Seizure Detection Using Least EEG Channels by Deep Convolutional Neural Network

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Introduction

Monitoring brain activity through EEG is critical for epilepsy diagnosis. To capture seizure events that may occur sparsely, neurologists have to visually scan vast amount of EEG data that is extremely time consuming and may be subjective due to inter observer variance. Computer aided seizure detection approach would serve as valuable clinical tool for the scrutiny of EEG data in an objective and much more efficient manner. In this purpose, various Deep Learning (DL) approaches have been proposed. Hugle et.al.[1] proposed a Convolutional neural network (CNN) designed for implantable microcontroller by using only 4 electrodes selected a priori by expert. Ullah and colleagues [2] developed a pyramid CNN, and a typical 13-layer CNN model is created in [3], both using Bonn University database which has only 3.27 hours of EEG data. The latter deep CNN structure has about 100k parameters, however neither dropout nor batch normalization is used to regularize the deep CNN.

Dataset

Data used in this study is from KK Women's and Children's Hospital, Singapore. IRB was acquired from the hospital review board. EEG data of 29 pediatric patients diagnosed with typical absence seizures are included in this study. The data are extracted from Nikon Kohden EEG-1200K and EEG-9100K recording systems (reading setting: Cal Voltage=$50\mu V$, HFF=$70Hz$, LFF=$0.53Hz$, Sensitivity=$7-10\mu V/mm$, sampling rate=$200\ or\ 500Hz$). The length of patients' EEG recordings range from 25 to 66 minutes. In total the data contains 1037.6 minutes of EEG recording with 24.95 minutes seizure data distributed among 120 seizure onsets.

Baseline Method – BPsvm

A SVM-based classifier [4] using hand crafted spectrum band power features is adopted as a baseline method. In this study, we preserve the 5-second epoch for analysis across different approaches. To obtain features in higher resolution, as done in [4], we split the 5-second epoch into 5 1-second windows for spectrum transformation and band power feature extraction.

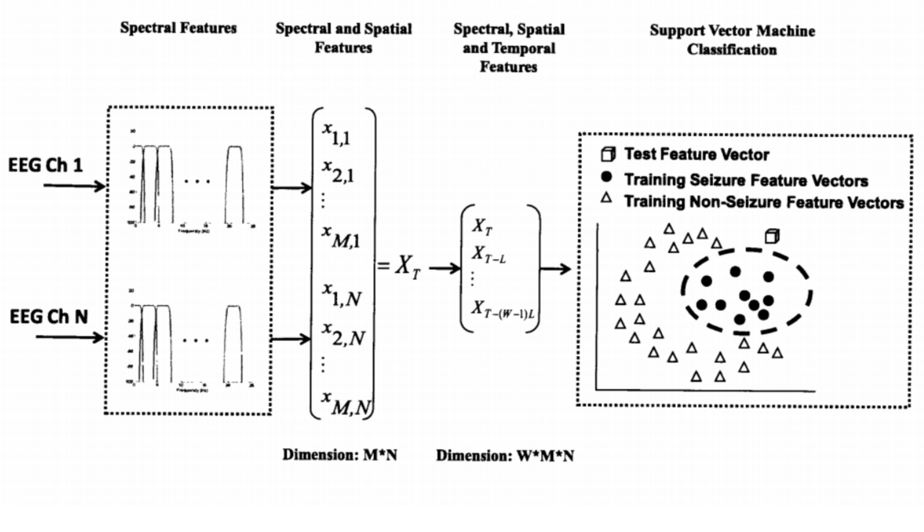

Figure 1: Shoeb's seizure onset detector architecture

In Shoeb's work [4], 8 bands from 0.5-24 Hz are chosen. As our window size is 1 second, the lowest frequency we can analyze is 1 Hz, therefore sub-bands are defined as [1-3, 3-6, 6-9, 9-12, 12-15, 15-18, 18-21, 21-24] Hz. Spectrum band power features in the sub-band signals on every 1-second are calculated and then concatenated into one instance for every 5-second epoch. Afterwards, SVM classifier is trained based on extracted features by using radial basis function (RBF) kernel.

