Deep Learning-based Detection and Analysis of interictal epileptic activity in stereotactic EEG

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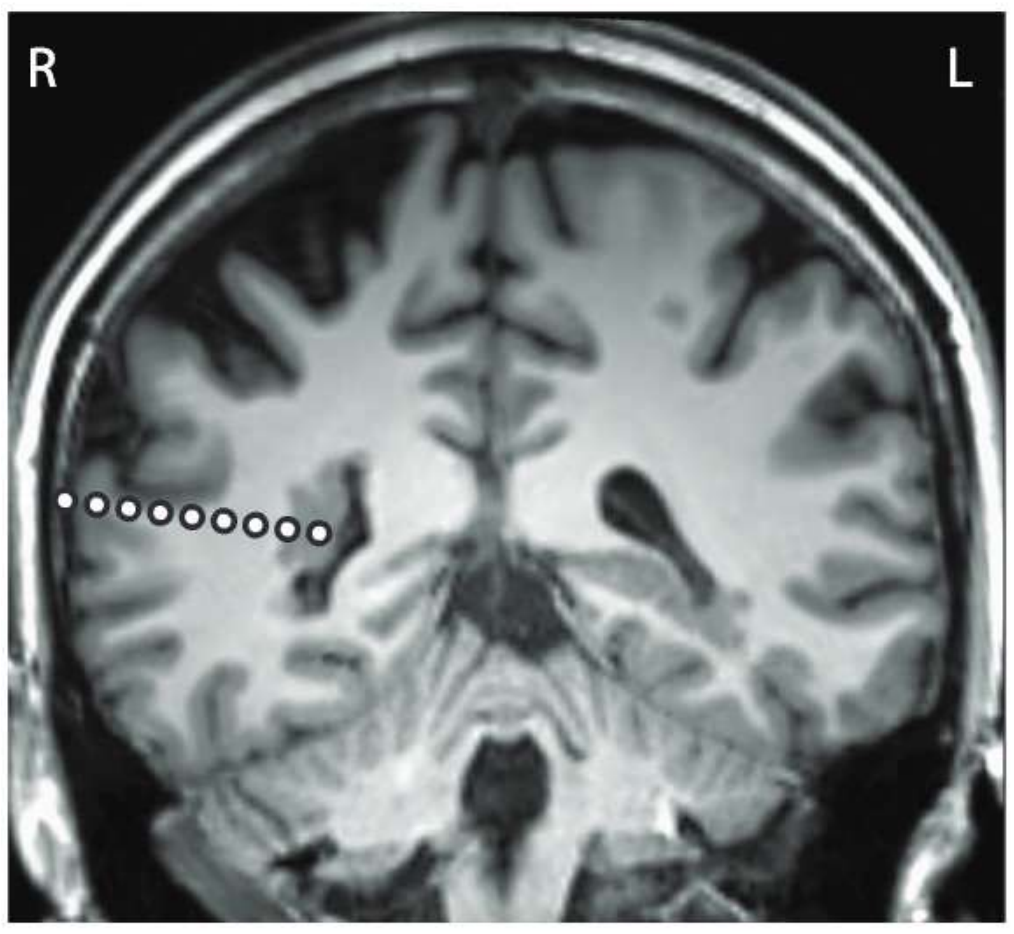
Motivation

1 out of 3 patients with epilepsy do not respond to medication. Those with focal epilepsies might benefit from surgical removal of epileptic brain tissue. Stereotactic electroencephalogram (sEEG), in which electrodes are implanted in suspect regions, might then be necessary to precisely locate the source of ictal (seizures) and interictal (non-seizure) activity. This diiP project targets to **design** effective deployment schemes of modern **deep learning techniques on interictal pattern detection in sEEG electrodes**, with a focus on real-world applications for neurology and clinical neuroscience [1].

