CLEMSON UNIVERSITY

Automatic detection of epileptiform events in EEG

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Introduction

An electroencephalogram (EEG) is the most important tool in the diagnosis of seizure disorders. Between seizures, epileptiform neural activities in EEG recordings occur in the forms of spikes or spike-and-slow-wave complexes with durations ranging from 110-900 ms. Although distinct from background signals, epileptiform events are often confused with artifacts that originate from a variety of sources such as eyes movement, the heart and muscles (Fig.1).

Seeking for an automated EEG interpretation algorithm well-accepted by clinicians has been a research goal stretched for decades. Recently, in a joint effort to develop a standardized EEG dataset and visualize attempted algorithms' performances, an online platform, eegNet, has been under development by the Medical University of South Carolina (MUSC) and Clemson University School of Computing. As an integral part of this project, we continue to look for optimal algorithms that detect epileptiform activities in EEG recordings and attempt to automatically highlight the findings with "yellow boxes" on the eegNet interface (Fig. 2).

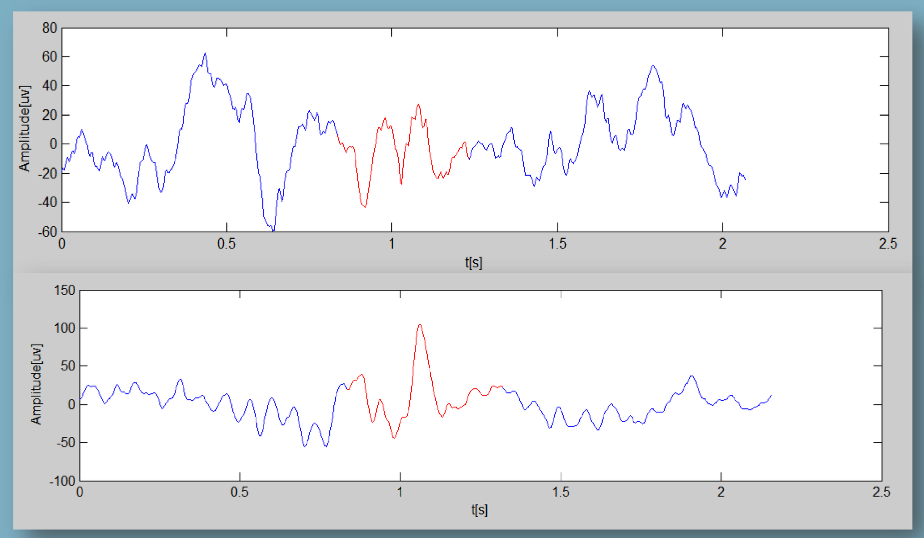

Fig. 1 Epileptiform spike-slow-wave complex (Above) and spike (Below) marked in red on one channel of EEG recordings

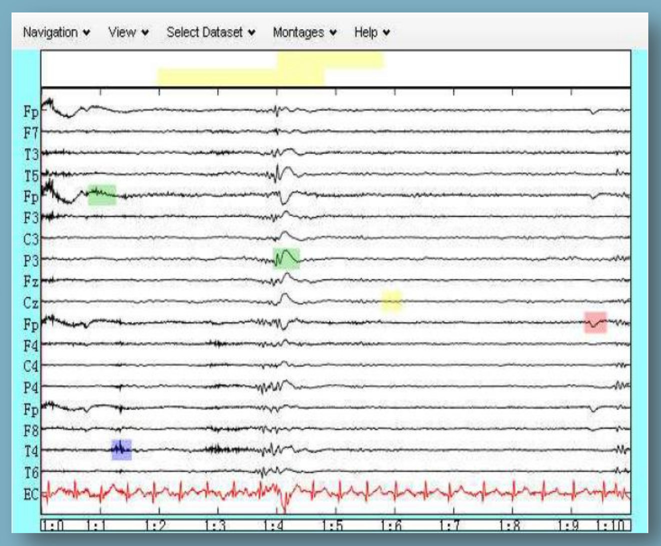

Fig. 2 eegNet interface, url: http://eegnet.clemson.edu. Paroxysmal activity findings are marked by EEG specialists.