Deep Learning Method – SeizNet

	Layer	Output
Input	$(1000 \times n^*)$	$(1 \times 1000 \times n)$
Conv 1	$8 \times Conv2D(1 \times 10)$	$(1 \times 991 \times 8)$
	MaxPool2D (1×2)	$(1 \times 495 \times 8)$
	Dropout (0.2)	$(1 \times 495 \times 8)$
Conv 2	$16 \times Conv2D(1 \times 10)$	$(1 \times 486 \times 16)$
	MaxPool2D (1×2)	$(1 \times 243 \times 16)$
	Dropout (0.2)	$(1 \times 243 \times 16)$
Conv 3	$32 \times Conv2D(1 \times 10)$	$(1 \times 224 \times 32)$
	MaxPool2D (1×2)	$(1 \times 112 \times 32)$
	Dropout (0.2)	$(1 \times 112 \times 32)$
Conv 4	$64 \times Conv2D(1 \times 10)$	$(1 \times 93 \times 64)$
	MaxPool2D (1×2)	$(1 \times 46 \times 64)$
	Dropout (0.2)	$(1 \times 46 \times 64)$
Flatten	Flatten	(2944)
	Dense (50)	50
	Dropout (0.5)	(50)
Output	Dense (2)	(2)

Table 1: SeizNet Architecture

We develop a deep CNN network, SeizNet, as an end-to-end seizure detection solution. Comparing to [3], SeizNet contains additional **dropout** layers and **batch normalization** after every convolution layer to avoid overfitting. The number of filter at each convolution layer is multiplied by **two** every time like VGGNet [5]. It enables SeizNet to have less number of filters at low levels in which filters learn basic shapes, while to have more filters at the higher levels where filters are capable of grasping sophisticated patterns.

As an activation function ReLU is used and other hyper-parameters of the model such as number of filters and filter sizes at each layer as well as number of unit in the fully connected layer are cross-validated over a broad range. Detailed architecture of SeizNet can be found in table 1. The total number of parameters for SeizNet-2chn and SeizNet-18chn are $200,592$ and $201,872$ respectively, both include 240 non-trainable parameters.

Results

Results obtained from different experimental settings can be found in Table 2. In both BPsvm and SeizNet, models using 18-chn reduce false alarms with a boost in sensitivity compare to the 2-chn models. But to our surprise, SeizNet-2-chn model despite using much less number of channels **outperforms** BPsvm-18-chn model at all performance metrics measured. It is also observed that for subject 2 and subject 23, BPsvm-2chn could identify all the seizures while not triggering more false alarm than SeizNet-2chn which could not find all the seizures for these subjects.

Model	BPsvm		SeizNet	
Channel used	2-chn	18-chn	2-chn	18-chn
Seizure detected	104/120	108/120	112/120	115/120
Sensitivity (%)	86.6%	90%	93.3%	95.8%
False alarms	33	14	10	3
FAR^* (fp/h)	1.91	0.81	0.58	0.17
Mean Latency(sec)	4.42	3.75	3.26	3.80

*FAR–false alarm rate

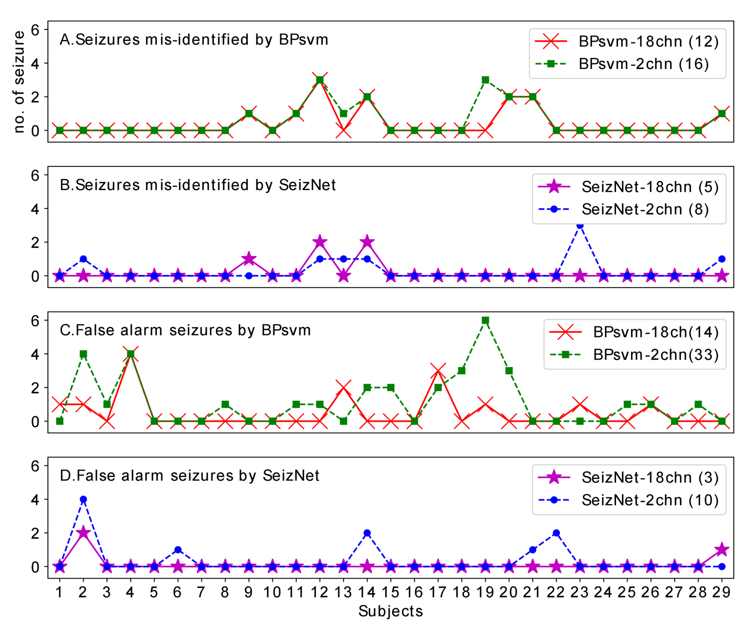

Figure 2: Comparison of SeizNet & Baseline Method

Decoding Convolutional Filters

To understand what representation features are learned in SeizNet, we use Activation Maximization (AM) method. In this work, AM is implemented with keras-vis library [6].

