Journal of Theoretical and Applied Information Technology
15th June 2018. Vol.96. No 11

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

TIME-FREQUENCY ANALYSIS IN ICTAL AND INTERICTAL SEIZURE EPILEPSY PATIENTS USING ELECTROENCEPHALOGRAM

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ABSTRACT

Conventional method to distinguish normal and seizure EEG by an epileptologist's visual screening is tedious and operator dependent. Normal DWT-based seizure detection technique established before suffers from deteriorating of performance due to increasing number of non-relevant features by wavelet decomposition. PCA approach has been utilized in this paper to overcome this problem. Energy, amplitude dispersion and approximate entropy (ApEn) of each sub-band were used as feature of interest and fed to Support Vector Machine (SVM) classifier. Differences between ictal, interictal and normal EEG based on these features were explored. There are significant differences in delta, theta and alpha band in sub-band energy, whereas ApEn changes are found in beta and alpha for ictal EEG. Amplitude dispersion illustrates changes in all sub-bands. PCA approach has been proven to have better accuracy (98%) compared to non-PCA approach (97%) in detecting ictal seizure. The proposed method produced the highest accuracy (98%) compared to other existing methods. The algorithm shows potential to be used clinically.

Keywords: *Time Frequency Analysis, Discrete Wavelet Transform (DWT), Approximate Entropy (ApEn), Principal Component Analysis (PCA), Support Vector Machine (SVM), Epilepsy, Seizure Detection*

1. INTRODUCTION

Epilepsy is one of the most common neurological disorders beside stroke and Alzheimer. According to WHO, about 2.4 million people are diagnosed with epilepsy every year, summing up estimation of 50 million people across the globe have epilepsy. Nearly 80% of epilepsy occur in low and middle income countries, including Malaysia [1]. In Malaysia, epilepsy affects about 1% of the population, whereby a rough estimation of 200,000 people is diagnosed with this disease till 2015 [2].

Epilepsy, which is characterized by recurrence of seizures, is a chronic non-communicable disorder of the brain that affects people of all ages. One of epilepsy symptoms is epileptic seizure which is defined as a transient occurrence of signs and/or symptoms due to abnormal excessive or synchronous neuronal activity in the brain [3]. According to International League against Epilepsy (ILAE) 2011, seizures have been classified into focal seizure, generalized seizure and aetiology seizure. Aetiology seizure has been further divided into idiopathic, symptomatic and cryptogenic. Epilepsy may cause by an abnormality of electrical activity or bio-chemistry in the brain, brain structure, spinal cord or other nervous system. Virus infections, trauma due to head injury or genetic factor are also other causes of epilepsy. However, only 30% to 40% of epilepsy patients have known causes [4]. Among the main complications of epilepsy include death due to the underlying neurologic disorder in symptomatic epilepsy, such as the phenomenon of sudden unexpected death in epilepsy (SUDEP) syndrome [5].

The growth of medical technology has assisted epileptologist in diagnosing and monitoring epilepsy more efficiently yet there are many limitations to be addressed in clinical practice. EEG continues to become the main contribution in

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

diagnosing and management of epilepsy compared to other method such as MRI, PET and CT because of its availability and relatively inexpensive methods to demonstrate the abnormality of brain activity [6]. This abnormality can be distinguished by looking at the features such as frequency, voltage, morphology, synchrony and periodicity from the EEG itself [7].

Conventional method used to distinguish normal and seizure EEG, such as visual screening is known to be time consuming and limited accuracy in clinical practice among developing countries. Researchers came out with ideas to develop automated seizure detection to eliminate these drawbacks, generating potential to replace visual screening. Among fundamental components to develop seizure detection method is transformation domain and feature extraction. Transformation domain, such as frequency domain or wavelet domain are advantageous in bio-signal analysis in acquiring further information from the signal that is not readily available in raw signal [8]. Selection of features to be extracted are significant as it is aim to clearly describe the information that characterize the signal [9]. This is to ensure the signal that belong to particular groups can be distinguished efficiently. Table 1 shows a combination of transformation domain and feature extracted by prior researchers.

