Optimizing Dynamical Similarity Index Extraction Window for Seizure Detection

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Abstract— **This paper addresses an optimization problem in choosing optimum window length for feature extraction in automatic seizure detection. The processing window length plays an important role in reducing the false positive and false negative rates and decreasing required processing time for seizure detection. This study presents an approach for selecting the optimum window length toward the extraction of dynamical similarity index (DSI) feature. Then, the optimal window value in DSI extraction was used to detect seizure onset automatically. The algorithm was applied to electroencephalogram (EEG) signals from European Epilepsy Database. Although the main purpose of this study was not the seizure detection and mainly focuses on proposing an approach for finding an optimum window length for feature extraction towards the early seizure detection, the results showed that the proposed method achieves 83.99% of sensitivity in seizure detection. The low false positive rate per hour (FPR/h) was also significant due to continuous EEG analysis. The method showed fast computation speed which promises a potential for the real time applications. The proposed method for the window optimization in feature extraction of DSI can be implemented for other features to further improve the performance of seizure detection.**

I. Introduction

Epilepsy is one of the most common neural disorders that affects nearly 1% of population in all over world [1] and is not a disease of itself, but a symptom of a disease. It basically emerges from recurrent abnormal electrical activities in brain which appear as electrical discharges inside brain called seizure attacks. Many pathological changes can originate seizure. They can include side effects of having a trauma, inflammation and vascular events or even inherited genetic tendency in the family for epilepsy [1]. It can also cause paralyzing or malfunctioning normal activities of body in different levels like sensation, awareness and body movement which affects patient's daily life. Currently, recording brain signals using electroencephalogram (EEG) systems and applying signal processing techniques is the most feasible method to the problem of seizure detection. The term of "seizure detection" usually means using an automated algorithm to recognize if a seizure occurred through analysis of recorded EEG signals [2]. Essentially, the goal is to perform this detection as quickly, efficiently, and accurately as possible. Methods for automatic seizure detection have been studying for several years. One of the first developed techniques was introduced by Gotman *et al.* [3]. Later, different methods including wavelets [4], radial basis function networks [5], support vector machines [6], Gaussian process models [7], genetic programming [8], mixed-band wavelet-chaos-neural networks [9], fuzzy logic [10][11] and correlation dimension [12] were utilized for seizure detection. Almost all algorithms for seizure detection apply a moving window analysis to EEG signals. In each window, one or more quantifying measures are computed from the EEG data and changes in their values are monitored. Then, differences between the latter moving window and former non-seizure window are compared. In case of having significant changes, the time for that window is identified as a seizure event [13]. Thus, choosing a precise window size for extracting feature from EEG signal is critical for seizure onset detection. On the other hand, choosing a reasonable window size for feature extraction to discriminate seizure events from normal EEG is crucial since large window sizes could cause missing seizure events easily and small ones result in high computational time. The use of very short windows for feature extraction could conceal the feature track before and during seizures and results in increasing the false negative cases in detection. One of the previous studies in selecting a proper widow size was done by Esteller *et al.* [14] which proposes a methodology for tuning the window length or any other feature parameter. The analysis was for the particular problem of seizure onset detection.

In this paper, we propose a method to find a minimum window length for extracting a nonlinear univariate feature, i.e., dynamical similarity index (DSI), in order to detect seizures with highest sensitivity based on golden search optimization method. It should be mentioned that the proposed algorithm could be generalized and used for other features as well. Section II describes the mathematical background for selected feature and golden search optimization method. It also explains the proposed method

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and the database that was utilized. Section III and VI provide the results and conclusion of the proposed method, respectively.

II. METHODS AND MATERIALS

A. Database

The utilized database in this study comes from European Epilepsy Database [15]. The intracranial EEG was obtained from four patients; each had different number of seizures and electrodes. The total number of seizure for patient 1 to 4 during one week was 8, 9, 22, 9, respectively (48 seizures in total) and the number of electrodes varies from 60 to 71. A total of 144 hours of data were analyzed for feature extraction. Each one hour data is called one block. Since the performance evaluation of the algorithm on long-term continuous data was primary objective; we made sure that at least 3 hours preictal and ictal recordings were used for each analyzed seizure. The sampling frequency for data recording was 256 Hz.

