Optimal EEG Window Size for Neural Seizure Detection

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***Abstract*— In this paper, different window sizes for EEG signal segmentation are investigated in order to optimize the performance of seizure detection systems. To differentiate between epileptic and non-epileptic epochs, the time axis of the EEG signal is divided into non-overlapping windows. The window period should be long enough for the lapse to be informative but not too long for it to stay stationary. Hence, the KPSS test is used to determine signal stationarity for different window sizes, then the optimal window is chosen such that it corresponds to the smallest number of non- stationary segments in the signal of interest. The seizure detection system is then applied to the piece-wise stationary segments. Compared to the exhaustive examination, it is found that the KPSS test optimal window results in the highest sensitivity.**

***Index Terms*–** Seizure Detection, Segmentation, Window Size, KPSS.

I. INTRODUCTION

Epilepsy is a neurological disease characterized by recurrent episodes of involuntary movement called seizures [1]. According to the World Health Organization, about 5 million people of the world population currently live with active epilepsy [2]. Seizures cause psychological conditions and severe physical problems that include loss of awareness and sensation.

Multiple studies have aimed to choose the optimal detection device by studying seizure types and their main semiological components. One approach is muscle activity analysis with surface electromyography (SEMG) since epileptic seizures have a motor component [3]. However, SEMG sensors cannot detect all seizure types and are easily detached from the skin [3,4]. Another approach is electrocardiogram (ECG) measurement since electrovascular changes can be easily monitored[5]. One disadvantage of ECG in seizure detection is low specificity in heart beat changes [5]. A third approach is the analysis of brain signals with electroencephalographic (EEG) devices. EEG is a representation of the brain electrical signals obtained by connecting multiple electrodes on patient's scalp. EEG has been the most frequently used technique in seizure detection for years. Patients wear scalp electrodes or portable devices that can be attached to a belt [6]. EEG signal processing is widely used for assessing disorders of brain function, especially for epilepsy diagnosis. The traditional method used to identify seizures is dependent on the visual analysis of the EEG recordings by the trained professionals. This is a very costly as well as tedious task to review a 24-hour continuous EEG recording, particularly if the number of EEG channels increases. Hence, automated seizure detection and prediction systems are evolving [2].

The detection process using EEG involves many stages: obtaining brain signal, removing artifacts, segmenting the EEG, extracting relevant features, calculating the value of each feature per segment, then using a classifier to determine whether the signal contains seizures or not. Signals have to be segmented into time epochs before applying machine-learning algorithms for easier processing.

Signal segmentation is an established approach in EEG analysis since EEG is not generally stationary and many analysis techniques are only defined for stationary signals [7]. This paper investigates the hypothesis that dividing the EEG signal based on stationarity optimizes the seizure-detection performance.

The rest of the paper is organized as follows. Section II presents a literature review of signal segmentation based on stationarity. Section III discusses the fundamental mathematics of the KPSS stationarity test. The simulation setup in section IV introduces some information about the datasets and the extracted features. Section V presents the results and discussion. Finally, section VI presents the conclusion.

II. LITERATURE REVIEW

To be stationary, the signal statistics should be constant. A lot of research has been done to further investigate the approach of signal segmentation based on stationarity and Gaussianity. However, not so many studies have attempted to find the correlation between EEG segmentation and seizure-detection performance. Researchers either rely on the approach of trial and error till they find the optimal window duration or segment signals based on the most-frequently used durations. However, each signal has an optimal window duration that maximizes the performance of seizure detection and prediction.

In 2015, authors in [8] used a window size of 4 seconds for seizure detection without justification of the choice. The work of Candera in [9] investigates the effect of window sizes on the classification of EEG- emotion signal. The work in [9] proposes that shorter window lengths achieve higher classification accuracy. However, the authors reported a maximum accuracy of only 65% using the wavelet entropy of 3 to 12 second signal segments [9]. Many studies feature different EEG classification methods and maximization of seizure-detection performance metrics but there is nothing that further investigates window-size optimization in this context. The lack of studies in this part is also highlighted in a degree project in [10]. This project in [10] is the most recent work in the state of the art regarding window length optimization. The approach iteratively tries many window sizes as inputs to determine the probability that a segment is pre-ictal using SVM (Support Vector Machines). It then evaluates the rest of the segment and finds the whole segment probability by averaging those of the individual window sizes. The reported results show that window sizes smaller than 60 seconds or greater than 180 seconds give inconsistent results with considerably-varying probabilities. However, the authors only reached a maximum accuracy of 80% around 90 seconds, mentioned that these are not the results they expected and attributed that to possible inefficiencies in the used software or not training enough data [10].