Methods

EEG specialists have used indefinite criteria in determining occurrence of an epileptiform pattern while visually inspecting EEG signals. An EEG pattern is often suspected when it contains a prominent increase in amplitude and a slow-wave accompaniment would reinforce diagnostic confidence. Taking into account the morphological variability of epileptiform patterns, a multi-resolution approach, which integrates information embedded in both space and frequency domains of EEG signals will be required.

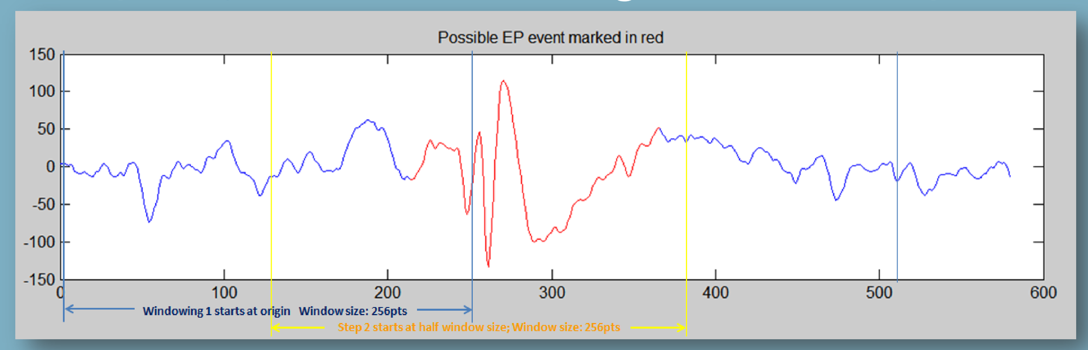

Fig.3 To eliminate inconsistency in results due to truncation of signal at window edges, a two-step sliding strategy is applied such that target patterns cut off by a window edge will be reconsidered.

Process flow

Data Acquisition

- 5 sets of 17-channel data from 100 epileptic patients with 256 Hz sampling frequency
- 60 sample epileptiform events scored by 11 EEG specialists
- All 17 channels of data were trained and tested with cross-validation in the machine learning stage

Feature extraction

In our research, features are extracted at each one-second time epoch from a sliding rectangular window (Fig. 3) with Wavelet Transform, which has proved to lend itself to representing EEG signal in previous studies (Fig.4 a-c).

Three different classification strategies, namely (1) Linear Regression, with a linear combination of features, (2) K-nearest Neighbor, (3) Support Vector Machine, are evaluated and compared in terms of their performances in categorizing EEG patterns into normal activities and epileptiform activities.

