Epileptic Seizure Detection using Bipolar Singular Value Decomposition

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Keywords: Epilepsy, Seizure Detection, Singular Value Decomposition, Coherency, Synchronization, Bipolar Electroencephalogram.

Abstract: We propose a robust method for automated detection of epileptic seizures using intracranial electroencephalogram (iEEG) recordings with two electrodes. The state-of-the-art seizure detection methods suffer from high number of false detections, even when designed to be patient-specific. The solution reported here aims to achieve very low false detection rate, while providing a high sensitivity. Two adjacent iEEG recordings are subtracted from each other to make the bipolar iEEG signal. The values achieved from singular value decomposition (SVD) of the bipolar iEEG signal are used as measure. A threshold is subsequently applied on the measure. Results indicate robustness of the proposed measure for seizure detection. The method is applied on 5 invasive recordings containing 54 seizures in 780 hours of multichannel iEEG recordings. On average, the results revealed 85.2% sensitivity and a very low false detection rate of 0.02 per hour in long-term continuous iEEG recordings.

1 INTRODUCTION

Epilepsy, the second common brain disorder is mainly characterized by recurrent and abrupt seizures. The highly coherent neural activities play the central role in the development of epileptic seizures, which usually last from seconds to minutes. Electroencephalogram (EEG) recordings are commonly used in the study of brain, its functions and related disease (Rho et al., 2010). Long-term continuous multichannel recordings produce huge amounts of data, sometimes up to several hundred megabytes for a single recording channel. Real-time monitoring of the long-term continuous EEG recordings by EEG experts (visual inspection) can be impossible, whereas offline analysis can also be very costly, tedious and tiresome. By automatically labeling the seizure onsets, long term monitoring, diagnosis and treatment can be highly facilitated. Researchers and neurologists will just be required to refer to the labeled EEG recordings. On the other hand early seizure detection could improve the living conditions of epileptic patients. Automatic drug injection or brain stimulation method can be triggered by adequately fast onset detection algorithm to suppress oncoming seizure (Bandarabadi et al., 2014c).

There are many existing seizure detection algorithms. They usually seek to optimize one of two competing goals; (1) fast seizure onset detection; the real-time detection of epileptic seizures without or with a negligible delay from onset initiation (Shoeb et al., 2004; Meier et al., 2008; Kharbouch et al., 2011; Bandarabadi et al., 2014b), and (2) accurate seizure event detection: the accurate labeling of the occurrence of seizures with high sensitivity and specificity (Varghese et al., 2009; Sharma et al., 2014; Adeli et al., 2007; Acharya et al., 2011; Hassanpour et al., 2004). The first approach is best suitable for closed-loop therapeutic as well as for patient care systems, where only onset detection delay times of few seconds can be tolerated. The second approach is much appropriate for offline labeling of recorded EEGs for future studies, and can tolerate longer detection lags. High number of false detections is the main drawback of most current approaches, which makes them unacceptable for clinical applications. Furthermore they have been applied mainly on short recordings, and have not been validated satisfactorily for long-term continuous recordings with several weeks length, including extensive interictal periods.

In the framework of the EPILEPSIAE project

Bandarabadi M., Rasekhi J., A. Teixeira C. and Dourado A..
Epileptic Seizure Detection using Bipolar Singular Value Decomposition.
DOI: 10.5220/0005193401780183
In *Proceedings of the International Conference on Bio-inspired Systems and Signal Processing* (BIOSIGNALS-2015), pages 178-183
ISBN: 978-989-758-069-7

(Klatt et al., 2012), the consortium has collected long-term continuous intracranial/scalp EEG (iEEG/sEEG) recordings of more than 275 patients. The current database includes detailed information about the epileptic seizures of all patients, such as type, onset/offset time, propagation, and seizure onset age. The recorded data of the patients was visually inspected by epileptologist experts, a both tedious and faulty process, requiring double checks. Such a demand for robust automated method with high sensitivity and very low false detection rate, which would require the neurologist just to refer to the detected epileptic seizures to extract extra information, motivated our team to study and develop new detection algorithms. We have recently developed a new seizure detection method using sub-band mean phase coherence (sub-band MPC) (Bandarabadi et al., 2014a). The raw iEEG data of two adjacent electrodes was first band-pass filtered using forward-backward method to obtain desired frequency bands. Subsequently, the mean phase coherence (MPC) measure of each sub-band was calculated. The proposed method could provide a sensitivity of 79% with a low false detection rate of 0.05 h^{-1}.