B. Preprocessing

A sliding window analysis was employed on continuous EEG recordings. The length of each window was chosen based on optimum window length with 20% overlap with the adjacent windows and to satisfy the criteria for stationary of EEG signals. Each of these segments can be considered as pseudo-stationary. A fourth order digital Butterworth IIR filter with cutoff frequencies at 0.5 Hz and 100 Hz was applied to each of these segments to mitigate high frequency noise and low frequency artifacts [16]. Moreover, a second order notch filter with cutoff frequency at 50 Hz was applied to reduce the effects of power line noise [16]. Zero phase digital filters were used for both cases.

C. Dynamical Similarity Index

It is assumed that the epileptogenic process can be modeled as a nonlinear deterministic dynamical system and non-epileptogenic process is a linear stochastic brain electrical activity. Therefore, DSI can be a sensitive feature to discriminate seizure events and non-seizure spikes [17]. The idea of the dynamical similarity index is to compare the dynamics of a sliding test window, S_t, with a fixed reference window, S_{ref}. The reference period is from an interictal phase and lasts 300 sec [17]. It is noticeable that the reference window should be far from any seizures. The following steps should be taken to extract DSI:

Step 1) Obtain a new time series I_n, based on positive zero-crossing of the original EEG recordings as a time series;

Step 2) Reconstruct a phase space for series I_n with the embedding with dimension m and the delay time τ, A_n=($I_n, I_{n-1}, I_{n-2}, \dots, I_{n-m+1}$);

Step 3) Project the trajectory matrices, $A(S_t)$ and $A(S_{ref})$ on the principal axes of the reference window by means of a singular value decomposition (SVD), producing $X(S_t)$ and $X(S_{ref})$, respectively;

Step 4) Select $Y(S_{ref})$ from $X(S_{ref})$ randomly and comparing with $X(S_t)$ using the cross-correlation integral [17]:

$$C(S_{ref}, S_t) = \frac{1}{N_{ref}N_t}\sum_{i=1}^{N_{ref}}\sum_{j=1}^{N_t}\Theta\left(\|Y_i(S_{ref} - X_j(S_t)\| - r\right) \quad (1)$$

where ‖.‖ indicates the Euclidian norm, Θ the Heavyside step function, and N_{ref} and N_t the number of points in the phase space of the reference and test window, respectively;

Step 5) Improve the discriminatory power between two dynamics. The autocorrelation integral $C(S_{ref}, S_{ref})$ and $C(S_t, S_t)$ are used to defined DSI γ as [17]:

$$\gamma(S_{ref}, S_t) = \frac{C(S_{ref}, S_t)}{\sqrt{C(S_{ref}, S_{ref})C(S_t, S_t)}} \quad (2)$$

γ varies from 0 to 1 and gives a sensitive measure of the closeness between two dynamics [17].

D. Golden Search Method

The golden section search is a technique for finding the minimum or maximum of a function [18]. Having an objective unimodal function in given interval $[a, b]$, function values are computed at two points whose relative locations in the interval are determined by the golden ratio. Comparison of the resulting values results in discarding part of the interval because of not including the minimum. The process is repeated on the new, shorter interval until the minimum has been reached as accurately as desired. The algorithm is extended version of Fibonacci search [18].

E. Window Length Optimization for Feature Extraction

The applied database has all information regarding the origin of seizures in channels as well as early propagation and late propagation [15]. The goal is to detect seizure as early as possible with good accuracy, so the primary focus is on original seizure channels. Once the first two seizures of each patient were used to find the optimum window length for dynamical similarity index extraction, the algorithm was tested on other seizures of patient in all channels randomly. The proposed optimization program based on golden search seeks the best window length for feature extraction. The fitness function is defined as average proportion of DSI of seizure region on all over non-seizure regions during three hours before and including seizure event. The method needs to be given a time interval $[a, b]$ to start seeking the best window length inside the interval. We chose this time interval starting from at least 3 seconds till 53 seconds based on the following fact. For the low frequency sampling rate, 256 Hz, less than 3 seconds window size does not produce valuable information and more than one minute window size might miss the seizure features if the seizure length is too short. Three different intervals were chosen to make a comparison among optimized window sizes in test seizure blocks. Before feature extraction, we calculated bi-channel cross-correlation between all original channels in the first two seizure blocks for each patient. Since the cross-correlation was so high for all of them, we averaged all origin seizure channels and used the averaged data for finding optimum window length over all channels to save time. Once the optimum window length is calculated, it is used for extracting the DSI in other seizure blocks to evaluate the performance of optimization method. As a post processing step, a median filter was applied. The length of median filter was adaptively determined based on minimum number of seizure feature points at that block which was obtained with optimum window length.