III. KPSS TEST

In 1991, Kwiatkowski proposed today's most-used segmentation test known as the KPSS test. KPSS examines the null hypothesis that a time series is trend stationary against the alternative hypothesis of a unit root [11]. Let the signal of interest be a time series:

$$y_t,\ \text{t= 1,2,...,T},$$

which can be expressed as the sum of deterministic trend, random walk, and stationary error:

$$y_t = \zeta\text{t} + r_t + \epsilon_t$$

The random walk

$$r_t = r_{t-1} + u_t,$$

where the u_t are independent and identically distributed random variables iid(0,σ^2). Verifying the null hypothesis indicates that the random walk has a zero variance, σ^2= 0 [11]. Therefore, In this paper a proposal is presented to use the KPSS test to determine the optimal window size that maximizes the sensitivity of seizure detection and prediction. This is done by applying the test on the signal with different window sizes and choosing the window size that results in the minimum number of non-stationary time epochs.

IV. SIMULATION SETUP

Two datasets are used in this paper to answer the research question of the correlation between signal segmentation and detection performance. The first dataset is published by MIT. It has been collected at the Childrens Hospital Boston from 22 subjects with intractable seizures. For each subject, 23 channels have been recorded from different electrodes [12]. The second dataset is released by Kaggle in a data science competition. The data includes records of patients and dogs with naturally occurring epilepsy. Dogs EEG has been sampled from 16 electrodes at 400 Hz while patients EEG with varying numbers of electrodes has been sampled at 5000 Hz. The seizure detection system in [13] is used to measure the performance, in terms of sensitivity, of all window sizes starting from 3 seconds up to 10 seconds [13]. The system consists of a combination of 3 features that are used along with a linear support vector machines (SVM) classifier.

The KPSS test is used to determine the window size with the smallest number of non-stationary segments. This window size is then compared to the results of the exhaustive method to determine whether or not this duration has the optimal performance. We extracted the following feature list [13]:

1- Standard Deviation (STD)

$$\text{STD} = \sqrt{\tfrac{1}{N-1}\textstyle\sum_{i=1}^{N}(x_i - \overline{x})^2}$$

2- Fractal Dimension (FD)
Fractal dimension includes information about the geometrical structure of the signal. It is calculated using Higuchi's algorithm with k=5.

3- Hurst Exponent
It is used to discriminate between white noise and information within the signal.

4- Skew
Skew measures the asymmetry in a signal.

$$\text{Skew} = \tfrac{1}{M}\textstyle\sum_{i=1}^{N} \tfrac{X}{\sigma-\mu}^{3}$$

5- Kurtosis

It has the same formula as the skew with higher order.

$$\text{Kurtosis} = \tfrac{1}{M}\textstyle\sum_{i=1}^{N} \tfrac{X}{\sigma-\mu}^{4}$$

6- Variance

$$\sigma^2 = \frac{\sum_{i=1}^{n}(x_i-\mu)^2}{n}$$

7- Permutation Entropy
It measures the degree of disorder in the signal.

8- Approximate Entropy (ApEn)
It measures how ordered or disordered the EEG signal is.

9- Shannon Entropy
It estimates how many bits are needed for encoding.

10- Renyie Entropy
It is a generalization for the Shannon entropy.

11- Average Energy

$$\text{E} = \textstyle\sum_{i=1}^{N} x_i^2$$

12- Fluctuation Index (FI)
FI measures signal fluctuation during seizure and non-seizure periods.

$$\text{FI} = \sum_{i=1}^{N} |x_{i+1} - x_i|$$

13- Hjorth parameter: Mobility
Mobility is the ratio between the square root of the first derivative variance and signal variance.

14- Hjorth parameter: Complexity
Complexity tracks frequency changes with respect to a sine wave.

15- Mean absolute value (MAV)

$$\text{MAV} = \frac{1}{N} \sum_{i=1}^{N} |x_i|$$

16- Maximum Absolute Value
It is the maximum absolute value of each segment. Zhang and Chen used this feature to obtain an accuracy of 98%[14].

17- Minimum Absolute Value
It is the minimum absolute value of each segment.

18- Root mean square (RMS)

$$\text{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} x_i^2}$$

Sensitivity, which is the true positive rate, is the performance metric used in this paper.

$$Sensitivity = \frac{TP}{TP + FN}$$

V. Results and Discussion

After feature reduction by trial and error on all feature combinations, we used two feature combinations from the above list; combination A and combination B. Combination A includes the following features: fractal dimension, Hurst exponent and fluctuation index. The following features are included in combination B: mean absolute value, maximum absolute value and minimum absolute value. The KPSS test is applied as follows. A signal of duration x seconds is divided into n segments of length $\frac{x}{n}$ seconds. The KPSS test is applied to the n segments to return the number of non-stationary segments found in the whole x second signal. Thus, the smaller the number of indicated non-stationary segments, the better the expected performance. While iteratively using different window sizes and obtaining detection sensitivity for each one, we have been applying the KPSS test on each case to determine the optimal window sizes. The results of both methods show high consistency. The column "Window in seconds" indicates the window size in seconds. The columns "A sensitivity" and "B sensitivity"

