Determining Appropriate Window Size and Window Function for Epileptic Seizure Forecasting

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***Abstract*—The aim of this study is to determine the appropriate window size and windowing function for studies related to epileptic seizure forecasting. Firstly, in order to accomplish this aim, a suitable data set is obtained. Afterwards, tests are performed for 12 different window durations and the most suitable windowing time is determined. Determined window duration, windowing functions of 5 different properties are applied and performance rates are examined. As a result of the findings obtained in future studies, it is aimed to increase the success rate by conducting test operations with different features and classifiers.**

***Keywords*—iEEG;window size; window function, linear discriminant analysis.**

I. Introduction

Epilepsy is one of constant disorders of human nervous system, and impacts negatively humans' quality of life in 1% of global population. Discharges of epileptogenic tissue may cause abnormal electrical activity in brain areas, therefore patient can loss motor control and consciousness. Seizures occur spontaneously, constantly, and usually unexpectedly. If the epileptic seizure can be predicted before the time, patients can be stimulated and possible physical injuries can be prevented [1].

Previous studies related to epilepsy, EEG records are divided into 4 classes which have ictal, preictal, postictal and interictal by experts [2]. The ictal class represents the period of seizure. The preictal class symbolizes the period before the seizure. The postictal class implies after the seizure period. The interictal class represents the region between two seizures. While epilepsy detection studies compare to each other differences between two class interictal class and ictal class, epilepsy prediction studies distinguish between preictal and interictal classes. In this study, we have focus on a algorithm for epilepsy seizure forecasting.

In audio analysis, frame duration varies from 10 ms to 50 ms [3]. However, EEG related works, frame duration size between 10s and 40s is generally preferred [4]. Therefore, the frame duration varies depending on the nature of the signal used. Reyes et al. [5] in their work, minimum size of a window was evaluated. Malhotra [6] in works, to design a FIR filter cosh window's characteristics are compared with other windows like Kaiser window, Hamming window. Zarjam et al. [7] used the EEG signals to determine the mental workload of participants. Window duration of 5 seconds was preferred. Candra et al. [8] have proposed a method which recognize their patients' emotional state using EEG signals. They tested with 10 different window size such as 60, 30, 20, 15, 12, 10, 8, 6, 3, and 1 second. Nisar et al. [9] proposed a method which has adaptive window selection. Tzimourta et al. [10] evaluated different window size for seizure detection. They tested 24 different window duration with 50% overlap, and evaluated four different classifiers.

When starting work on epilepsy forecasting, two factors must be selected very carefully. The size of window and the type of window. There is no general rule for choosing size of window. So the size of window is difficult to decide. If the window size is selected too long, then sudden frequency values cannot detected. If the window size is selected to short, then sudden frequency values can detected, but it is very sensitive to frequency changing.

When scientist generally started the same works, after literature searching, appropriate window size and window function are chosen. However, the window duration and the window function may vary depending on the state of the problem and the data set used. Therefore, in this study, the appropriate window size and window function are carried out in the form of trial and error. Consequently, this study is important because it constitutes the first step of epileptic seizure forecasting study. If it is started with a suitable window duration and windowing function, it is likely to achieve high performance in subsequent steps of the work.

II. Material and Methods

Fig. 1 shows the block diagram of the system used for the training and testing phase. As it is seen in the fig. 1, the system used consists of 4 steps: pre-processing, feature extraction, classification and post-processing. First, in the pre-processing step, each 10 minutes EEG clip is broken down to short window size. In the second step, the each short window size is transformed to frequency domain using STFT, afterwards calculatee to features for each short window size. In the third step, the each frequency features are classified using Linear Discriminant Analysis (LDA) technique. The fourth step, short-term window labeled for each 10-minute clip are collected and compared to the threshold value. As a result, the value 1 (preictal class label) and the value 0 (interictal class label) for each 10-minutes clip are assigned. All tests which have feature extraction and classification are performed with a laptop in MATLAB environment.

