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# Automatic Detection of Epileptiform EEG Discharges based on the Semi-Classical Signal Analysis (SCSA) method

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*Abstract*— **In this paper we utilize a signal processing tool, which can help physicians and clinical researchers to automate the process of EEG epileptiform spike detection. The semi-classical signal analysis method (SCSA) is a data-driven signal decomposition method developed for pulse-shaped signal characterization. We present an algorithm framework to process and extract features from the patient's EEG recording by deriving the mathematical motivation behind SCSA and quantifying existing spike diagnosis criterion with it. The proposed method can help reduce the amount of data to manually analyse. We have tested our proposed algorithm framework with real data, which guarantees the method's statistical reliability and robustness.**

*Clinical relevance*— **The effectiveness of our detection model implementation is achieved by presenting a low false detection rate (FDR) , which can help physicians to save their time in visually checking epileptic spikes and also save their device's storage space by eliminating the need to store long EEG recordings.**

## I. INTRODUCTION

Epilepsy is a prevalent neurological disorder in humans, by which approximately 1% of the world's population suffers[1]. It is characterized by unforced, repeated, and often draining seizures, which can range from loss of consciousness, jerking movements of arms and legs or brief lapse of concentration to prolonged and severe convulsions. They may also have uncontrollable jerking movements of the legs or the arms. Moreover, epileptic patients may also have symptoms of staring blankly for a few seconds during seizure. What's worse, epileptic activities can cause several damages , and without rapid treatment, the heart and brain can become overburdened and permanently damaged, resulting in death in the worst case. Therefore, timely and comprehensive diagnosis of seizures are important.

Accurate classification and diagnosis of seizures often require visual identification and detailed examination of inter-ictal epileptiform discharges (IED) from experienced physicians and clinical experts. Several types of signals such as Electroencephalography (EEG) and magnetoencephalography (MEG) can be used to diagnose IED. Both EEG and MEG are non-invasive testing methods which contains a wealth of information about the state of a patient's health, as well as the different physiological states of the brain. In this paper, we will use EEG signal as a source of diagnose IED for several reasons. From hardware and clinical environment perspectives, the EEG hardware cost significant lower than other technics (fMRI, MEG..) and EEG only requires a quiet room and briefcase-size equipment while MEG recording requires magnetically shielded room. Due to these factors, it can be recorded over a long period of time which is useful for monitoring incidental disorders like epileptic seizures or discharges which are not permanently present in the recordings. These EEG recordings are visually inspected for detecting epileptic spikes and seizures. which are then used for clinical diagnosis and possible treatment plans.

A major drawback however, is that reviewing them is time-consuming[2] and therefore the amount of data needed to be stored is large. Furthermore, the diagnostic yield is relatively low, partially due to the relative short duration of each routine EEG recordings. Because of this, multiple routine recordings are typically required before signs of inter-ictal epileptiform activity are found[3]. Unfortunately, longer recordings also result in more time required for visual analysis for EEG reviewers, a burden that is best avoided. Another challenge is that, Given that clinical experts have different levels of training and experience, the need to improve the reliability by establishing a consensus guideline for EEG interpretation is also known to exist[4].

As a result, research effort has been devoted for developing automated spike detection techniques which might help not only to speed up this process but also reduce the amount of data to be stored. Also, computerized assistance with the detection of epilepsy activities can release the burden of physician diagnosis, and as an added benefit, ensure more consistency between reviews that will lower inter-rater variability[4][5]. Considering the existing spike detection algorithms, a major challenge is to minimize the number of false detections rate (FDR). If this number is too large, a reviewer will still be required to inspect most of the data and automated detection will be of no use. In summary, developing a practical and reliable system with high detection accuracy can also be of great interest as well.

We aim at quantifying existing spike detection criterions and automating epilepsy spike detection process by using semi-classical signal analysis (SCSA) method as a tool for feature extraction. Semi-classical signal analysis (SCSA) method has been introduced for pulse shaped signal analysis in [6] and has been successfully implemented in different applications such as blood pressure waveform [7], [10], [11], [12]. In this paper, we motivate to use SCSA to

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quantify existing epilepsy spike visual inspection criterion. By extracting features as the input for machine learning algorithms, we automate the process of spike diagnosis and save time and efforts for physicians and clinical experts.