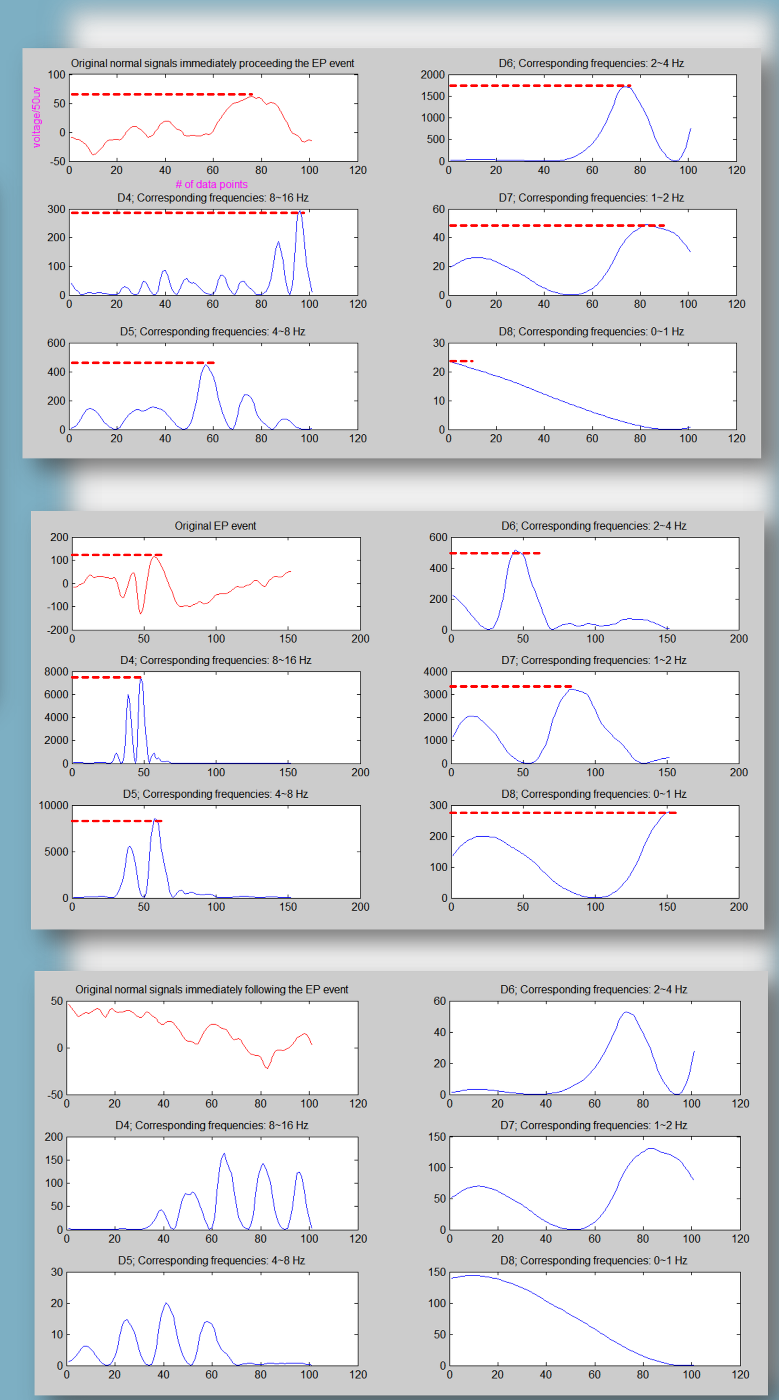

Fig. 4 Using the Wavelet Transform, signals are decomposed at decomposition levels of 4,5,6,7,8 respectively and reconstructed, generating five detail components. We square the components and use the maximum of the squares as a distinct feature for the signals at each level. This strategy results in a 5 dimensional feature set. The decomposition levels are chosen such that those parts of the signal that correlate well with the frequencies required for classification are retained in the reconstructed signal. Mother wavelet: Daubechies 4.

Classification

Depending on clinical needs, further analysis that precisely localizes the epileptiform events may be desired. We have proposed a "percentile filter" approach (Fig. 5) which is sensitive to local amplitude change . However, this approach is still in testing phase and requires to be complemented by other types of morphological analysis.

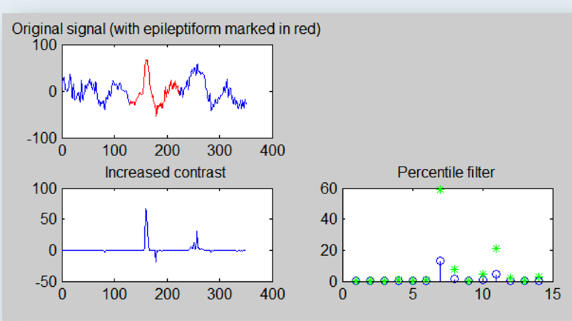

Fig.5 Typical epileptiform events contribute higher percentages to the sum of amplitudes within a signal window. Precisde detection is made when percentage exceeds the 15-percent threshold learnt from linear regression.