A considerable amount of literature has reported the advantages of wavelet as transformation domain in automated seizure detection technique as it had superior resolution and high performance for visualization and representation of epilepsy activity [8], [16], apart it is suitable to analyse non-stationary signal [22]. Often, energy is extracted in each wavelet decomposition level as a feature due to high energy discharge during seizure caused by excessive neuronal activity [3] compared to non–seizure. Amplitude dispersion is another good feature to distinguish between seizure and non-seizure due to the dispersing of amplitude during seizure activity [23]. Approximate entropy (ApEn) has shown a good performance as feature in previous research to characterize the regularity of signal [24]. It is worth noting that, time-frequency analysis using discrete wavelet transformation (DWT) will increase the number of features depending on the wavelet decomposition level as the features need to be extracted in each level [24], [25]. This may increase the number of non-relevant features during this transformation, resulting in higher computational demands and poor performance [26].

Table 1: EEG Domain Analysis and Feature Extraction Summary

Researcher	Domain	Feature extracted
Runnarson [10]	Time	Amplitude difference and minima
Yoo [11]		Energy of the signal sub-bands
Dalton [12]		Variance, mean, zero-crossing rate, entropy and autocorrelation with template signal.
Rana [13]	Frequency	Phase-slope index
Khamis [14]		Power spectral density
Acharya [15]		Approximate and sample entropy
Zhou [16]	Wavelet	Lacunarity and fluctuation index
Liu [17]		Amplitude, relative energy, coefficient of variation and fluctuation index.
Khan [18]		Relative energy and normalized coefficient of variation
Tafreshi [19]	Empirical Mode Decomposition (EMD)	Min from Intrinsic Mode Function
Guarnizo [20]		Average frequency and amplitude
Vanrumste [21]	Singular Value Decomposition (SVD)	Dipole parameters, relative residual energy (RRE)

Our core concern in this research is to assist the epileptologist in epilepsy diagnosis by identifying potential ictal or interictal seizure segments using the proposed seizure detection algorithm. Current algorithm [23], [24], [27] that uses DWT suffers from lack of performance due to large number of non-relevant features. To address this issue, we developed a DWT-based seizure detection algorithm with Principal Component Analysis (PCA) incorporated. The outcome of our research is to develop a potential improved technique in detecting ictal or interictal seizure EEG segment using classification. The seizure detection algorithm is developed based on wavelet as domain and sub-band energy, amplitude dispersion and ApEn as the features of interest. Principal Component Analysis (PCA) is implemented in this paper to remove ineffective features extracted due to wavelet decomposition level. Support Vector Machine (SVM) is employed as a classifier to complete the development of seizure detection algorithm. The

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

performance of our method using PCA and non-PCA is compared with existing technique. In addition, we explore the differences between seizure and non-seizure based on these features.

2. METHODOLOGY

In this research, the pre-process online EEG data is decomposed into sub-bands by using Discrete Wavelet Transform (DWT). Signal during seizure in each sub band then is distinguished from normal EEG signal by extracting features based on their energy, amplitude dispersion and entropy. PCA is utilized as a dimensionality reduction method. PCA and non-PCA features then are fed into SVM classifier with Radial Basis Function kernel. Fifty data will be utilized for training while the other 50 data are used to classify for each 4 datasets that will be discussed later. Finally, the accuracy of this method is compared with existing technique. The process workflow is shown as in Figure 1.