## II. Methods

### A. Spike detection criterion

Mausby and Gloor proposed a set of spike detection criterions (visual) [13] [14] for recognizing spike waves:

1) Multiple phases of waves with sharp or spiky morphology (pointed peak with time duration of around 200 ms)
2) Different wave frequencies than the ongoing background activity
3) Asymmetry of the waveform: The rising phase and decaying phase have different time duration, with one significantly faster or slower than the other
4) The transient is followed by an associated after coming slow wave
5) The presence of the epileptiform discharges disrupts the background activity

Kural later recalled them[15] and assessed the accuracy of these IFCN criteria in a clinical validation study, using a robust gold standard, derived from video-EEG recording of the patients habitual clinical episode. They've found out criterion (1), (2) and (4) will yield acceptable accuracy. However, these criterions commonly adapted by clinicians and experienced experts, have not been quantified by existing research with automated algorithms. In the following sections, we will use SCSA as a signal decomposition tool and extract EEG features based on the existing criterion sets.

### B. Semi-Classical Signal Analysis method

In this subsection, we briefly introduce the SCSA method. A positive signal $y(t)$ is decomposed into a set of $L_2^2$-normalized squared eigenfunctions of the Schrödinger operator which correspond to the negative eigenvalues. The reconstructed signal $y_h(t)$ is given by the following formula (refer to [6])

$$y_h(t) = 4h \sum_{n=1}^{N_h} \kappa_{nh} \psi_{nh}^2(t), t \in \mathbb{R}, \tag{1}$$

where $\lambda = -\kappa_{nh}^2$, with $\kappa_{1h} > \kappa_{2h} > \cdots > \kappa_{nh}$ are the negative eigenvalues, and $\{\psi_{1h}, \psi_{2h}, \cdots, \psi_{nh}\}$ are the corresponding $L_2^2$-normalized eigenfunctions ($n = 1, 2, \cdots, N_h$) such that

$$-h^2 \frac{d^2\psi(t)}{dt^2} - y(t)\psi(t) = \lambda\psi(t). \tag{2}$$

$h$ is a positive parameter known as the semi-classical constant. $N_h$ is the number of negative eigenvalues. The reconstructed spectrum $y_h$ converges to the true spectrum $y$ when $h$ tends to zero. When $h$ increases then the number of negative eigenvalues increases, which allow to include more eigenfunctions in the signal representation. A useful property of the SCSA is that eigenfunctions associated to large eigenvalues (in absolute value) represent the profiles of the peaks, whereas the remaining functions provide the details of the signal and thus for the more oscillating ones, the noise.

### C. SCSA-based EEG feature extraction

In this section, we will analyze the reasoning behind choosing the SCSA parameters as standard features for the detection algorithm.

From eq. (2), as $h \to 0$, the eigenvalues assume the values of the signal $y(t)$. Numerically, the SCSA algorithm converges under a non-zero value of $h$, therefore we can write:

$$|y_{\max} - \kappa_{1h}^2| < \epsilon(h) \tag{3}$$

where $\epsilon(h) > 0$ is the resulting error of finite $h$ and $y_{\max}$ is the maximum value of the signal (in our case, the maximum of the EEG channel waveform in a specific frame). Since $\kappa_{1h}$ is made from an operator which contains morphological information of the input signal, such a feature will be significant for the classification, playing possibly the role of an enhanced criterion (1). Note that the actual feature is the $\kappa_{1h}^2$ since this the one that corresponds to the signal $y(t)$. To account for the wave duration feature in criterion (2), we use the arguments of the quasi-classical approximation, as referred in [16]. Specifically, the eigenfunctions follow a behavior of [16]:

$$\psi_{nh}(t) \sim e^{\frac{i}{h}\int \sqrt{y(t)-\kappa_{nh}^2}\, dt} \tag{4}$$

It becomes clear that near the region of the peak, the first eigenfunction has an oscillatory behavior which is captured by the ratio of the $\kappa_{1h}$ to the value of $h$. For the remaining signal characteristics (3)-(5), we use similar arguments to incorporate the median value of the $\kappa_{nh}$. Since there is no direct mapping to these elements, we finalize the feature vector by adding the value of convergence $h$ and the number of components $N_h$. The value of $N_h$ is highly important, as it additionally encodes the shape information of the input EEG signal. Mathematically, $N_h$ is approximated by [16]

$$h\, N_h \approx \frac{1}{\pi} \int \sqrt{y(t)} dt \tag{5}$$

Therefore, the integral of the square-root of the signal can capture the regions of interest in criterion (3)-(4). The median of the eigenvalues is mainly dedicated to criterion (5). In fig. 1, a random frame of EEG and its respective SCSA representation is depicted. Additionally, the first SCSA component (under proper scale) and the squared eigenvalues are present, to indicate the motivation behind choosing the SCSA parameters for the feature vector. The resulting feature vector becomes:

$$f = [h\ N_h\ \kappa_{1h}\ \kappa_{1h}^2\ \text{med}(\kappa_{1h})\ \text{med}(\kappa_{1h}^2)\ \frac{\kappa_{1h}}{h}\ \frac{\text{med}(\kappa_{nh})}{h}]^T \tag{6}$$

where $\text{med}(\kappa_{nh})$ is the median of the $\kappa_{nh}$. After applying process of reducing the number of features in $f$, we derive:

$$f_{\text{optimum}} = [h\ N_h\ \kappa_{1h}\ \text{med}(\kappa_{1h})\ ]^T \tag{7}$$