This paper makes two contributions. First, it proposes a robust seizure detection method using singular values extracted from space-differential (bipolar) recordings to improve the parameters of sensitivity and specificity. Second, it evaluates the efficiency of proposed measure on long-term continuous iEEG recordings that are longer than one month.

2 METHODOLOGY

The methodology is based on singular values (SVs) extracted from windowed bipolar iEEG signal, and the phenomena of unique bipolar signal manifestations during a seizure event. Figure 1 presents the block diagram of the proposed method for automated seizure detection, including a manual channel selection, a segmentation stage, building bipolar iEEG, a singular value decomposition (SVD), and a threshold box for decision-making.

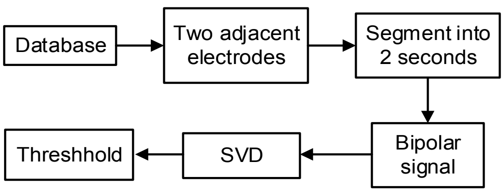

Figure 1: The block diagram of the detection algorithm.

2.1 Dataset Description

In order to evaluate the proposed method, we use real iEEG data recorded using two adjacent electrodes placed over the focal area, from European database on epilepsy (Klatt et al., 2012). The five candidate patients with refractory focal epilepsy were monitored continuously for several days, during their pre-surgical studies. Focal seizures are localized to specific brain regions, while generalized epileptic events may initiate and spread across the whole brain tissue. The two electrodes are nearly satisfactory when working with partial seizures, however more electrodes should be considered for the study of other seizure types.

Recordings were obtained with sampling rate of 1024 Hz at the epilepsy unit of the University Hospital of Freiburg, Germany. Onset times, and their initialization and spatial propagation on the electrodes were marked by epileptologists by visual inspection of iEEG recordings and using video recordings of patients during their stay in hospital. Information of both electrographic and clinical onset/offset times is available in the database, and electrographic onsets were considered here. Patient characteristics are summarized in Table 1.

Table 1: Information for the 5 studied patients.

Patient ID	Gender	Patient age (y)	Onset age (y)	Localization of seizures [a]	Recording time (h)	No. of seizures	Mean seizure duration (s)
A	F	29	10	RMT,RLT	183	9	82.3
B	F	32	1	LMT	162.6	9	121.9
C	F	11	3	RMT	155	14	122.7
D	F	32	8	RBF,LMT,RMT	151.6	9	122.5
E	F	18	6	L-T,L-F	127.8	13	86.5
Mean		24.4	5.6		780	54	107.1

[a] RMT/LMT (right/left mesial temporal lobe), RLT (right lateral temporal lobe), RBF (right basal frontal lobe), L-T (left temporal lobe), L-F (left frontal lobe).