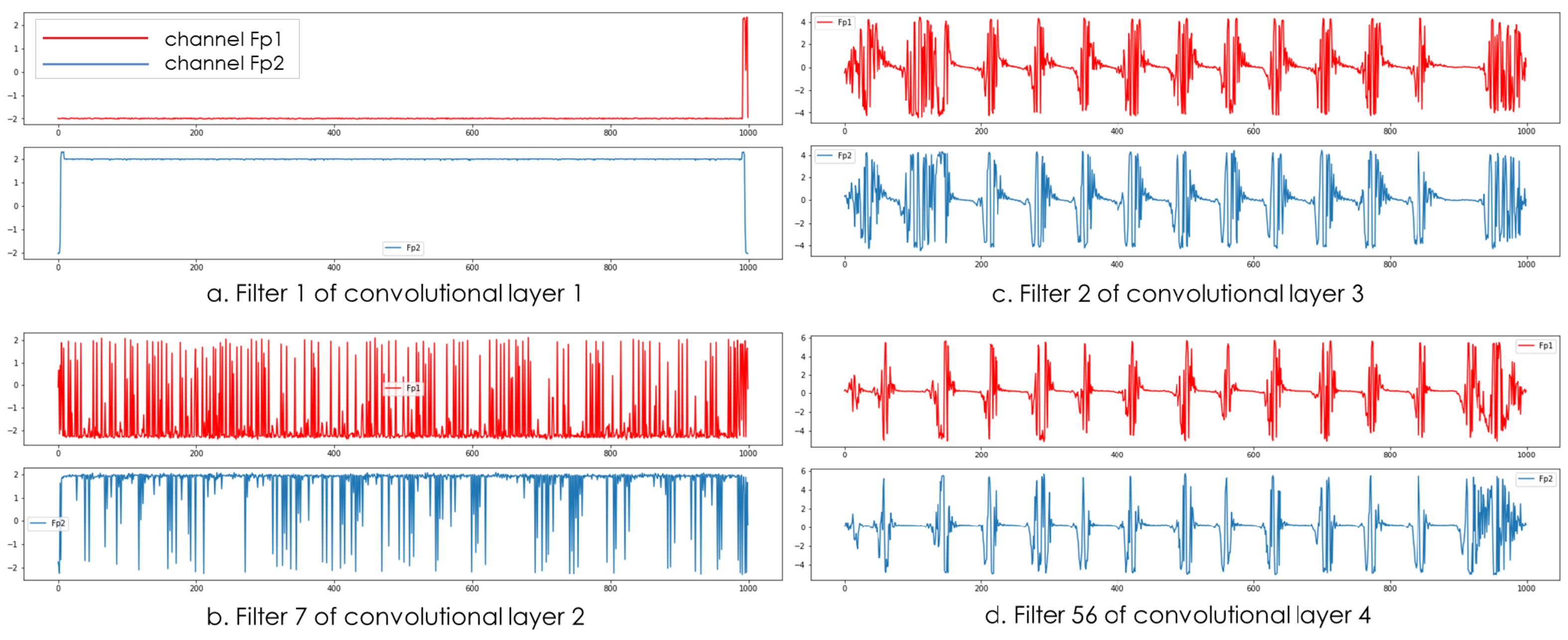

Figure 3: Filters from different convolutional layers

In SeizNet, the first layer filters are very basic shapes as depicted in Fig 3. While interpreted as color encoding from the perspective of image analysis, for SeizNet the filters can be thought to **encode EEG channel information**, since there are filters that have high and constant value for channel 1 and low and constant value for channel 2, and vice versa. Another possible interpretation could come from EEG montage perspective where **bi-polar signal represents the difference of two electrodes**, since the filters indeed subtract the channels one another.

