EPILEPTIC SEIZURE DETECTION USING SINGULAR VALUES AND CLASSICAL FEATURES OF EEG SIGNALS

Technical Paper

By

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Submitted to the Electrical & Electronics Engineering Programme
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CERTIFICATION OF APPROVAL

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Approved:

_____

Supervisor's Name
Project Supervisor

UNIVERSITI TEKNOLOGI PETRONAS
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September 2014

CERTIFICATION OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.

AHMED ELSAYED ELMAHDY AHMED

ABSTRACT

This project aims at developing an automated epileptic seizure event detection algorithm. The proposed algorithm depends on using five features which are singular values, total power, delta band power, variance and mean. In this algorithm a sliding window of one second is utilized to check for epileptic seizure at each second and the classification method used is support vector machine (SVM). The proposed algorithm was tested through using CHB-MIT Scalp EEG Database which was recorded in the children hospital in Boston. The results were evaluated in terms of accuracy, sensitivity, specificity and failure rate. The results showed that the proposed algorithm is successful in identifying epileptic seizures. An average accuracy of 94.82% was achieved.

ACKNOWLEDGEMENTS

I would like to show my appreciation and to send my sincere thanks to all who have helped me during my final year. My deepest gratitude goes to my supervisors Assoc. Prof. Dr. Nidal Kamel and Ms. Norashikin Binti Yahya for their great support and advice. I would like to thank Mr. Arsland Shahid, for his time & effort with me and for acting as a mentor.

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1. INTRODUCTION

This chapter identifies the main problem which the project is developed to solve. In this chapter also, the objectives of the project are defined. Furthermore some background information about epileptic seizures and seizures detection algorithms is given.

1.1.Background

Epileptic seizure is a widely spread disorder that millions of people suffer from it. Several studies have stated that around 1% of the whole population of people on earth suffer from epilepsy. According to “International League Against Epilepsy” (ILAE) and “The International Bureau For Epilepsy” (IBE), epileptic seizures can be defined as excessive or over-synchronized electric discharges. Epilepsy is a family of syndromes which can be classified into either partial (Focal) seizures or generalized seizures depending on how limited the brain area where the seizure takes place. It has been proven that Electroencephalogram signals (EEG) can be used to identify epileptic seizures. Several automated seizure detection algorithms have been proposed over years. These algorithms are capable of extracting specific features within EEG signals analyzing them and determining whether an epileptic seizure took place or not.

1.2.Problem Statement

Nowadays there has been a need for an efficient and an accurate recognition of epileptic seizures. The only way to meet these requirements is through developing an automated algorithm which is capable of extracting features, analyzing them and determining whether an epileptic seizure exists.

1.3.Objectives and scope of study

The objectives of the project are:

1. To develop an algorithm capable of recognizing epileptic seizures.
2. To validate the developed algorithm through using existing epilepsy databases and comparing it with recent algorithms.

1.4.Significance

This project is significant as it can be used in research purposes such as determining the relation between specific stimuli and seizures, generating a seizure predictor algorithm, converting from seizure event to seizure onset detector and etc.

2. LITERATURE REVIEW

In this chapter, a brief explanation of the neural activities is given which involves clarifying how brain signals are being transmitted and the functions of various brain parts. This is followed by an overview of electroencephalography (EEG) signals. Furthermore this chapter provides a brief overview about epileptic seizures' definition, different forms and symptoms. In addition this chapter explains the singular values decomposition theorem and the relation between singular values and energy distribution. Last but not least, several algorithms for detecting epileptic seizures are being reviewed.