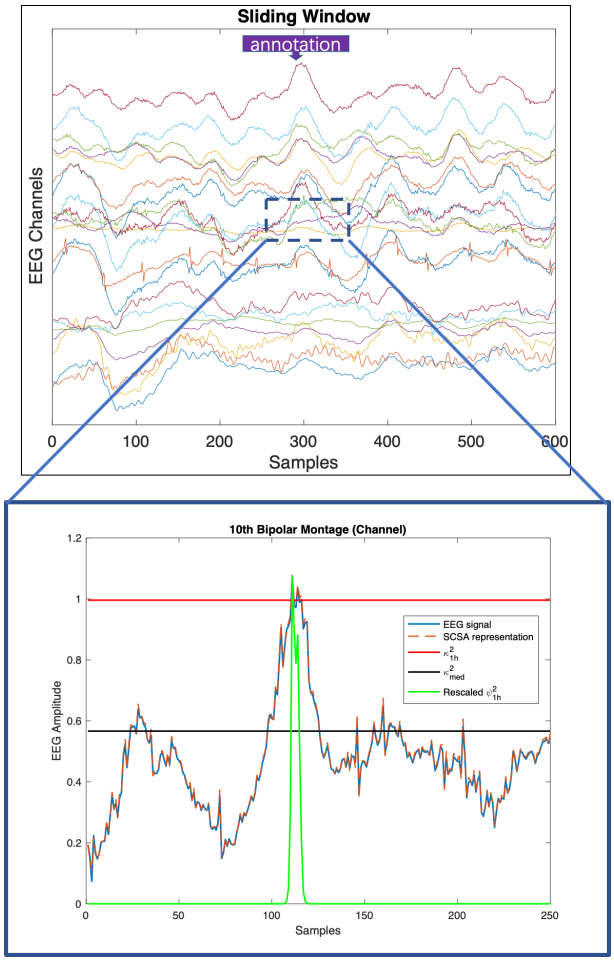


Fig. 1. **Examples of Interictal Epileptiform Discharges (IED) in patient ID EPI002 (segment1) Upper:** A sliding window containing an epileptic spike (positive frame). **Lower:** Zoomed-in example EEG channel and SCSA decomposition.

Regarding the value of $h$, the numerical implementation of SCSA will attempt to minimize the function

$$||y - y_h||_2^2 \tag{8}$$

As explained in [16], the convergence time of SCSA can be high and the value of $h_{\min}$ appeared to provide equally good results. For this exploration, we will use that specific value, which is:

$$h_{\min} = \frac{1}{\pi}\sqrt{y_{\max}} \tag{9}$$

### D. Algorithm frameworks

*1) EEG signal framing:* The multi-channel EEG signals are segmented into frames using sliding windows, where a sliding segment of size 250 sample points (0.5 seconds) with step = 10 samples as shown in fig. 1. The frames are classified into positive and negative as follows:

- **Positive frame**: A positive frame includes one or more epileptic spikes in a single frame of 21 channels of the 4 epileptic patients.
- **Negative frame**: A negative frame includes no epileptic spikes in a single frame of 21 channels of the 4 epileptic patients.

*2) Feature extraction:* In each sliding window (frame), there is a two-stage process of extracting features. In the first step, suppose there are $m_i$ number of peak events related to the $i$th channel. In the $i$th channel, noting the prominence[1] of the $k$th peak activity as $P_k$ and the maximum of prominence as $\max(P_k)$ with index $p_{\max-i}$, we select a channel according to the following: (in the average$(P_k)$ term, $k \neq p_{\max-i}$)

$$\text{Channel-Index} = \underset{i}{\operatorname{argmax}} \frac{\max(P_k)}{\text{average}(P_k)} \tag{10}$$

In the second step, we use Channel-Index to extract the corresponding EEG segment where SCSA is applied to extract features $f_{\text{optimum}}$ according to eq. 7.