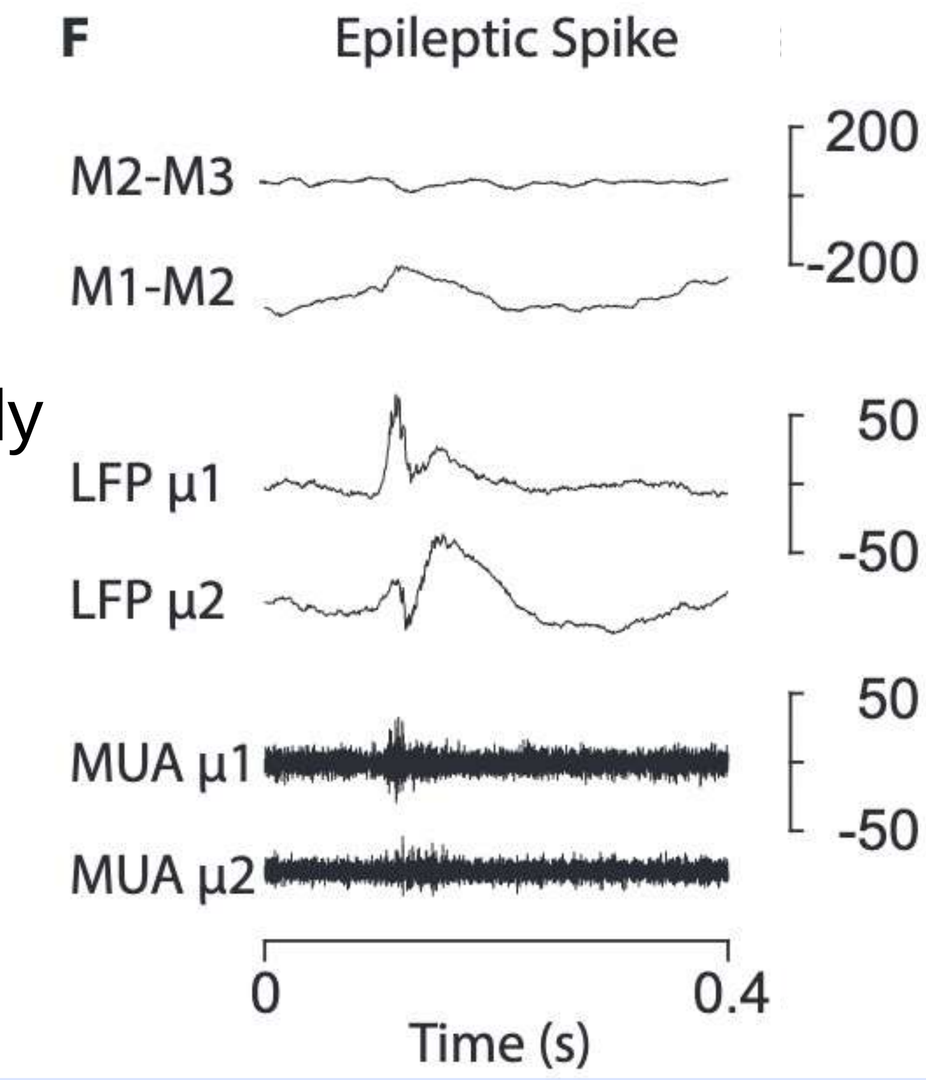


Dataset Description

8 datasets were retrieved from an existing clinical database (Hôpital de la Pitié Salpêtrière). Data consists of multichannel sEEG recordings (4KHz), recorded continuously for up to 2 weeks, as part of standard surgical evaluation. Interictal epileptic activities of each patient were manually annotated during 24 hours.

continuously

recording



Problem Statement

Automatically and accurately **identify interictal epileptic activity in continuous sEEG recordings**.

Challenges

-- **Extremely imbalanced dataset:** Only a few interictal patterns vs. a majority of normal behaviors. This commonly triggers a high false alarm rate and damages the reliability of the predictions.

-- **Morphology differences across patients:** the shapes and amplitudes of epileptic patterns from different patients are heterogeneous.

-- **Interpretability of the model:** need to identify the ranges, or channels, where the most discriminative information for the classification was extracted from.

Proposed Solution

++ **Model design**

Based on variants of Deep Convolutional Neural Network (CNN), with a special focus of capturing frequency-domain information by the architecture [2]

++ **Extremely imbalanced dataset**

Employ surrogate loss functions of a training subset for the whole labeled dataset

Corresponding sampling methods will be designed to provide a representative training subset.

++ **Morphology differences across patients**

Adopt active learning for minimizing the extra human intervention when data from new patients arrive.

++ **Interpretability of the model**

Tailor the Class Activation Maps (CAM) techniques for our specific architecture designs.

sEEG Epilepsy Detection

CNN Imbalanced Training

CAM Active Learning

References

[1]. Valerio Frazzini, Stephen Whitmarsh, et al: In vivo Interictal Neuronal Signatures of Human Periventricular Nodular Heterotopia. bioRxiv (2020): 816173.

[2]. Jingyuan Wang, Ze Wang, et al: Multilevel Wavelet Decomposition Network for Interpretable Time Series Analysis. KDD 2018: 2437-2446

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