2.1.Overview of neural activities

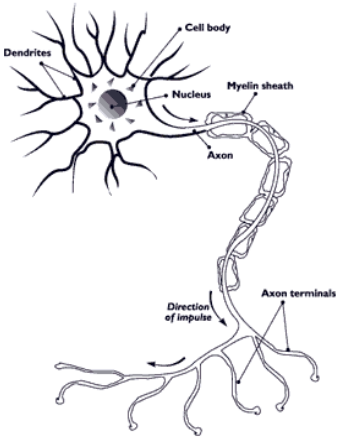

Figure 1: nerve cell (neuron) [1]

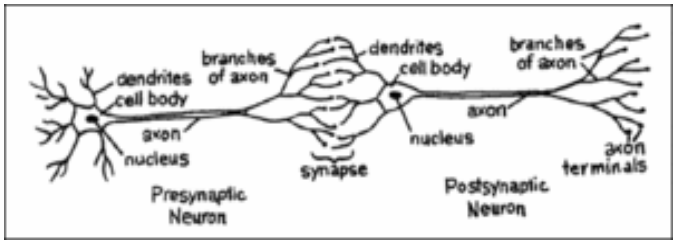

Figure 2: Neuron-neuron information transmission [2]

In order to explain how brain signals are being transmitted, it is necessary to have a basic understanding of the brain and cell structure. The central nervous system consists of two types of cells which are gila cells and neurons. The function of gila cells is to support and protect the neurons through providing nutrients and oxygen, destroying pathogens, etc. On the other hand a nerve cell or neuron consists of three parts which are

axon, dendrites and cell body. Dendrites acts as receptors while axons acts as senders. The space between one neuron's axon and the next neuron's dendrites is called the synapse and it acts as a communication site between cells. The structure of the neuron is shown in both Figure 1 and Figure 2 [3].

Within the axon terminal there are sacs which are filled with several chemicals that are called neurotransmitters. A neuron can send a particular message to other neurons through using a specific neurotransmitter.

So in order to send a signal from one neuron to another one, the axon will release specific neurotransmitters to the dendrites of the other neuron through synapse.

So basically all what is needed to transmit a specific signal from one neural cell to another is neurotransmitters (chemical reaction), however the cell still needs to transmit the received signal from its dendrites to its axon. This is done through electricity. The interaction between the neurotransmitter and receptor (dendrites) will make the cell membrane more porous which will allow external positive ions to go through the membrane and into the cell. This will result in making the cell positively charged. So in order to restore the resting state, the positive charge will start to move along the axon till it reaches its terminals resulting in releasing the appropriate neurotransmitters outside the cell [3].

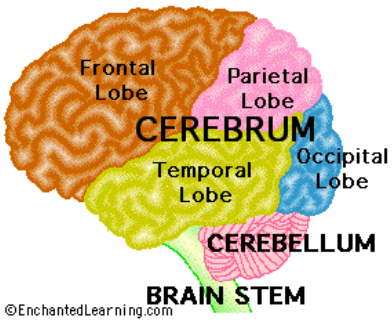

Figure 3: Brain Regions [5]

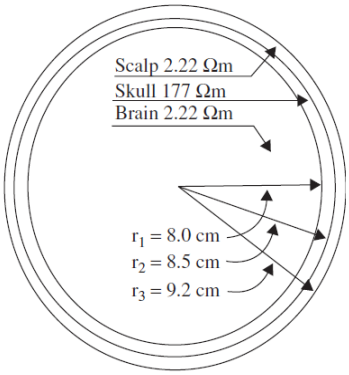

Figure 4: Resistance within the brain [4]

As seen in Figure 3, the brain is divided into three parts which are

1. The cerebrum: It contains regions which are responsible for several functions such as movement, awareness, analysis, etc.
2. The cerebellum: This region is responsible for coordinating muscles voluntary movements and maintaining balance.
3. The brain stem: This region of the brain is in charge of involuntary functions such as regulation of the heart and breathing [4].