2.1 Bipolar iEEG Signal

The iEEG recordings are technically bipolar by nature, since they are recorded with reference to a fixed electrode. Positioning of electrodes and reference channels can both affect the nature of the recorded signal (Nunez et al., 1997). By tradition however, these channels are called monopolar, and the difference of two monopolar channels, selected physically in close proximity (in the range of few millimeters), is known as bipolar. For sufficiently close-by configurations, the bipolar signal may be considered as an approximation of the tangential component of brain's electric field. In contrast to the monopolar EEG, the bipolar approach is less susceptible to artifacts (Aarabi et al., 2007). Bipolar processing can remove common mode interferences mounted evenly on two adjacent electrodes. These common mode interferences may include power line noise (50 or 60Hz and their harmonics) and movement artifacts (EMG). Furthermore it provides better spatial resolution in contrast to the monopolar iEEG recordings (Srinivasan et al., 1996; Nunez et al., 1997; Tang et al., 2007). Bipolar recordings better reduce the volume conduction effects compared to the monopolar recordings, by acting as a high-pass spatial filter (Nunez et al., 1997). Moreover, topographical variations invisible to monopolar recordings can be identified using bipolar schemes (Baranov-Krylov and Shuvaev, 2005). Bipolar channels were derived by differencing two immediately adjacent electrodes, selected from candidate probe array on focal area. Arrays can be in the form of grid, strip, or depth probes.

2.2 Singular Value Decomposition

SVD as a common computational tool employed in signal processing and pattern recognition, acts as a mathematical factorization of data matrices obtained from the patients, to highlight the dominant properties of their underlying patterns. The core idea of SVD is to take a collection of data, find the patterns having the highest correlation with that data, and then sort these patterns in a descending order based on their importance. In fact, SVD decomposes data to its correlated parts, with the larger singular values (SVs) corresponding to those parts with more energy (Bandarabadi et al., 2010). The process decomposes the original matrix *M* into the product of three sparse matrices (1),

$$M_{m.n} = U_{m.m}\Sigma_{m.n}V^{*}_{n.n} \tag{1}$$

where Σ is singular value matrix, *U* and *V* are left and right singular vector matrices respectively. *U* and *V* are orthogonal matrices, and Σ is a rectangular diagonal matrix with its nonnegative real elements sorted in a descending way (2).

$$\Sigma = \begin{pmatrix} \sigma_1 & & 0 \\ & \ddots & \\ 0 & & \sigma_m \end{pmatrix}, \quad \text{if} \quad m = n \tag{2}$$

$$\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_m \geq 0$$

The singular values (σ_i) indicate the significance of the corresponding left/right singular vectors. The pair of singular vectors related to the highest SV, contain more information about the dominant patterns than other singular vector pairs (Hassanpour et al., 2004). By highlighting the dominant epileptic activities within a bipolar iEEG data, SVD can be used as a tool for detecting epileptic events. In order to apply SVD, the raw EEG data should be first expressed in the form of a square matrix. Hankel operator is a square matrix with constant skew diagonals, and is employed here to build such a matrix. Suppose $X = [x_1, x_2, ..., x_n]$ as a segment of EEG signal, and *n* being a positive even integer. Then the Hankel matrix of X can be written as (3).

$$H_X = \begin{pmatrix} x_1 & x_2 & \dots & x_{n/2} \\ x_2 & x_3 & \dots & x_{n/2+1} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n/2} & x_{n/2+1} & \dots & x_{n-1} \end{pmatrix} \tag{3}$$

Since the computational cost of SVD is high, the iEEG signal is downsampled from 1024 to 512 Hz to boost the computation time. The iEEG signal is segmented into 2-sec windows with 50% overlap, to provide feature samples every second. The length of window is selected by a tradeoff between two extremes: it should be long enough to cover the trends related to brain's current state, and short enough to be considered as quasi-stationary. The Hankel matrix of the bipolar iEEG is first built, after which SVD is calculated to obtain the SVs. Considering 2-sec windows having 1024 samples, the Hankel matrix would have the size of *512*512* elements. The SVD operator will thus produce 512 SVs (σ_i, *i=1,..., 512*), ordered in a descending way.

The main characteristic of an epileptic seizure is the highly coherent activity of the neurons, generating nearly the same electrical voltages by two very close bunches of neurons. This highly coherent and synchronous state during seizure events, specifically prior to seizure termination (Schindler et al., 2007a; Schindler et al., 2007b), leads to a significant increase in the level of common mode signal of the adjacent channels, taking more similar waveforms. SVs represent the level and importance of the energies contained within the correlated parts of signal. As a result of excessive coherency during seizure, the energy of the resulting bipolar signals and their correlated parts will decrease. Figure 2 shows the extracted SVs of sample seizure.

