ESANN 2022 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium) and online event, 5-7 October 2022, i6doc.com publ., ISBN 978287587084-1. Available from http://www.i6doc.com/en/.

1D vs 2D convolutional neural networks for scalp high frequency oscillations identification

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Abstract. Scalp High Frequency Oscillations (HFOs) are promising biomarkers of epileptogenic zones. Since HFOs visual detection is strenuous, there is a real need to develop accurate HFOs automatic detectors. In this paper, we present a comparative study of two detectors: one-dimensional (1D) Convolutional Neural Networks (CNN) running on High-Density Electroencephalograms signals and two dimensional (2D) CNN on time-frequency maps of those signals. Experimental results show that 1D-CNN enables easy end-to-end learning of preprocessing, feature extraction and classification modules while achieving competitive performance.

1 Introduction

The objective of this study is to propose a deep learning architecture to identify scalp High Frequency Oscillations (HFOs). HFOs are brief events (between 15 to 100 ms) with regular small-amplitude oscillations ranging from 80 to 500 Hz clearly distinguishable from EEG background They are specific biomarkers to localize brain regions responsible of epilepsy. HFOs were first detected in invasive EEG electroencephalogram (iEEG). Recently, HFOs were also found in scalp EEG allowing a non-invasive, affordable approach that is more applicable clinically and making accurate source localization when recorded with High Density Electroencephalogram (HD-EEG) [1]. So far, visual marking of HFOs remains the gold standard marking. Visual detection requires expertise, is subjective and highly time consuming, especially in scalp EEG. Thus, there is a real need to develop efficient automatic scalp HFOs detectors. In last decades, HFOs detectors were developed using a long pipeline including artefact rejection, filtering, feature engineering, feature selection and eventually a classification step for false detection rejection [2] Recent studies perform feature extraction using supervised or unsupervised machine learning techniques [3, 4]. Most detectors are developed for iEEG, very few methods were proposed to automatically detect HFOs from scalp EEG [5–7] and most of them are extensions of iEEG HFOs detectors, are semi supervised and require definition of threshold(s) [5, 6] . The only non-threshold based scalp HFOs detector was proposed in [7] using a semi-supervised k-means algorithm followed by a mean shift algorithm to

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classify suspicious HFOs. To overcome all the thresholding and post detector visual reviews, we propose here an automatic classification between HFOs (80-500 Hz) and EEG signal outside this frequency range (non HFOs) based on deep learning. Our method doesn't require any threshold definition, no distinction is performed between Ripples (R - [80-250 Hz]) and Fast Ripples (FR - [250-500 Hz]). After a review of scalp HFOs detectors, our methods are presented and experimental results are discussed.

2 Material and methods

2.1 HD-EEG recording and visual marking

Three epileptic patients were prospectively enrolled for 18 hours of continuous HD-EEG combined with video in the awake and sleep states. All patients are children with pharmaco-resistant focal epilepsy leading to the occurrence of at least one seizure per day and with epileptogenic lesion visible on MRI. HD-EEG was recorded using HydroCel Geodesic Long term monitoring Sensor Net with 256 electrodes. To ensure the quality of the recording signal, electrode-skin impedances were maintained at $\leq 50K\Omega$. EEG was recorded using EGI's Net Station with 1 kHz sampling rate and 0,1 Hz High Pass filter.

Ten minutes of sleep stage 2 or 3 EEG segments were selected. Two experts visually labelled the HFOs on raw EEG signals displayed one second per page on a 10-20 reference montage as shown on the top of Figure 1. Every oscillatory event with minimum 3 regular oscillations clearly distinguishable from background, with frequency above 80 Hz was marked as HFOs without distinction between Ripples and Fast Ripples. Selected events were then high-pass filtered and mapped in time frequency (TF) domain to confirm the detection.

2.2 Preprocessing

For each electrode, EEG signal was normalized and high pass filtered using a 30 order Butterworth Finite Impulse Response filter with 80 Hz cutoff frequency. Within each electrode, EEG signals non-belonging to HFOs were considered Non HFOs (NHFOs) zones. For 2D-CNN based detection, each detected HFO central time was computed and 100 ms EEG signal was selected before and after the center. 150 ms segments were randomly selected from NHFOs zones and considered as NHFOs. EEG segments were then converted to time frequency maps using Short Time Fourier Transform. Each image was labeled, resized to 256×256 pixels and decomposed over the 3 red, green and blue color channels resulting in 4 sets of images: RGB images, and grayscale R, G and B images with respectively red, green or blue channel only. Inputs of 1D-CNN detector are EEG segments of W ms. W was defined by adding mean and standard deviation of the duration of all marked HFOs. For each HFOs and NHFOs selected for 2D-CNN, EEG signal of W ms centered on the event's middle was labeled and considered as an input of 1D-CNN.