2.2.Overview of EEG recordings

The current that is produced during information transmitting between nerve cells generates a magnetic field that can be measured by electromyogram (EMG) machines and an electrical field that can be measured by electroencephalogram (EEG) systems. The electrical signals can be detected by connecting electrodes (in pairs) to the scalp. After which the signals will be amplified and recorded. [4]

The attenuation produced while measuring the signal can be classified according to its source into three groups which are:

- Internal noise: produced within the brain
- External noise: such as power supply noise
- The skull: as shown in Figure 4, the resistance of the skull is much higher than both scalp and brain. This relative high resistance can weaken the signal.

2.3.Brain rhythms:

Brain waves can be classified into five major groups based on their frequency ranges. These groups are explained in more detail in both Figure 5 and Table 1.

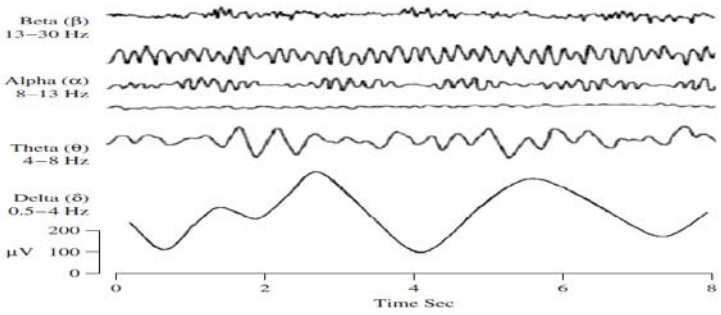

Figure 5: Brain Waves [4]

Brain Rhythms	frequency ranges in Hz	Associated with
Delta (δ)	0.5–4	Deep sleep state
Theta (θ)	4–8	Creative inspiration and deep meditation
Alpha (α)	8–13	Relaxed awareness
Beta (β)	13–30	Active thinking and attention
Gamma (γ):	above 30	Brain diseases

Table 1: brain waves

2.4.Overview of epileptic seizures

According to "International League Against Epilepsy" (ILAE) and "The International Bureau For Epilepsy" (IBE), epileptic seizures can be defined as excessive or over-synchronized electric discharges (brain activity).

Epileptic seizures can be divided into two main categories which are Partial (Focal) Seizures and Generalized Seizures. Partial (focal) seizures take place when the abnormal electrical activity remains in a limited area in the brain. Partial seizures can be further divided into Simple Partial Seizures and Complex Partial Seizures. The main difference between them is that in simple partial seizures, person's awareness and/or memory are not affected. However in complex partial seizures, a person's awareness and/or memory are affected [6].

Symptoms of Partial seizures differ based on the brain region where the seizures took place, the symptoms usually include but not limited to the following:

- Hallucinations
- Abdominal pain or discomfort
- Nausea
- Sweating
- Abnormal muscle contraction

Generalized seizures affect both left and right brain hemispheres. Generalized seizures can be further divided into several groups, they all involve loss of consciousness. The main six groups are described briefly Table 2 below [7].

No	Seizures	Brief Description
1	Absence (Petit Mal)	▪ They are usually short in period (seconds) ▪ They have a sudden start and termination
2	Tonic	▪ The muscle will stiffen up ▪ The eyes will roll back into the head
3	Clonic	▪ Can last for several minutes (long compared to absence seizures) ▪ Arms and Legs muscle contractions
4	Tonic-Clonic (Grand Mal)	▪ Rigid muscles ▪ Difficulty in breathing ▪ Inability to control urine or stool ▪ violent muscle contractions
5	Atonic	▪ Loss of muscle tone.
6	Myoclonic	▪ Arms and Legs muscle contractions ▪ They are usually short in period (seconds)

Table 2: Generalized seizures

2.5.Singular Value Decomposition (SVD)

The theory of Singular Value Decomposition is based on linear algebra. The theorem states that a rectangular matrix (A) of dimensions mxn can be decomposed into three other matrices which are

1. An orthogonal matrix (U) whose columns represent the left singular vectors.
2. A diagonal matrix (S) which contains singular values arranged in descending order.
3. A transpose of an orthogonal matrix (V) whose columns represent the right singular vectors.