Post - classification

Results

Classifier	LR	SVM	KNN
Average number of detections made in every 10 min	53.4	84.9	164
Average elapsed time before a new detection is made (s)	11.2	7.1	3.7
Sensitivity (%)	53.3	66.7	75
Specificity (%)	91.2	86	73.8
Positive predictive Value (%)	2	1.6	0.96
Percent of detections that are generic paroxysmal events (%)	9.6	15.5	26.5

Fig. 6

As viewed in Fig. 6, attempted classifiers have a blend of merits and demerits. Most importantly, a single classification approach usually has its sensitivity compromised by elevated false-positive rates (as inferred by Positive Predictive Value), which are caused mainly by the influence of artifacts. This result may suggest better system performance with adoption of a hybrid classifier.

According to our collaborator from MUSC, high false-positive rate is generally not a big disadvantage in practice, although low false-positive rate is always ideal. In fact, because precise characterization of paroxysmal events similar to epileptiform patterns would aid recognition and eventual elimination of artifacts and leads to a clearer insight into neurological diseases such as epilepsy, highlighting all possible paroxysmal activities on the eegNet interface is a separate primary goal to be achieved.

Fig. 6 Classifier performance comparison chart. A larger size of the circle generally indicates better performance in corresponding category.

Fig. 7 A sample of 15-s single-channel EEG recording marked as having epileptiform events in window #387 and #395 after performing classification with SVM. Letter E indicates a window is determined as having an Epileptiform event while N represents "Normal."

datasetId	chanNum			
9	9			
Win#	Original class	Class assigned by SVM	Class assigned by LR	Class assigned by KNN
...	...	...	...	...
382	N	E	N	E
383	N	N	N	N
384	N	E	E	E
385	N	N	E	N
386	N	N	N	E
387	N	E	E	E
388	N	N	N	N
389	N	N	N	E
390	N	N	N	N
391	N	N	N	N
392	N	N	N	N
393	N	N	N	N
394	E	N	E	N
395	E	E	E	E
...	...	...	...	...

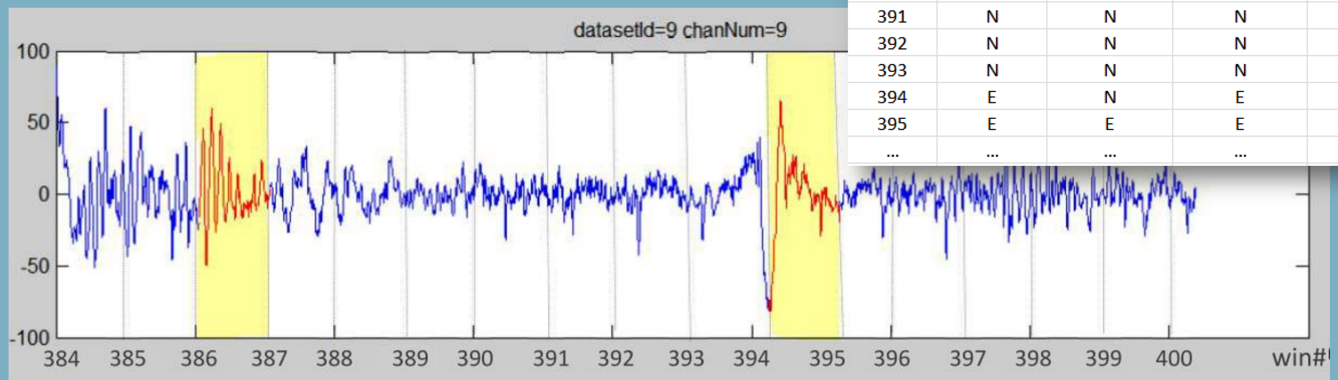

Fig. 7

Summary

We attempted feature sets with reduced dimensionality and algorithms with feasible execution time to deal with the variability of epileptiform and non-epileptiform EEG patterns. Possible feature sets and classifiers were tested on reliable sample data using a two-step sliding window approach that treats the problem of signal truncation. Preliminary results suggest competency of the selected wavelet feature set, which may desire modifications depending on types of paroxysmal events of interest in future work. Meanwhile, development of hybrid classification system and an integrated post-classification solution remain to be open projects.