCNN model. The average test accuracy of the two models is shown in Table 3. The results of some other methods are summarized in Table 4.



Results of 1D-CNN and FCNN model with Bern Barcelona dataset, test accuracy vs. number of epochs. Redline (1D-CNN model) and Blueline (FCNN model): Average of classification test accuracy (10-folds), Gray area: Standard deviation (10-folds).

Table 3: Average test accuracy of 1D-CNN and FCNN model

Model	Accuracy [%] (Mean & Std)
Entropy & FCNN	80.83 (1.29)
Entropy & 1D-CNN	86.23 (0.50)

Table 4: Localization results of focal and non-focal iEEG data of published articles (accuracy in [%]).

Article	Method proposed	Performance
[4]	DWT, SVM	83.07
[5]	DWT, Entropy, LS-SVM	84
[7]	TQWT, Entropy, LS-SVM	84.67
	Entropy, 1D-CNN	86.23 (0.50)

V. CONCLUSION

In summary, the feature extraction method of entropy and filter and classification by the 1D-CNN model is applied for the epileptic focus localization problems. Because epilepsy is caused by abnormal discharge, entropy is very suitable for extracting the feature of iEEG. In the classification, we use 1D-CNN as the classifier, and compared to the FCNN model, the 1D-CNN achieves better performance. Compared with other articles, the proposed method shows better effectiveness. In our future work, we will focus on further improving the performance of the model.

VI. ACKNOWLEDGMENTS

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