The Singular Value Decomposition equation is shown below

$$A_{mxn} = U_{mxm} S_{mxn} V_{nxn}^{T} \quad (1)$$

Singular Value Decomposition can be used to improve the representation of matrix variables; it can be used to show the variables' relationships in a much clearer way. Furthermore it can also be used as a way of determining the data points that represent the main variation. Therefore it can be used for data reduction by representing and approximating the original data using fewer dimensions [8].

As stated before, the singular values are the diagonal values of the matrix (S). In this project singular values will be used to indicate the distribution of energy within the matrix which will be utilized as a feature to indicate epileptic seizures. The relationship between singular values and oriented energy is based on a theorem which states that the square of i-th singular value is equal to the oriented energy measured in i-th left singular vector direction. Furthermore the oriented energy magnitude will be equal to the sum of squared singular values if taken at an arbitrary direction. The theorem also states that if the matrix is not full rank, then there will be directions that contain no energy.

From this theorem we can conclude that by calculating the singular values we can have an indication of the energy distribution within the matrix [9].

2.6.Previous algorithm

An epileptic seizure detector can be classified into two groups. The first group is seizure onset detector whose function is to identify epileptic seizures with the minimum possible delay, however not necessarily the highest possible accuracy. The second group is seizure event detector whose function is identifying epileptic seizures with the highest possible accuracy, but not necessarily with the shortest time delay. Previous seizure event detector algorithm will be reviewed since this project falls in the category [10].

One of the first algorithms developed in this category was proposed by Gotman et. al. The algorithm developed by Gotman uses frequency spectrum analysis to identify certain features as the dominant spectral peak's frequency and width. Furthermore the

algorithm identifies the relative power of the dominant spectral peak compared with the power of the background spectrum. The drawbacks of the algorithm are its incapability to detect seizures within EEG recordings that has several frequencies as well as high frequencies with low amplitude. Also spikes caused by artifacts were recognized as a seizure [10].

Another algorithm was proposed by Liu. According to Liu, the basic feature that can successfully identify epileptic seizure in EEG recordings is periodicity. He was able to recognize the level of periodicity though using autocorrelation function for intervals of duration half a minute [10].

Later, another algorithm was proposed by Hassanpour et al. In this algorithm, the EEG recording was divided into intervals of 30 seconds each. The intervals were represented using time-frequency domain representations. Singular values were used to represent the intervals. After which the extracted singular values were rearranged as a vector that is fed into a classifier to differentiate between epileptic and non epileptic periods [10].

A recent algorithm was proposed by Rafiuddin et. al. In this algorithm the EEG signals are subjected into 5 level decomposition using daubechies (db4) wavelet. Four features are being extracted. The first two features are energy and coefficient of variation which relates to the rhythmic behavior displayed by during the seizure. The third feature is the interquartile range (IQR) which is an indication of the signal statistical dispersion. The fourth and the last extracted feature is the median absolute deviation which is basically the ratio of the standard deviation to the mean. Both interquartile range and median absolute deviation are calculated using the raw data [11].

A new method was proposed by Shahid et. al which utilizes Singular Value Decomposition as a way to identify epileptic seizures. Singular values are calculated for a matrix representing EEG values generated from 18 channels for a sliding window of 1 second long. The singular values represent the distribution of energy within the matrix. The values are then fed to a classifier which determines if a seizure took place [9].

3. METHODOLOGY

In order to be able to identify epileptic seizures, several steps have to be followed. This chapter explains all the steps carried out to implement the algorithm. The steps are shown in the block diagram in Figure 6 below.