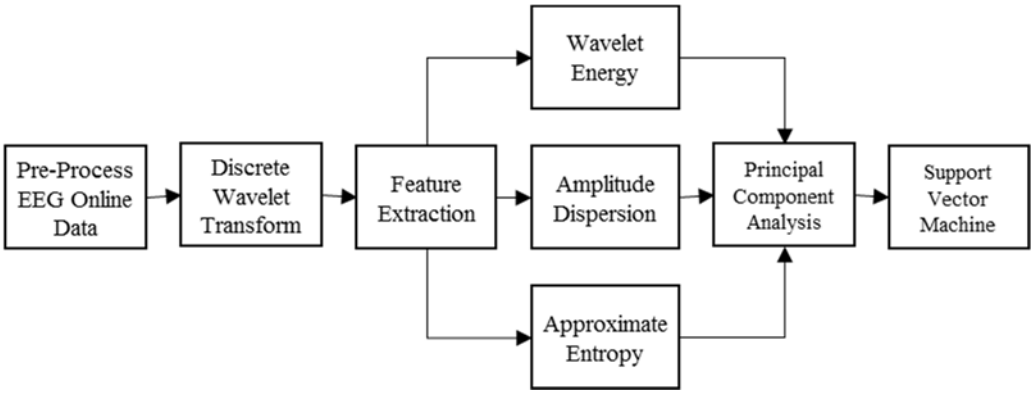

Figure 1: Process Flowchart for The Study

2.1 Online Database Management

This study utilizes four sets of public EEG data (A, B, C and D) which were downloaded from the Department of Epileptology, University of Bonn database [28]. Each set contains 100 single channels that were recorded using 128-channel amplifier system. The duration of each data is 23.6 seconds, sampled at 173.61Hz and were band-pass filtered from 0.53 Hz to 40 Hz. Set A consists of 5 healthy subjects where the subjects were awake and relaxed with eye opened. For set B and C, which are interictal, the EEG were recorded within the opposite brain of epileptogenic and within epileptogenic region respectively. Both of these set were recorded during seizure free intervals and only set D contained seizure activities (ictal seizure). The electrodes placements are according to international 10-20 system and the summarization of data sets detail are as in Table 2.

Table 2 Summary of clinical data

	Set 1 (A)	Set 2 (B)	Set 3 (C)	Set 4 (D)
Subject Condi-tion	Healthy subject with eyes open	Epileptic subject with non-seizure activity	Epileptic subject with non-seizure activity	Seizure activity subject
Electrode place-ment	10-20 systems	Opposite hemisphere of epileptogenic zone	Within epileptogenic zone	Within epileptogenic zone

2.2 Signal Processing and Feature Extraction

2.2.1 Discrete wavelet transform

The wavelet transform is a mathematical technique where it can convert the signal into a scaled and shifted version of the mother wavelet and express it in terms of frequency and time [29]. The main advantage of DWT is it gives accurate information regarding frequency when the data signal frequency is low, but very reliable information in time when the data signal frequency is high. This is because most of the signal in biomedical field has a long duration of low

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

frequency signal including EEG itself [30]. The wavelet transformation can decompose a signal into a sub-band frequency that can be described by the Eq. (1):

$$f(t) = \sum_{j \in Z} 2^{j/2} c_j(k) \varphi(2^j t - k) + \sum_{j=0}^{j-1} \sum_{k=0}^{\infty} 2^{j/2} d_j(k) \omega(2^j t - l) \quad (1)$$

where ϕ(t) is a scaling function, ω(t) is a mother wavelet function. The signal undergoes high pass filter and low pass filter that will produce an approximation of f(t) and detail of f(t) respectively which will be presented in finer scale. This technique is known as discrete wavelet transforms. When the wavelets are orthogonal [31], these coefficients can be calculated as in Eq. (2) and (3)

$$c_j(k) = \int_{-\infty}^{\infty} f(t) \varphi(2^j t - k) dt \quad (2)$$

$$d_j(k) = \int_{-\infty}^{\infty} f(t) \psi(2^j t - k) dt \quad (3)$$

Where cj(k) and dj(k) are approximations (low pass) and detail (high pass) coefficients respectively. The signal frequency in low pass filter will be divided by two in each level according to Nyquist theorem [32]. This decomposition can be repeated to any level based on frequency band we desire and as the decomposition level increase, the bandwidth length will decrease and the detail will increase. In each level the frequency resolution will be doubled while time resolution is reduced by half.

For this research, DWT act as pre-processing and the level decomposition use is 5 (1 detail coefficient and 5 approximation coefficient). The Daubechies 4 (db4) is selected as basis function because it yielded the lowest mean square error [33]. The signal is decomposed into 5 levels so that it is easy to categorize into delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz) and gamma wave (>30Hz). The sampling rate for the EEG data is 173.71 Hz and it will be divided by two according to Nyquist Theorem. Each band represented by coefficient can be observed in Table 3. By using MatLab, the raw EEG signal is decomposed into sub bands and the features are extracted.