In the second convolutional layer, nothing meaningful to us has been observed. However, from the third convolution layer onwards we observe substantial characteristics of seizures, therefore our hypothesis for the second layer is that it serves as the **middle man** bringing basic information in the lower layers into complex like-seizure signals in the higher layers.

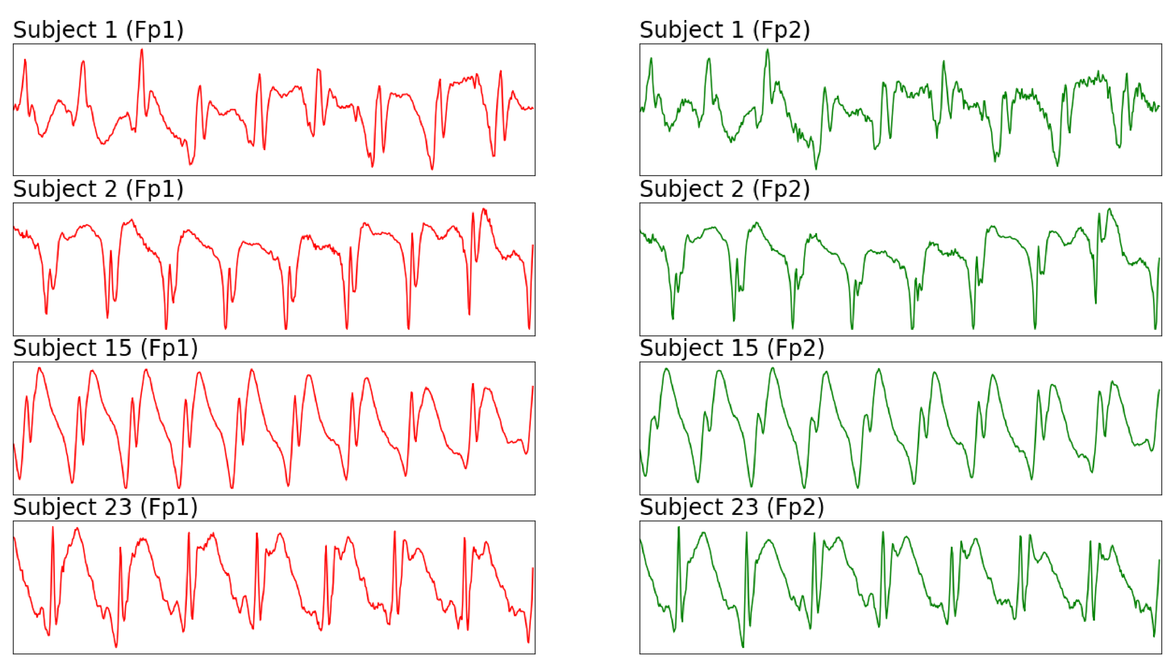

Figure 4: Examples of Seizure Waveform(3 secs)

Characteristics of the seizures are observed at the third convolution layer and become clearer at the last convolution layer. It can be inferred that SeizNet has learned absence seizures create **periodic and 3 Hz signals**. Nonetheless, clearly SeizNet focuses on spike-and-wave happening three times in one second and try to capture it rather than capturing a whole shape of a seizure. One possible reason behind is that seizure patterns often vary from subject to subject as can be seen from the Fig 4, therefore it is reasonable for filters of a generalized model to learn the **common and salient** characteristics of seizures.

Conclusions

- CNN architecture, SeizNet, is more suitable for a generalized solution unlike the SVM which indeed has been often implemented in subject-specific models.
- Interestingly, SeizNet trained by only 2 channels is able to outperform traditional approach trained with full scalp EEG data.
- Nevertheless, as observed in Fig 2, frequency domain features can be more discriminative than the features extracted from time-domain for some subjects. This is also consistent with the fact that even EEG experts are to check the spectrogram in some cases in order to finalize their decision.

References

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Acknowledgements

*Corresponding author. #The work was carried out under SIPGA scholarship from Agency for Science, Technology and Research (A*STAR), Singapore.