Figure 1 presents an example of EEG segment considered as HFO.

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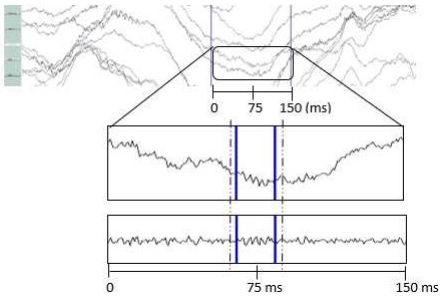

Fig. 1: *Top:* One second raw EEG signal. Vertical lines point out a 150 ms time interval centered on HFO1; *Middle:* focus on time interval selected for TF maps, electrode 37; *Bottom:* 80Hz-High-passed HFO1. *Blues bold lines marked HFO1 beginning and end, dashed lines marked 35 ms segment selected for 1D.*

2.3 CNN architecture

The next step consists on classifying TF maps images (2D) or selected EEG signal segments (1D) as HFOs or NHFOs using a binary CNN.

CNN are generally designed with 4 kinds of layers. The convolution layer performs convolution operations between input data and filters in order to detect features of interest. A filter corresponds to a concatenation of multiple kernels which are small 1D or 2D matrix containing trainable weights. For images, kernels are squared matrices of dimension $f \times f$. In 1D-CNN, kernels are matrices of dimension $f \times W$. Each kernel matrix is slid across the input image or signal and multiplied with the scanned part of the data. The sum of this element-wise multiplication corresponds to the cross-correlation between the data and the filter, resulting in a 2D matrix for images and 1D for signal.

The maxpooling layer extracts the maximum values of the features matrices output from convolutional layer. The flatten layer stacks the values of the features matrices output from the last maxpooling layer and provides a feature 1D matrix as input to the following layer. At this stage the features extraction part of the CNN is completed. Finaly, the convolutional step output matrix is provided as input to the dense layer, a multilayer perceptron responsible for the classification part of the CNN. The output layer returns a vector of size corresponding to the number of classes, in which each component represents the probability for the input data to belong to the corresponding class.

In our 1D and 2D-CNN models, several configurations were tested varying the number of convolutional layers and the number of filters in respective convolutional layers as follows: 16, 32 and 64 filters for model1; 64, 32 and 16 filters for model2 and 16, 32, 64, 32 and 16 filters for model3. Kernels used for convolutional layers are all of size f=3. Moreover, for each model, a maxpooling layer was added after each convolutional layer for 2D-CNN or at the end of all convolutional layers for 1D-CNN. For convolutional, dense and output layers an

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activation function has to be defined to switch on or not each neuron. Several non-linear activation functions can be used. In our CNN, the Rectified Linear Unit (ReLU) and Leaky ReLu functions were tested on convolutional and dense layers whereas sigmoïd and softmax functions were compared to activate the output layer. Our models used one 500 neurons hidden layer and a 2 neurons (HFO, NHFO) output layer. Figure 2 summarizes the CNN architecture used.

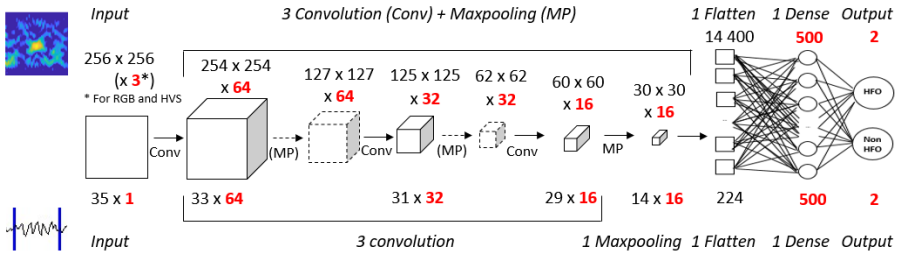

Fig. 2: Convolutional Neural Network model2 used to classify HFO/NHFO. *Top: 2D-CNN; Bottom: 1D-CNN. Numbers correspond to layer output size.*

2.4 Training, Validating and testing CNN

Input datasets were randomly resampled into 3 different HFOs-NHFOs balanced datasets: 60% for training, 20% for validation and 20% for testing. Fitting the CNN models weights were performed on training sets using batch size of 100 in 50 epochs unless early stopping was activating when loss accuracy does not improve after 10 epochs. In case of early stopping, model weights are restored from the end of the best epoch. Validation datasets were used to evaluate model loss and accuracy at each epoch. Performance metrics were computed from labels predicted by the best epoch of the classification model running on testing datasets. Precision, sensitivity, specificity and F1-score were calculated to compare models. In order to check the robustness of our models, 12 runs were performed per model on random splits of datasets.