2.3 Preprocessing of Features

The average of each singular value for the first 60 minutes of recordings and for each patient was calculated, and the SVs were normalized by dividing to that average. The range of SVs (σ_i , $i=1,\ldots, 512$) were equalized by this normalization (Figure 3). Afterward, the 32 best performing SVs were selected and average of their normalized values was used as a single measure. Specifically the SVs from 9 to 40 performed better in our study for seizure detection, and were considered to make a unique measure.

Furthermore the coherent epileptic neuronal activities last for several seconds, thus smoothing the feature vector by a rectangular moving average window of 4 consecutive samples, decreases the likelihood of short coherent events that are not ictal from reaching threshold. The smoothing would greatly reduce the number of false alarms.

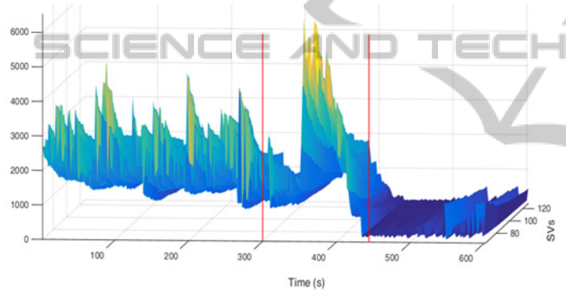

Figure 2: SVs (65-128) extracted from 10 minutes of bipolar iEEG signal contains one seizure. Vertical red lines indicate onset and offset times. The SVs first start to increase by seizure development, and then suddenly decrease approaching the seizure termination.

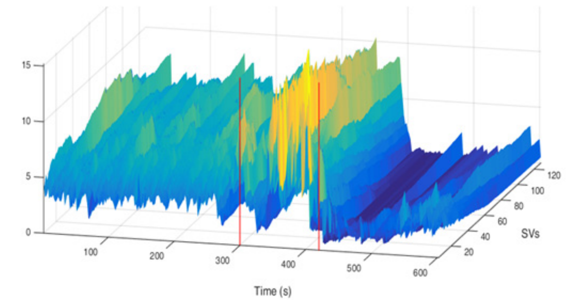

Figure 3: Normalized SVs of a sample seizure from patient B. The range of SVs is equalized after normalization. Vertical red lines indicate onset and offset times.

The singular values mostly start to increase with seizure initiation, while suddenly decrease once seizures are well developed and approach their termination. Although looking for increase in singular values provide less detection delays, they generate higher numbers of false alarms and lower sensitivity values than looking for decrease in singular values, when used for detecting seizure events. Therefore the inverse of the measure, obtained from average of normalized SVs from 9 to 40, was considered as a candidate measure to highlight this decrease.

2.4 Alarm Generation

A threshold based classifier is used for the detection of epileptic seizures. Threshold value is selected for each patient separately, ranging from 1.5 to 2.5, and are applied on the candidate feature. Upon the measure passing of the threshold, an alarm will be raised, after which further alarm generation will be blocked for 4 minutes. This limitation guarantees the raising of just a single true alarm per seizure.

3 RESULTS

Sensitivity (SS) and false detection rate (FDR) of the raised alarms were used to evaluate the methods. Sensitivity is the fraction of correctly detected seizures within the total seizures, and the FDR value is the number of false detections per time unit (hour). Table 2 presents the results of seizure event detection using two methods, first from bipolar SVs, and the other using sub-band MPC method (Bandarabadi et al., 2014a), obtained from same patients and same channels.

Table 2: Results obtained for 5 studied patients.