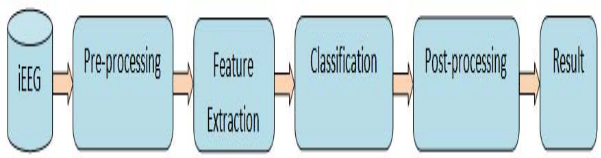

Fig. 1. System Architecture

In this study, only STFT is used as feature extraction. In addition, LDA is preferred as classifier. The reason is that the focus of this study is to examine the effect of the window size and window function, so the feature extraction and classification steps are not evaluated deeply.

A. The Dataset

In this work, we have used dataset presented by the American Epilepsy Society [11]. A summary of this dataset is presented in Table I. The data set was obtained from 7 different subject who have epileptic seizures. Five of them consist of records obtained from dogs, and the other two are records obtained from humans. The records obtained from the dogs were recorded as 16-channel EEG recordings except for dog5 and the sampling frequency was recorded as 400 Hz. Recordings from humans consist of EEG recordings of 15 and 24 channels, respectively, and the sampling frequency is 5000 Hz. Each subject record is presented in the form of a .mat file with 10-minute clips. Each clip is labeled by experts in the form of a preictal or interictal. The training data is sequentially arranged, but the test data is randomly arranged.

TABLE I. SUMMARY OF THE USED EEG DATASET

Subject	Sampling Frequency	Seizures	Interictal	Preictal	Test
Dog 1	400	4	480	24	502
Dog 2	400	7	500	42	1000
Dog 3	400	12	1440	72	907
Dog 4	400	17	804	97	990
Dog 5	400	5	450	30	191
Patient 1	5000	3	50	18	195
Patient 2	5000	3	42	18	150

B. Pre-processing

First step in signal processing, it is preferred a window function to diminish spectral leakage. There are many types of windowing function in signal processing applications, such as rectangular, Hamming, Hanning, Gaussian and Blackman. Each window function has its own characteristic to effect the signal's frequency response. Therefore, they are slightly different form each other in their performance. Among them, Hanning and Hamming window functions have been mostly preferred in related EEG applications [12].

Firstly, the DC component of each EEG channel is discarded and 60 Hz noise is suppressed with a notch filter. Secondly, each EEG channel is applied to the whole data set for 12 different window durations such as 1, 3, 5, 10, 15, 20, 25, 30, 45, 60, 90, 120 seconds. Overlapping period is chosen 50%. There is an imbalance problem in this dataset. To overcome this problem, overlapping ratio of preictal class is reduced such as 5% in training part. 50% overlap ratio is preferred in the test data. Third step, it is tested for 5 different windowing function such as rectangular, Hamming, Hanning, Gaussian and Blackman.

C. Feature Extraction

In this study, it was used the short-time Fourier transform (STFT) for feature productions [13]. Usually in biomedical signal processing, the EEG signal is directly subdivided into sub-frequency bands instead of calculating the spectral power of the entire frequency band. For each sub-frequency band, the spectral power values in the range of the starting and ending frequency values are calculated. EEG records for each channel are separated into 9 sub-frequency bands. These are delta [0.1 - 4Hz], theta [4 - 8Hz], alpha [8 - 13Hz], beta_1 [13 - 20Hz], beta_2 [20 - 30Hz], gamma_1 [30-70Hz], gamma_2 [70 - 110Hz], gamma_3 [110 - 150Hz] and gamma_4 [150 - 200Hz]. However the sampling frequency of the patient-1 and patient-2 was 5000Hz, so additional 4 different sub-frequency bands were calculated such as gamma_5 [200-400Hz], gamma_6 [400-1000Hz], gamma_7 [1000-1500Hz], gamma_8 [1500-2000Hz] and gamma_9 [2000-2500Hz].

D. Classification

Linear Discriminant Analysis (LDA) is one of the most talented linear classifiers in machine learning [14]. The LDA is classifier which has strong, low model complexity and fast outcome. Therefore, we have chosen the LDA as the classifier.

E. Post-processing

The duration of each preictal and interictal classes in the data set is 10 minutes. In this study, we divide these 10 minute clips into short window time (from 1sec to 120sec). To obtain the final class label forever 10 minutes clip, each short window time label values are added and compare with the threshold value, then last label of predicted class (1 or 0) is determined.