Table 3 Coefficient and percentage of representation of sub-bands

Coefficient	Frequency Band (Hz)	Type of wave	Level of Decomposition
D1	43.40-86.81	Noise	1
D2	21.70-43.40	Beta-Gamma	2
D3	10.85-21.70	Alpha-Beta	3
D4	5.43-10.85	Theta-Alpha	4
D5	2.71-5.43	Delta-Theta	5
A5	0.5-2.71	Delta	5

2.2.2 Wavelet Energy

Total of 5 wavelet energy is obtained for every EEG epoch by calculating the area under the graph using Eq. (4) where C represents a coefficient.

$$Energy = \sum_{-\infty}^{\infty} \left| C_{Approximate\ or\ Detail} \right|^2 \quad (4)$$

Percentage wavelet energy then is extracted as feature using Eq. (5) where E_C is coefficient energy while E_T is total energy of the EEG.

$$Energy\ Percentage = \frac{E_C}{E_T} \times 100 \quad (5)$$

2.2.3 Amplitude dispersion

Amplitude dispersion is calculated by using standard deviation formula as in Eq. (6)

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - \mu)^2} \quad (6)$$

where N is numbers of point, x_i is individual point in time series and μ is mean. The purpose of amplitude dispersion is to see how disperse the amplitude in each sub-bands of all four sets of data. Figure 2 shows dispersion of the amplitude of the raw EEG signals for the four EEG data sets.

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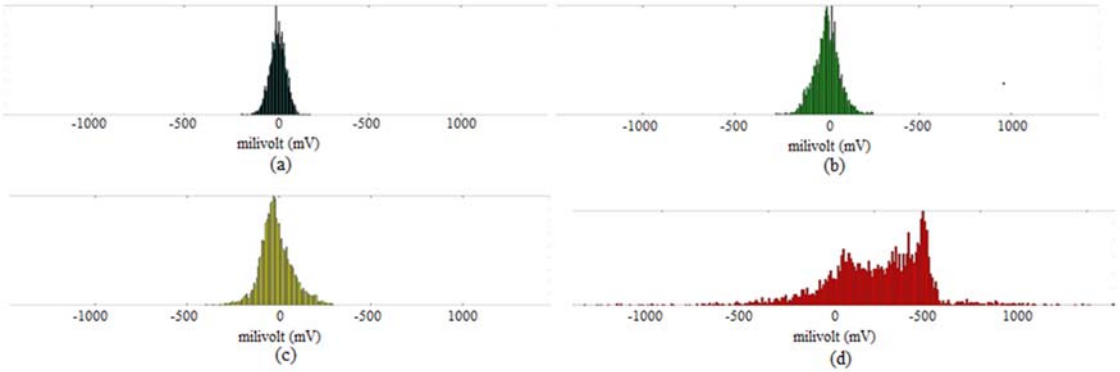

Figure 2: Sample of distribution of EEG amplitude from the data (a) Set A has normal distribution (bell shape) and center amplitude (b) Set B has normal distribution (bell shape) and center amplitude (c) Set C has normal distribution (bell shape) and center amplitude (d) Set D dispersion distribution with multiple amplitudes

2.2.4 Regularity and predictability measurement

Approximate Entropy first was developed by Pincus to measure system complexity [34]. In signal analysis, ApEn helped to measure the regularity and predictability of a signal [35]. The slow and spike EEG pattern during epilepsy caused by synchronous discharge of neurons will make the EEG signal appear regular and repetitive, thus making it a suitable feature to be extracted to differentiate between the normal EEG and seizure EEG. The value of ApEn can be determined by following procedure.

1) Let a data sequence containing n data points be S_n = {u(1), u(2), u(3),….,u(n)]
2) Choose value of m and r where m = pattern length and r = criterion of similarity
$r = k \times SD$ for k=0, 0.1, 0.2, 0.3, …, 0.9. SD will be present as standard deviation of data S_n
3) Let X be sequence of x(i) such that x(i)=[u(i), u(i+1), u(i+2), …, u(i+m-1)]
where i=1, 2, 3, …, (n-m+1)
4) Find the distance between vector x(i) and x(j) by using formula
$d[x, x^*] = \max_a |u(a) - u^*(a)|$, if $d[x, x^*] < r$ the pattern are likely similar
5) Calculate $C_i^m = \frac{number\ of\ d[x,x^*] less\ than\ r}{(n-m+1)}$
and $C_i^{m+1} = \frac{number\ of\ d[x,x^*] less\ than\ r}{(n-m+1)}$
6) Define $\Phi^m(r) = \frac{\sum_{i=1}^{n-m+1} \ln(C_i^m(r))}{n-m+1}$ and $\Phi^{m+1}(r) = \frac{\sum_{i=1}^{n-m+1} \ln(C_i^m(r))}{n-m+1}$
7) ApEn(m,r,n) is determined as follow: $ApEn(m,r,n) = \Phi^m(r) - \Phi^{m+1}(r)$

If the value of ApEn is large, it indicates that the signal is unpredictable and irregular while a small value of ApEn shows high regularity and repetitive pattern. To determine the ApEn, the (m) and (r) are set to 2 and 0.2xSD respectively based on [35] to obtain the highest percentage of efficiency. The ApEn is calculated in each sub bands and the average ApEn is obtained. Figure 3 shows example spike and wave pattern of raw seizure EEG data.