F. Seizure Detection Method

The main approach in this algorithm for seizure detection focuses on the changes of slope of DSI feature and continuity in high frequency changes. The general model for detection algorithm can be summarized as follows:

(1) For each input data, the DSI feature was extracted using the optimum window length which obtained from first two seizures of the same patient.

(2) The derivative of feature function was calculated.

(3) Maximum slopes were determined. Technically the maximum slopes can be the start points of seizure as they reflect abrupt changes in EEG amplitude which mostly happens in seizure occurrence.

(4) To discriminate seizure events from sharp spikes and even subclinical short seizures, the consistency of high frequency changes was evaluated for original EEG for each moving window.

(5) All quantifying values were compared to some thresholds based on normal EEG data.

The length of sliding window on data was 180 seconds which scans the data for all above calculations. The maximum variance and maximum zero crossing of windows were evaluation criteria to determine relative continuity in high frequency changes. The zero crossing points just before seizure pick could be considered as early seizure indicators. If the algorithm faces with two following windows with relative high values of variance, zero crossing, and amplitudes, it repeats all mentioned calculation on the combination of these two windows with 50% overlap. This method also gives an option to have an estimation regarding the seizure duration.

III. Results and Discussions

In optimization algorithm we calculated the optimum window length over three different time intervals including [3, 21], [3, 33], and [3, 53] seconds as start and end points of golden search method in the first two seizure blocks in patients. Fig. 1 shows the averaged error functions for all three trials. Table I shows the results of running these three different time intervals for finding the optimum window length in one patient.

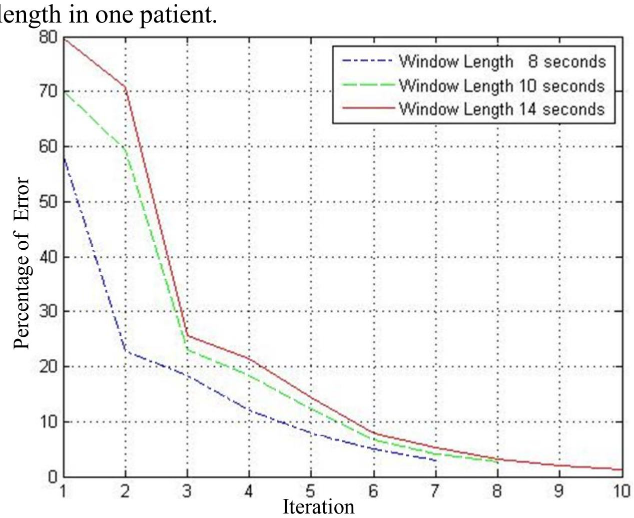

Figure 1. The percentage of error for three different optimum windows.

TABLE I: THE OPTIMUM WINDOW LENGTH AND FITNESS FUNCTION VALUE FOR THREE DIFFERENT TIME INTERVALS.

Time Interval (seconds)	Optimum Window Length in seconds (Samples)	Fitness Function Value
[3, 21]	7.86 (2012)	4.906
[3, 33]	9.44 (2417)	5.372
[3, 53]	12.08 (3092)	5.876

As the results show the average of the optimum window length for feature extraction is obtained around 10 seconds. Although the percentage of error and iteration number are less for shorter window size, e.g., 8 seconds compare to 10 seconds, however, 10 second window size showed better accuracy in terms of seizure detection in the tested blocks. Fig. 2 shows the original EEG and extracted DSI feature for one seizure block from one EEG channel with window length of 10 sec. In order to evaluate the optimization method performance, we applied this averaged window length for DSI extraction in the other blocks of seizures at the same patient. It should be mentioned that the seizure does not happen in the same channels for the first or second block.

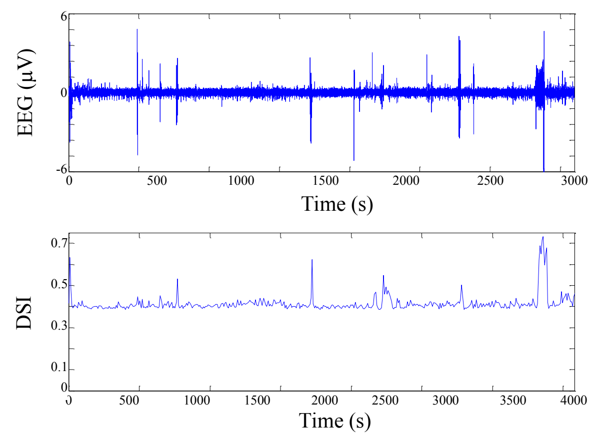

Figure 2. Top) original EEG for one hour with sampling rate 256. Below) dynamical similarity index feature extracted with window length 10 seconds.