III. EXPERIMENTAL RESULTS

ROC curve (receiver operating characteristic curve) is a used to measure for performance of classifier [15]. ROC curve is plotted using two metrics, such as true positive rate (TPR) and false positive rate(FPR). The curve shape is converted to a single numeric value. Therefore, calculation of the area under ROC curve (AUC) is preferred. AUC numerically indicates whether classifiers are capable of distinguishing the classes. In this study, we have evaluated using AUC measurement metric to compare for each LDA output results.

TABLE II. RESULTS OF THE RECTANGULAR WINDOWING FUNCTION

Window Size	D1	D2	D3	D4	D5	P1	P2	AUC
1sec	0.66	0.55	0.55	0.77	0.55	0.52	0.56	0.59
3sec	0.74	0.62	0.53	0.79	0.49	0.60	0.60	0.62
5sec	0.76	0.65	0.54	0.81	0.49	0.55	0.61	0.63
10sec	0.76	0.71	0.54	0.80	0.49	0.70	0.59	0.66
15sec	0.75	0.74	0.58	0.79	0.47	0.58	0.59	0.64
20sec	0.74	0.76	0.59	0.80	0.47	0.65	0.59	0.66
25sec	0.72	0.76	0.60	0.81	0.46	0.63	0.56	0.65
30sec	0.75	0.76	0.60	0.78	0.46	0.60	0.57	0.65
45sec	0.70	0.77	0.62	0.77	0.48	0.58	0.56	0.64
60sec	0.70	0.77	0.62	0.77	0.46	0.61	0.56	0.64
90sec	0.71	0.78	0.62	0.74	0.46	0.66	0.60	0.65
120sec	0.73	0.78	0.62	0.77	0.44	0.78	0.55	**0.67**

As depicted in Table II, the highest individual AUC score is 0.81% for dog4 at 10 sec and 25 sec, on the other hand, the lowest individual AUC score is 0.46% for dog5 at 25 sec and 30 sec. The highest overall AUC score is 0.67% for a window time of 120 seconds. For all that, the lowest overall AUC score is 0.59% for a window time of 1 seconds. A gradual change of overall AUC score about %5 is observed between 3 sec and 90 sec. We can see clearly that it is more successful time duration at 120 seconds for rectangular

TABLE III. RESULTS OF THE HAMMING WINDOWING FUNCTION

Window Size	D1	D2	D3	D4	D5	P1	P2	AUC
1sec	0.66	0.53	0.55	0.76	0.56	0.56	0.60	0.60
3sec	0.70	0.59	0.52	0.78	0.49	0.53	0.55	0.59
5sec	0.71	0.62	0.52	0.79	0.49	0.63	0.56	0.62
10sec	0.74	0.67	0.56	0.79	0.49	0.64	0.58	0.64
15sec	0.75	0.70	0.57	0.81	0.49	0.57	0.57	0.64
20sec	0.78	0.71	0.56	0.81	0.47	0.59	0.59	0.64
25sec	0.76	0.74	0.58	0.81	0.47	0.60	0.56	0.65
30sec	0.70	0.74	0.59	0.81	0.49	0.54	0.55	0.63
45sec	0.72	0.75	0.61	0.80	0.46	0.51	0.57	0.63
60sec	0.70	0.75	0.60	0.78	0.47	0.50	0.55	0.62
90sec	0.69	0.76	0.62	0.76	0.47	0.64	0.59	0.65
120sec	0.70	0.78	0.61	0.74	0.46	0.80	0.59	**0.67**

As shown in Table III, the highest individual AUC score is 0.81% for dog4 at between 15 sec and 30 sec, on the other hand, the lowest individual AUC score is 0.46% for dog5 at 45 sec and 120 sec. The highest overall AUC score is 0.67% for a window time of 120 seconds. For all that, the lowest overall AUC score is 0.59% for a window time of 3 seconds. A gradual change of overall AUC score about %3 is observed between 5 sec and 90 sec. We can inform distinctly that it is more accurate time duration at 120 seconds when it is compared with other time duration for Hamming windowing function.