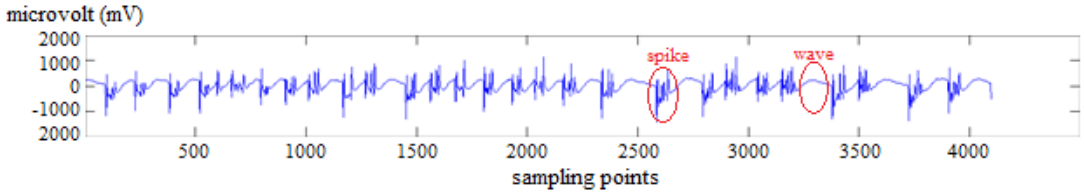

Figure 3: Example of spike and wave in Set D showing repetitive patterns

2.3 Dimensionality Reduction

PCA is proposed in this paper as its ability to remove non-relevant feature, thus decreasing computational complexity [26]. PCA works by finding uttermost variance of data by casting aside the data that have lesser variance [36]. The eigenvector and eigenvalue must be obtained first. Eigenvector is the direction where the data has the most variance, whereas eigenvalue represents a number that indicates how much the data scatter throughout the direction. Principal component will

Journal of Theoretical and Applied Information Technology
15th June 2018. Vol.96. No 11

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

be chosen based on eigenvector that has the largest eigenvalue direction [37].

2.4 Classification

SVM is supervised classifier that works by constructing a hyperplane with largest margin to separate between two groups [38]. Supervised classifier requires data to be trained first before classifying. 50 EEG data for each set were selected randomly to be trained while remaining 50 EEG data is for classifying. Radial basis function (RBF) is choose as SVM kernel because of its ability to handle the relation between attributes and class labels that are non-linear [39]. SVM is known for its ability to handle large dimension of features [40]. In this research, we will able to see the performance of SVM in handling very low feature vector.

3. RESULT AND DISCUSSION

3.1 DWT of Sub-Bands Energy

Figure 5 shows the average percentage of wavelet energy with standard deviation for each data sets and Table 4 shows the numerical values. The wavelet energy is divided into A5, D5, D4, D3, D2 and D1 based on their frequency range as mentioned in Table 3. This coefficient helps us to see the differences in the brainwaves pattern in each data set and bring us to the conclusion that during a seizure, brain will produce specific patterns of brainwaves. Set D which contain seizure activity shows sudden drops of energy in coefficient A5 while scores the highest energy for coefficient D5, D4 and D3 among all sets. For epilepsy patients during seizure free subject (Set B and Set C), the energy shows declining pattern from A5 to D1. In terms of brainwaves level, set D (EEG during seizure) has high energy level for coefficients containing theta wave (D5) and alpha wave (D4 and D3) compare to other brainwaves in all other data sets. Our findings support the claims by [41]. Quiroga stated that the pattern of seizure EEG could be characterized by reduction of delta while increasing of theta and alpha. Compared to our method, Quiroga used Gabor Transform and difference EEG data.

Figure 5 also shows the standard deviation of discrete wavelet energy of the four different EEG datasets. Seizures data set shows the highest standard deviation in all coefficient except in D2. The large standard deviations of seizure imply that it has large varying energy value and can be misinterpret as normal condition.

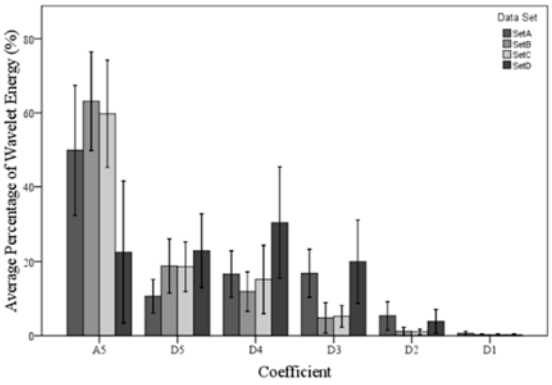

Figure 5: Error bar graph consisting average percentage of wavelet energy with their standard deviation.

