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FAST AND EFFICIENT REJECTION OF BACKGROUND WAVEFORMS IN INTERICTAL EEG

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1. INTRODUCTION

Epilepsy is often associated with the presence of epileptiform transients (ET) in the EEG. Traditionally, experts detect the ETs from EEG recordings by visual inspection, which is very time consuming, and there is substantial disagreement between experts. Since Interictal EEG data contains mostly background waveforms, we first try to eliminate most of them using simple, fast classifiers. We develop a cascade of simple classifiers to eliminate most of the background waveforms in the EEGs. Each stage makes use of one specific quick-to-compute EEG feature.

2. METHODS

Interictal scalp EEG data:

- 30min EEG of 100 patients with epilepsy
- 19,255 ETs, CAR montage
- Cross-annotated by 2 neurologists

Fig. 1: Schematic of background rejection method.

Features:

- Morphological features
- Nonlinear energy operator
- Continuous and discrete wavelet coefficients
- All features in 5 main EEG frequency bands

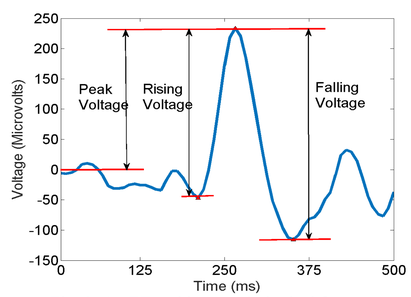

Fig. 2: An ET and its morphological features.

Designing the cascade:

- 0.5s windows of ETs and randomly sampled background waveforms
- Find the CDF, and select the thresholds such that 99% of the ETs are preserved
- Select the feature with the highest background rejection rate
- Same procedure for the following stages, on the remaining data
- Evaluate the performance of the cascade by applying the thresholds determined in the training stage on the entire dataset

3. RESULTS

Feature	Processing time on test data (min)
DWT	3.64
CWT	4.85
NLEO	3.7
Voltage & Slope values	6.62
Line Length	3.23
10-step Cascade	9.87

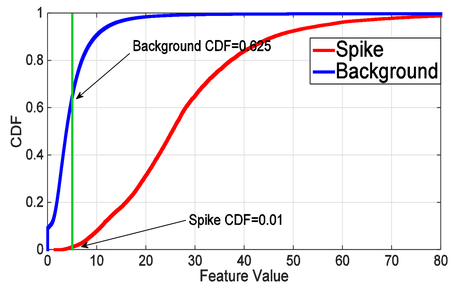

Fig. 3: Empirical CDF plot for the most discriminative feature (applied in the first step of the cascade), and the corresponding threshold.

Sensitivity: Number of ETs preserved after rejecting backgrounds, divided by total number of ETs fed to the algorithm

Specificity: Number of background waveforms correctly rejected, divided by total number of background waveforms fed to the algorithm

Step	Feature	Rejection (%) (Training)	Rejection (%) (Testing)
1	CWT (s=4, 4–12Hz)	62.48	64.47
2	Peak Voltage (4–12Hz)	77.15	78.88
3	DWT (D1, 4–12Hz)	81.97	85.84
4	NLEO (k=1, <4 Hz)	84.67	89.23
5	Rising Voltage (8–12Hz)	88.26	94.53
6	CWT (s=7, 0.1-64Hz)	90.15	97.48
7	NLEO (k=8, 0.1–64Hz)	91.13	97.9
8	DWT (A1, 0.1–64Hz)	91.69	98.2
9	CWT (s=12, 8–12Hz)	92.66	98.45
10	Rising Slope (4–8Hz)	93.26	98.65

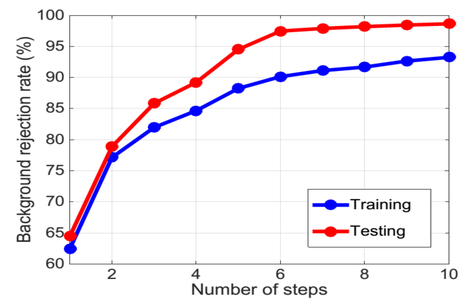

Fig. 4: The overall background rejection rate versus the number of steps taken. 90.6% of the ETs are preserved after 10 steps of the cascade.

<u>After 5 stages:</u>
Sensitivity=96.1
Specificity=94.53

<u>After 10 stages:</u>
Sensitivity=91.3
Specificity=98.65

4. CONCLUSIONS

We proposed a method to perform fast multi-step background rejection on (interictal) EEG of epilepsy patients, using a sufficiently large dataset consisting of 100 subjects.

In future work, we will expand the feature space for example by using different types of mother wavelets. We will increase the threshold as well, such that fewer ETs would be lost in each stage.

To develop an efficient ET detection algorithm, we plan to process the remaining waveforms by more sophisticated machine learning algorithms.

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