ID	Bipolar SVD		Sub-band MPC	
	SS [a]	*FDR* [b]	*SS* [a]	*FDR* [b]
A	100	0.02	78	0.06
B	100	0.01	78	0.05
C	71.4	0.08	71	0.09
D	66.7	0.01	66	0.02
E	100	0	100	0.04
Mean	85.2	0.02	79	0.05

[a.] SS: Sensitivity of raised alarms in percent.
[b.] FDR: False detection rate of raised alarms per hour

The results of bipolar singular values provide on average, a sensitivity of 85.2% and a FDR of 0.02 per hour (16 false alarms in 780 h of recordings), while the previously proposed method (sub-band MPC) could averagely provide a sensitivity of 79%

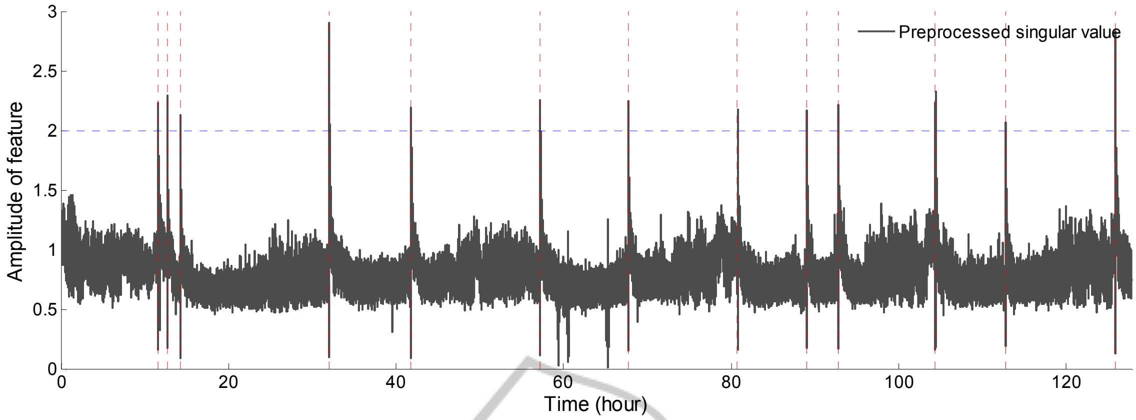

Figure 4: Proposed measure for entire recording of patient E. Black line is the measure, and the vertical dotted red lines are seizure onsets. The optimum threshold value is 2 for this patient, which is indicated by horizontal dotted blue line.

and a FDR of 0.05 h^{-1}. The results were achieved by a tradeoff between SS and FDR. However, slightly higher sensitivity could be reached by setting lower threshold values, which lead to higher FDRs. Figure 4 illustrates the proposed measure extracted from whole recording of patient E.

4 CONCLUSIONS

When two adjacent iEEG signals become increasingly correlated, difference of those signals (bipolar iEEG) will contain less energy, causing the SVs of bipolar signal to decrease. Therefore the observation of sudden decreases in the SVs would coincide with seizure termination. Moreover, according to the results, the SVs extracted from bipolar iEEG signals were apparently robust to the changes in the state of the iEEG data throughout the patient's daily life, producing just 18 false alarms in 780 hours of iEEG recordings. Furthermore, we observed that patterns of coherency are recurring evenly for all of the seizures for each particular patient. This indicates that the build-up, propagation, and termination of the seizures for a specific patient follow a common neuronal mechanism.

Furthermore, channel selection affects significantly the sensitivity parameter of proposed algorithm. If the recording channels are not placed close enough to the focus, the seizure spread may not reach that channel, thus decreasing average sensitivity. Overall, both placement and number of selected iEEG channels can substantially affect detection sensitivity and delays and had be taken into consideration. In this work, the seizure focuses were known. Additionally all patients were suffering from partial epilepsy. Therefore the selection of two channels on the focus was suggested to satisfactorily detect seizure events.

ACKNOWLEDGEMENTS

This work was partially supported by EU FP7 211713 EPILEPSIAE Project and iCIS project (CENTRO-07-0224-FEDER-002003). MB would particularly like to acknowledge the Portuguese Foundation for Science and Technology (FCT - SFRH/BD/71497/2010).

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