TABLE I
MIT patient 1 sensitivity ratios for different durations

Window in seconds	A Sensitivity	B Sensitivity	KPSS
3 sec	100%	85.7%	9
4 sec	100%	100%	0
5 sec	100%	100%	0
6 sec	87.5%	87.5%	22
7 sec	85.7%	100%	26
8 sec	83.3%	100%	16
9 sec	80%	90%	11
10 sec	100%	91%	15
Best Performance	3,4,5,10	4,5,8	4,5

TABLE II
MIT patient 2 sensitivity ratios for different durations

Window in seconds	A Sensitivity	B Sensitivity	KPSS
3	96.4%	78.57%	0
4	95.4%	77.27%	0
5	94.12%	88.23%	0
6	86.66%	66.66%	4
7	84.6%	84.615%	6
8	90.9%	63.63%	4
9	80%	70%	7
10	88.88%	66.66%	10
Best Performance	3,4,5	5,7,3,4	3,4,5

TABLE III
MIT patient 3 sensitivity ratios for different durations

Window in seconds	A Sensitivity	B Sensitivity	KPSS
3	95.8%	91.66%	0
4	94.4%	94.44%	0
5	91.8%	93.33%	0
6	91.66%	91.66%	4
7	81.81%	81.82%	6
8	88.88%	88.88%	4
9	87.5%	87.5%	7
10	87.5%	87.5%	10
Best Performance	4,5,3,6	5,7,3,4	3,4,5

TABLE IV
Kaggle Dog 2 sensitivity ratios for different durations

Window in seconds	A Sensitivity	B Sensitivity	KPSS
3	66.6%	66.6%	1
4	100%	100%	0
5	100%	100%	0
6	100%	100%	0
7	100%	100%	3
8	100%	100%	1
9	50%	100%	1k8
10	50%	100%	1
Best Performance	All except 3,9,10	All except 3	4,5,6

TABLE V
Kaggle patient 1 sensitivity ratios for different durations

Window in seconds	A Sensitivity	B Sensitivity	KPSS
3	100%	100%	0
4	100%	100%	0
5	100%	100%	0
6	100%	100%	1
7	100%	66.66%	1
8	100%	100%	1
9	100%	100%	1
10	100%	100%	1
Best Performance	All	All except 7	3,4,5

indicate the detection sensitivity of feature combinations A and B respectively. The column labeled ”KPSS” includes the number of non-stationary segments found in the signal of interest when the KPSS test is applied.

The first row of the first table reads as follows: for a window size of 3 seconds, combination A shows detection sensitivity of 100%, combination B shows sensitivity of 85.7% and the number of non-stationary segments returned by the KPSS test in the EEG signal of patient 1 is 9 segments. As shown in Table I, the best performance of combination A which is 100% is obtained by dividing the signal into window sizes of 3, 4, 5 or 10 seconds and that of combination B corresponds to window sizes 4,5 and 8 seconds. Applying the KPSS test to the patient 1 from MIT dataset indicates that the signal is maximally stationary for durations of 4 and 5 seconds because these window sizes guarantee zero non-stationary segments in the EEG signal. As expected, the 4 and 5 seconds indicated as optimal windows by the KPSS test are the optimal window sizes combination A and combination B have in common. What these results tell about patient 1 is that instead of trying all window sizes in search for the optimal performance, a researcher can rely on the stationarity test and only use a window size of either 4 or 5 seconds for the highest sensitivity regardless of the feature combination used.

Table II shows that the KPSS results of MIT patient 2 EEG are consistent with those found by examining all durations as the windows with maximum performance in combination A are 3, 4 and 5 seconds, in combination B are 5, 7, 3 and 4 and in the KPSS test are 3, 4 and 5 seconds. We observe that all the windows indicated by the KPSS test correspond to high performance in combination A and combination B but the opposite is not true. The 7 second window is not one of the best windows indicated by the KPSS test although it is the second best window obtained from feature combination B. This is because a window of 7 seconds returns low sensitivity when combination A is used, 84.6%, and thus is not indicated as an optimal window that guarantees good performance regardless of the feature combination.

The same research methodology has been applied also on a dog and a patient from Kaggle dataset. In Tables IV and V, the optimal window sizes from the KPSS test result in a 100% performance for both feature combinations.

VI. CONCLUSION

The performance of seizure detection systems, regardless of the extracted features, depends on the duration of the processed EEG epochs. Thus, signal segmentation based on stationarity is a crucial step before feature extraction and classification. The KPSS stationarity test can be used efficiently to determine the best window in EEG signal segmentation for Seizure detection by applying it on the desired signal with different window sizes then choosing the window size with the minimum number of non-stationary segments. This proposal has been experimentally supported by testing it on MIT and Kaggle EEG datasets.

VII. ACKNOWLEDGMENT

This work was partially funded by ONE Lab at Zewail City of Science and Technology and at Cairo University, NTRA, ITIDA, ASRT, and NSERC.

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