3 Experimental results

Data set consists of 5182 events with 2591 visually labelled HFOs and 2591 NHFOs (TF images for 2D-CNN and EEG signals for 1D-CNN). Table 1 summarises means and standard deviations obtained from 12 runs of CNN best model for each set of images and signals.

For RGB images, the best performance resulted from model1 with ReLU activation function in convolutional layers and Sigmoïd function in dense layer. For all other sets of images and for signal, model3 provides the best metrics with Sigmoïd activation function in dense layer and Leaky ReLU function in convolutional layers for 2D-CNN and ReLu for 1D-CNN.

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	Precision	Sensitivity	Specificity	F1-score
RGB	**85.7%(1.6%)**	84.9% (2.9%)	**85.7%(2.1%)**	**85.3%(1.0%)**
R	83.9% (1.8%)	84.4% (2.5%)	83.7% (2.5%)	84.1% (0.9%)
G	83.4% (2.7%)	**85.2%(3.9%)**	82.9% (3.9%)	84.2% (1.3%)
B	81.2% (3.8%)	83.7% (4.5%)	80.2% (6.0%)	82.3% (1.5%)
1D	**87.5%(1.0%)**	**91.4%(1.3%)**	**86.9%(1.4%)**	**89.4%(0.5%)**

Table 1: CNN metrics summary: mean (standard deviation) from 12 random runs. *Bold values: best performance metrics for each CNN type.*

All models return very good metrics ranging from 80.2% to 91.4% with low variability. For 2D-CNN, precision, specificity and F1-score are higher and more robust for RGB images than for the other color sets. 1D-CNN on EEG signal segments provides better performance than all 2D-CNN.

4 Discussion

We show here that both 1D and 2D-CNN can be considered as an efficient classifier discriminating HFOs and NHFOs. Metrics obtained from 1D-CNN are particularly interesting since they are better than 2D-CNN. Besides, 1D-CNN has the advantage of running on original data (EEG signal, not TF), with no time consuming preprocessing steps.

As compared with existing HFOs classification studies, whose results are presented in table 2, our 1D-CNN gives similar performance as the best iEEG HFOs detector [4]. Moreover 1D-CNN precision and sensitivity are equal or better than those of scalp HFOs detectors. It is worthy to note that most scalp detectors are semi automated (need expert validation), used traditional machine learning techniques (features engineering before running a classifier), and need threshold definition [5–7]. Lastly, in [8] a 2D-CNN was used to detect scalp HFOs but the reported metrics for comparison to visual markings are lower than the ones we obtained with our 1D-CNN.

Our 1D-CNN model is simple using a single step for feature extraction and

Study	EEG	HFOs	Precision	Sensitivity	Specificity	F1-score
CNN [4]	iEEG	all	**88.7%**	**91.3%**	**91.5%**	**90.0%**
CNN [3]	iEEG	R	–	77.0%	72.3%	–
CNN [3]	iEEG	FR	–	83.2%	79.4%	–
SA/ T [5]	scalp	S+R	63.0%	62.8%	–	–
kmean [7]	scalp	R	–	68.2%	96.5%	–
SA/ T [6]	scalp	all	**87.5%**	**83.3%**	**100%**	–
CNN [8]	scalp	S+R	63.0%	62.7%	–	–

Table 2: Previous studies performance summary. *R: Ripples; F: Fast; S: Spikes, SA : Semi automated; T: Threshold. Bold values shows best performance.*

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classification and with signal preprocessing limited to normalization and High Pass filtering. Moreover, considering that our HFOs classification was performed on scalp EEG with a more tedious detection due to lower signal intensity and more artifacted signals, results obtained are very promising. Since our NHFOs were randomly selected, we are confident that they are representative of all kind of activities recorded in scalp EEG and that results will remain competitive when extending our detection on the whole electrodes.

5 Conclusion

The main contribution of this paper is to show that 1D-CNN can be used to identify accurately scalp HFOs. 1D-CNN has the advantages of needing no preprocessing steps and of outperforming 2D-CNN models learned on time-frequency maps. 1D-CNN performance computed on scalp EEG are comparable to those of iEEG. In future work, more deep learning architectures will be explored to detect HFOs, like Long Short-Memory networks. We will also use HFOs detector to compare epileptogenic zones delineated by HFOs with the ones defined using interictal epileptiform discharges and seizures.

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