Table 4 Average percentage of wavelet energy with standard deviation

	Set A	Set B	Set C	Set D
A5	49.93±17.35	63.13±13.25	59.74±14.42	22.51±19.01
D5	10.62±4.52	18.81±7.27	18.62±6.66	22.94±9.93
D4	16.63±6.25	11.91±5.26	15.16±9.18	30.50±14.87
D3	16.84±6.42	4.79±4.06	5.22±2.93	19.97±11.22
D2	5.35±3.78	1.152±1.11	1.03±0.73	3.85±3.18
D1	0.63±0.53	0.25±0.19	0.22±0.23	0.22±0.23

3.1 Dispersion of EEG in each sub-bands

Figure 6 shows the amplitude dispersion for all sets of data and exhibit that seizure activity subject is higher compared to the normal state subject for all coefficients. The result of high amplitude dispersion in all coefficients shows the brainwaves during seizure yield higher variations in voltage than normal condition, supporting previous claim [42].

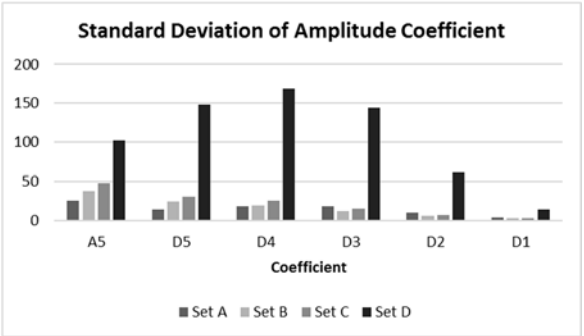

Figure 6: Dispersing of amplitude shown by using standard deviation

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

3.1 Regularity and predictability of EEG in each sub-bands

The graph in Figure 7 show the regularity for each coefficient. The four sets of data show very close ApEn value for coefficient A5, D5 and D4, but the value gap between normal and seizure condition become larger as the frequency of sub band increase starting at D3. Set A and set B has a very similar pattern compared to other sets, implying that the brainwaves in the opposite hemisphere of epileptogenic region has same regularity as normal subjects. In Set D perspective, the results show that the regularity and predictability remain nearly the same after coefficient D4.

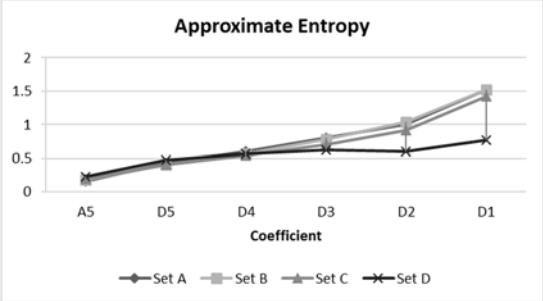

Figure 7: Approximate Entropy (ApEn) in each sub-band for each data set.

This finding supports the evidence that the pattern of neuronal firing represented by EEG is less organized and has greater chaoticity and complexity in normal brain activity compared to during seizure [43]. This finding is consistent with the one reported by [44]. In his research, the ApEn feature is extracted on seizure data without higher frequency bands such as beta and gamma taken into account. It is interesting to see that we discovered the higher frequency band are contributing the most in seizure predictability and regularity pattern based on decreasing of ApEn value.

3.4 Dimensional Reduction and Classification of EEG Signal

The total of 18 features has been reduced to three features when using PCA. The performance using PCA and non-PCA is distinguished using SVM as classifier. Table 5 shows the comparison of performance between PCA and non-PCA method using SVM. It is shown that PCA managed to increase the accuracy for set A vs set D, set C vs set D and set B vs set D while decreases others. This bring us to conclusion that the usage of PCA only can improve the classification involving ictal seizure with normal and ictal with interictal seizure. Decrease of accuracy when using PCA on A vs B, A vs C and C vs B because the lack of number of features to distinguish between them. In terms of sensitivity and specificity, PCA manage to enhance the accuracy and specificity in both metrics in set that contain ictal seizure such as set C vs D and set B vs D. However, the use of PCA for set A vs D has produces a slight drop in sensitivity but increase the specificity of the algorithm. Nevertheless, the sensitivity and specificity are both still high and desirable. Above all, PCA is able to produce overall good sensitivity and specificity differentiating normal EEG from the ictal EEG.