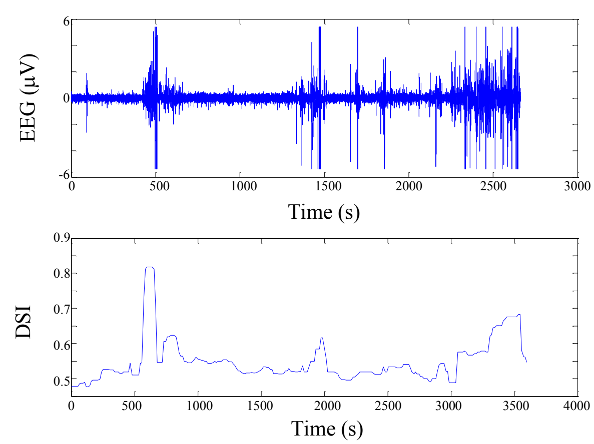

Figure 3. Top) original EEG for 45 minutes with sampling rate 256. Below) dynamical Similarity Index feature filtered with median filter with 8 points.

Fig. 3 shows the original EEG and the result of feature extraction using the optimum window length for a test seizure block with median filter 8 points length. The pick of DSI feature clearly indicate the occurrence of seizure. In seizure detection algorithm the slope of changes in DSI feature was evaluated for all channels. Once the changes are significant the variance and zero crossing are analyzed in original EEG for the same 180 seconds moving window. Fig. 4 shows the original EEG and slope changes of DSI for one randomly selected channel. Note that preprocessing and postprocessing operations removed artifacts similar to saturation and spikes.

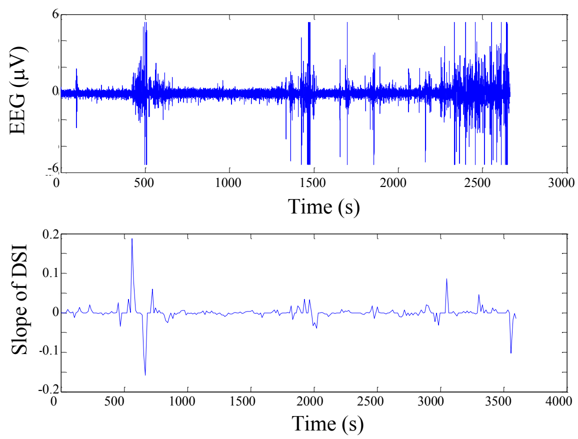

Figure 4. Top) original EEG for 45 minutes with sampling rate 256. Below) Slope changes of dynamical Similarity Index.

Table II shows the results after running the algorithm for all 48 seizures during 144 hours. The values for true positive (TP), false negative (FN) were calculated and the overall sensitivity of method was 83.33%.

TABLE II: THE PERFORMANCE PARAMETERS

Patient #	Seizure Occurrence	TP	FN	Sensitivity (%)	FPR/h
1	8	7	1	87.5	0.375
2	9	7	2	77.77	0.259
3	9	8	1	88.88	0.296
4	22	18	4	81.81	0.272
Total	48	40	8	83.33	0.303

IV. CONCLUSION

The results in optimization showed that the optimum window length is good enough to detect seizure picks and discriminate the seizure and non-seizure events. One of the advantages of this optimization is the application of adaptive filtering based on the maximum number of extracted seizure features in each window length. The proposed method also uses 20% of optimum window length as overlap for feature calculations. The proposed method can be easily extended to other features for seizure detection and prediction, e.g., mean phase synchrony. For seizure detection algorithm, the sensitivity is affected by the high number of FN cases because of having many window candidates for seizure occurrence. Although the high number of FP which are the product of sharp spikes and subclinical seizures in original EEG affects the specificity, but still FPR/h is in acceptable range due to continuous monitoring during long hours. Applying strong preprocessing algorithm for spike removal before feature extraction can improve the results further. Monitoring the change of slope in features or feature trend tracking is a good method for finding the some points before seizure's onset which can be indicators for seizure prediction.

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