*3) Classification models:* As adapted by most studies regarding this topic, supervised machine learning is introduced. We adapt linear support vector machine (SVM) as the learning model. Features are extracted using semi-classical signal analysis (SCSA) tools. We will test our algorithms against real database to guarantee statistical reliability.

*4) Evaluation:* The 5-fold performance of the classification model has been measured using the average of accuracy defined as follows:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{11}$$

where true positive (TP) is the number of positive frames determined by both the model and experienced clinical experts, false negative (FN) is the number of positive frames missed by the model but determined by experienced clinical experts, true negative (TN) is the number of negative frames recognized by both the model and experienced clinical experts, and false positive (FP) is the number of negative frames recognized as spikes by the model but not by experienced clinical experts.

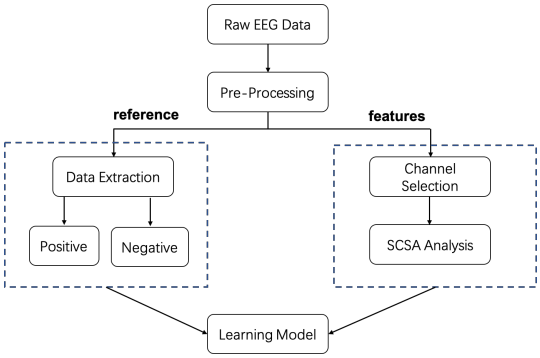


Fig. 2. **Classification algorithm framework:** EEG records pre-processing, feature generation (containing channel selection and SCSA analysis), reference extraction (extract positive and negative frames for the whole EEG recording, given specific frame size and step size) and classification models

## III. Experiments

### A. EEG data acquisition and pre-processing

EEG data recorded from patients with epilepsy in KFMC MEG Unit were used. All patients were diagnosed and

[1]For more information of the measurement of peak prominence: `https://www.mathworks.com/help/signal/ug/prominence.html`

managed according to the established standards of care. They were admitted to KFMC's epilepsy monitoring unit and underwent comprehensive clinical and neurological evaluation, long-term video-electroencephalography (EEG) monitoring. EEG signals were visually inspected to identify and remove noisy channels and time periods. EEG signals were further digitally band-pass filtered between 0.3 Hz and 70 Hz, with a notch filter at 60 Hz to remove the power-line noise. The resultant, cleaned data were visually inspected in 10-second windows to identify and manually mark the interictal epileptiform discharges (IEDs) spikes and sharp waves.

### *B. Results and discussion*

We tested our model (shown in fig.2) on 4 different patients' EEG recordings with 15-30 minutes duration. The obtained accuracy is higher than previous SCSA's application on MEG data analysis[17]. Considering the computational complexity aspect, the algorithm is of orders faster than [17]. This can be explained as the number of samples $n$ increases, $H$'s size in the Schrödinger equation (with size $n \times n$) also increases, which is the main factor that causes the slowdown of the analyse process. In [17], the channel segments are simply concatenated together resulting in bigger $n$ value for processing while in our case we only use the selected channel to analyse. Moreover, it has more clinical knowledge and expertise incorporated in this framework than the previous version. To the best of our knowledge, we proposed the first algorithm framework to incorporate clinical criterion in [13][14]. Also, the achieved accuracy is comparable with most studies in [18]. However due to a lack of a common dataset, comparisons between methods are still hard to make.

TABLE I

5-FOLD PERFORMANCE IN DIFFERENT PATIENT'S EEG RECORDING (PATIENT EPI002 HAS THREE DIFFERENT SEGMENTS)

| Patient ID | Accuracy | False Detection Rate (FDR) |
|---|---|---|
| EPI001 | 96.7% | 3.3% |
| EPI002(1) | 93.6% | 6.4% |
| EPI002(2) | 97.2% | 2.8% |
| EPI002(3) | 98.8% | 1.2% |
| EPI003 | 94.3% | 5.7% |
| EPI004 | 98.3% | 1.7% |

## IV. CONCLUSIONS

This paper presents a framework for reducing the amount of data needing to be manually analysed by physicians to identify IED within an epileptic patient's brain. With a simple learning model, it achieved a low FDR of 1.2%-6.4% for a clinical dataset with real patients' EEG recordings. This framework can potentially reduce burden of physicians to analyse huge amounts of data. As future work, we aim at solving the over-fitting problem due to imbalanced dataset (with few data being the positive classification value). In particular, we think of using a Generative Adversarial Network (GAN) to obtain more training data which can help alleviate this problem. In addition, we plan to standardize our dataset by implementing and comparing different algorithms in the same dataset.

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