Table 5 Comparison between PCA and non-PCA method based on accuracy (Acc), sensitivity (Sens) and specificity (Spec). Bold values indicate the highest accuracy based on dataset

		PCA				Non-PCA			
		TP and TN	Acc.	Sens.	Spec.	TP and TN	Acc.	Sens.	Spec.
A vs B	A (TP)	46	88.00%	85.20%	91.30%	49	**89.0%**	83.1%	97.60%
	B (TN)	42				40			
A vs C	A (TP)	48	92.0%	88.9%	95.7%	49	**99.0%**	100.0%	98.0%
	C (TN)	44				50			
A vs D	A (TP)	50	**98.0%**	96.2%	100.0%	47	97.0%	100.0%	94.3%
	D (TN)	48				50			
C vs B	C (TP)	24	64.0%	70.6%	60.6%	37	**68.0%**	66.1%	70.5%
	B (TN)	40				31			
C vs D	C (TP)	48	**98.0%**	100.0%	96.2%	40	90.0%	100.0%	92.6%
	D (TN)	50				50			
B vs D	B (TP)	50	**100.0%**	100.0%	100.0%	45	95.0%	100.0%	90.90%
	D (TN)	50				50			

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

To evaluate our proposed seizure detection method, two existing techniques are used as comparison. The first technique was developed by Ocak [24] using a 3 level DWT as pre-processing steps. Instead of classifier, ApEn threshold was used to distinguish seizure and non-seizure. More recent study by [45] has utilized 5 level Multi-wavelet Transform and Neural Network (NN) as classifier. No PCA was implemented in both studies. A summary of the techniques used by previous researchers compared to the proposed method described in this paper is tabulated in Table 6.

Table 6: Comparison technique used between previous researcher and proposed method

	Ocak	Sharanreddy	Proposed Method
Dataset	University of Bonn	Children's Hospital Boston	University of Bonn
Signal Processing	DWT 3 level decomposition	DWT 5 level decomposition	DWT 5 level decomposition
Features Extraction	ApEn		Wavelet Energy, ApEn, Amplitude Dispersion
Dimension Reduction	None	None	PCA
Classifier	ApEn Threshold	Neural Network	SVM

The accuracy of both existing technique is compared to the proposed method and the result is tabulated in Table 7, which highlights the result for normal versus ictal seizure.

Table 7: Accuracy of normal vs ictal seizure (A vs D) for the proposed method compared to existing techniques.

Ocak	Sharanreedy	Proposed Method	
		PCA	Non PCA
96%	83%	98%	97%

The superiority of the proposed algorithm in comparison to past researchers is the ability to identify the more relevant features for the ictal and interictal segment detection. The drawback of our proposed method is the increase in processing time due to the addition of PCA. The proposed algorithm reduced the performance in detecting interictal seizure but enhancing the ictal seizure detection which is more important in epilepsy diagnosis.

The most significant limitation in this study is the data being an anonymous online pre-processed data which does not have any demographic details. The proposed algorithm need to be validated against actual clinical EEG data.

4.0. CONCLUSION

Our main finding in this research is the development of ictal and interictal seizure segment detection algorithm that are potential to be used in clinical environment. Implementation of PCA managed to resolve the overstretched features in detecting ictal seizure by increasing its accuracy. PCA based interictal seizure detection has an accuracy of 92% in the present implementation based on the available data. The ability of the algorithm in identifying the presence of ictal and interictal seizure expected to assist the clinician's time management. Other findings show the sub-bands energy in delta, theta and alpha are able to differentiate the signal condition. Whereas, the amplitude dispersion variations indicate that seizure effect is potentially different between individuals. ApEn during seizure shows differences when the frequency is higher than upper alpha, while the lower frequency of all data sets exhibit similar regularity. SVM classifier is found to be effective in managing the low dimension features. In the future study, we will focus on clinical data collection in a single type of seizure or a particular age group along.

ACKNOLEDGEMENT:
This work was financially supported by the grant from Universiti Kebangsaan Malaysia (FRGS/1/2016/TK04/UKM/02/1)

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