As represented in Table IV, the highest individual AUC score is 0.81% for dog4 at 20 sec and 30 sec, the other hand, the lowest individual AUC score is 0.46% for dog5 at 45 sec and 120 sec. The highest overall AUC score is 0.67% for a window time of 120 seconds. For all that, the lowest overall AUC score is 0.59% for a window time of 1 second and 3 seconds. A gradual change of overall AUC score about %2 is observed between 5 sec and 90 sec. We can inference evidently that it is more effective time duration at 120 seconds when comparing other time durations for Hanning windowing function.

TABLE IV. RESULTS OF THE HANNING WINDOWING FUNCTION

Window Size	D1	D2	D3	D4	D5	P1	P2	AUC
1sec	0.61	0.53	0.50	0.76	0.56	0.56	0.58	0.59
3sec	0.68	0.57	0.54	0.77	0.50	0.54	0.54	0.59
5sec	0.72	0.59	0.52	0.79	0.49	0.58	0.56	0.61
10sec	0.73	0.63	0.56	0.79	0.50	0.60	0.58	0.63
15sec	0.75	0.68	0.55	0.80	0.49	0.57	0.62	0.64
20sec	0.76	0.70	0.56	0.81	0.48	0.57	0.62	0.64
25sec	0.77	0.72	0.58	0.80	0.48	0.61	0.60	0.65
30sec	0.72	0.72	0.57	0.81	0.49	0.54	0.60	0.64
45sec	0.72	0.74	0.61	0.79	0.46	0.51	0.61	0.63
60sec	0.71	0.75	0.60	0.79	0.47	0.51	0.61	0.63
90sec	0.70	0.77	0.62	0.76	0.47	0.54	0.58	0.63
120sec	0.70	0.77	0.61	0.75	0.46	0.79	0.58	**0.67**

TABLE V. RESULTS OF THE GAUSSIAN WINDOWING FUNCTION

Window Size	D1	D2	D3	D4	D5	P1	P2	AUC
1sec	0.61	0.53	0.55	0.77	0.56	0.57	0.59	0.60
3sec	0.68	0.56	0.54	0.77	0.50	0.54	0.56	0.59
5sec	0.71	0.59	0.52	0.79	0.49	0.60	0.58	0.61
10sec	0.73	0.63	0.57	0.79	0.50	0.60	0.59	0.63
15sec	0.76	0.68	0.56	0.81	0.49	0.58	0.61	0.64
20sec	0.77	0.70	0.57	0.81	0.48	0.59	0.58	0.64
25sec	0.77	0.72	0.58	0.81	0.47	0.60	0.56	0.64
30sec	0.72	0.72	0.58	0.81	0.49	0.56	0.58	0.64
45sec	0.72	0.75	0.61	0.80	0.46	0.51	0.61	0.64
60sec	0.73	0.75	0.60	0.79	0.47	0.50	0.61	0.64
90sec	0.71	0.76	0.62	0.76	0.47	0.62	0.60	0.65
120sec	0.70	0.77	0.61	0.75	0.46	0.77	0.55	**0.66**

As shown in Table V, the highest individual AUC score is 0.81% for dog4 between 15 sec and 30 sec, the other hand, the lowest individual AUC score is 0.46% for dog5 at 45 sec and 120 sec. The highest overall AUC score is 0.66% for a window time of 120 seconds. For all that, the lowest overall AUC score is 0.59% for a window time of 3 seconds. A slightly change of overall AUC score about %2 is examined between 5 sec and 90 sec. We have reached to conclusion that its is more success time duration at 120 seconds when comparing other time durations for Gaussian windowing function.

TABLE VI. RESULTS OF THE BLACKMAN WINDOWING FUNCTION

Window Size	D1	D2	D3	D4	D5	P1	P2	AUC
1sec	0.61	0.53	0.50	0.77	0.55	0.58	0.61	0.59
3sec	0.68	0.56	0.56	0.77	0.50	0.54	0.52	0.59
5sec	0.71	0.58	0.53	0.79	0.53	0.59	0.55	0.61
10sec	0.73	0.62	0.56	0.79	0.50	0.55	0.58	0.62
15sec	0.75	0.66	0.56	0.80	0.49	0.60	0.61	0.64
20sec	0.77	0.68	0.56	0.81	0.48	0.57	0.62	0.64
25sec	0.73	0.71	0.55	0.80	0.48	0.60	0.59	0.64
30sec	0.72	0.71	0.58	0.82	0.50	0.57	0.61	0.64
45sec	0.72	0.73	0.60	0.81	0.46	0.51	0.60	0.63

60sec	0.70	0.74	0.59	0.79	0.47	0.50	0.60	0.63
90sec	0.69	0.75	0.61	0.77	0.47	0.58	0.60	0.64
120sec	0.72	0.76	0.62	0.75	0.46	0.77	0.56	**0.66**

As depicted in Table VI, the highest individual AUC score is 0.82% for dog4 between 30 sec, the other hand, the lowest individual AUC score is 0.46% for dog5 at 45 sec and 120 sec. The highest overall AUC score is 0.66% for a window time of 120 seconds. For all that, the lowest overall AUC score is 0.59% for a window time of 1 and 3 seconds. A slightly change of overall AUC score about %3 is examined between 5 sec and 90 sec. We have reached to conclusion that its is more success time duration at 120 seconds when comparing other time durations for Blackman windowing function.

We have demonstrated that results of overall AUC scores of 5 windowing functions and 12 window times in fig. 2. As a result of the findings, the all windowing function has no huge effect on the change in the performance ratio. Merely by compared the others , it can be said that the rectangular windowing function has a slight difference. When we have criticized the results of the window duration, it is obviously concluded that best result is 120 sec.

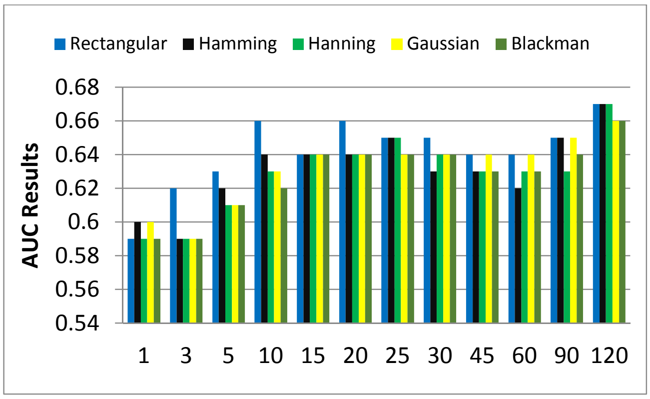

Fig. 2. Overall AUC Scores

Apart from all this point of results, we can say that the LDA classifier is successful when we look at the general results. Because the tests performed for the Dog1, Dog2, Dog4 and Patient1 subjects yielded an average performance rate of 77%. On the other hand, for Dog3, Dog5, and Patient 2, any windowing time, windowing function, there is not high successful rate level, especially Dog 5. Therefore, in subsequent studies, the development of this study for different features, a successful score value can be obtained.

EEG signals have disruptive effects like tissue noise, muscle movements, artefacts. That's why, the studies in related to epilepsy, it is needed to long-term records to building robust mechanism. As a result, training-testing processes take a long time. Especially in small window sizes (1 sec, 3 sec 5 sec), when the analysis is performed, test periods carried out in these time periods continue for days. On the other hand, for window times such as 30 sec -120 sec, decision results are executed in a shorter time.

IV. CONCULUSION

The data set used has an unbalanced data set structure. In real life, most of the data sets are like this. For this reason, the worth of the study becomes important at this point. Another important point is the first stage of software development studies related to epilepsy.

Studies on epilepsy have recently been the focus of interest of scientists. When obtained results are examined, small differences in performance results are seen, between 20sec and 60sec. Experimental result reveal that suitable window size is 120 seconds and window function is rectangular window function. Future studies, it is aimed to increase the performance rate by working on Wavelet transformation, non-linear features and different types of classifier structures such as bagging and boosting.

The windows size in biomedical signal processing is very vital role on investigation the changes of the EEG signals. Hence, this study is beneficial in terms of establishing the starting point of studies on epilepsy. The findings obtained in this study will be the milestone of the next studies.

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