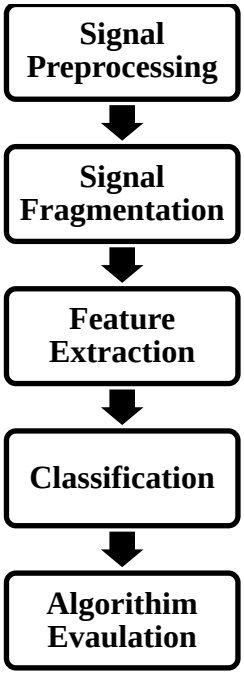

Figure 6: Block diagram for methodology steps

3.1.Signal Preprocessing

Signals must be preprocessed before being used. Several preprocessing activities are being implemented such as filtering specific frequency bands and converting the EEG recordings into a readable format in order to be recognized by the software.

3.2.Signal Fragmentation

In order to be able to deal with EEG signals more efficiently, EEG signals are divided into L-sec-long intervals. In other words the EEG recordings are divided into interval of predefined length. Since the sampling frequency for the EEG recording is 265 HZ, each one second in the recording is represented by 256 points. So in order to check for epileptic seizure at each second, the interval length used is 256.

3.3.Feature Extraction

What is meant by feature is any distinctive attribute that can help in differentiating between the two cases “Seizure” and “No Seizure”.

There are several types of features that can be used. Several example of the features that have been used before are shown below [12].

1. Physiological Features: an example of physiological features is synchronicity measurement. As it is believed that during epileptic seizures, neurons will generate electric signals synchronously.
2. Morphological Features: examples of morphological features are EEG spikes and waveform characteristics. It is possible to detect epileptic seizures by checking for certain distinctive attributes which are associated with EEG recordings such as sharpness, height, and duration of the spikes and shape and amplitude of the waveform. Another example of morphological features is sudden change in frequency in waveform.
3. Frequency domain Features: such as the relative power of specific band and the total power of the EEG signal (for a predefined interval) [12].
4. Time domain Features: Examples of time domain features are mean, variance (for a predefined interval) [12].
5. Others: other methods exist for feature extraction such as using genetic programming to create artificial features which may not have physical meaning [13].

In this project two main types of features will be utilized which are singular values and classical features. As explained in the literature review, singular values can be used as an indication for energy distribution. Singular values will be calculated using Singular Value Decomposition (SVD) formula which was shown before. Regarding classical features, several features will be extracted and examined such as power, mean and etc. these features will be presented and explained in more detailed manner in the results and discussion chapter.

3.4.Classification

What is meant by classification is assigning the features that were observed and extracted in the previous step into one of two classes “Seizure” and “No Seizure”. The classification must be carried out in a way that minimizes classification error. It is important to note that the success of the classifier used depends strongly on extracted features and how clearly they differentiate between the two classes.

So after the features have been extracted, they will be arranged in a vector which will be fed to a classifier. Generally speaking the features fed to the classifier are divided into the three sets which are

- Training Set: this data set will be used to train the classifier on differentiating between seizure and non seizure classes.
- Validation Set: the objective of this dataset is to minimize the over-fitting of the classifier training. In other words the validation data set is used to confirm that any increase in classifier training will result in higher accuracy in classification of data that has not been used for training. If low accuracy was achieved, then training must be stopped.
- Testing Set: the objective of the testing data set is to test whether the classifier is able to assign correctly a set of data.

All of the three data sets were pre-classified. Both validation and testing sets were not used in training the classifier.

Several methods of classification were used in previous papers such as the following [12].

1. Linear classifiers
2. Artificial Neural Networks (ANN)
3. Decision tree
4. Learning Vector Quantization
5. Probabilistic Neural Networks
6. Support Vector Machine

The software used to classify in this project is Weka Software. It is a machine learning program which can be used for data analysis classification, data modeling and etc. Regarding the classification method, Support Vector Machine (SVM) will be used. Support vector machine is an example of machine learning. In SVM a hyper-plane which is characterized by having a high dimensional space is created. This hyper-plane is divided into two halves i.e. one half for each class. In order to have a good separation between classes a large margin has to be achieved through increasing the distance between the hyper-plane separation and the existing data instances. SVM can be classified into linear and non linear. Non linear classifier is similar to linear classifier with the major difference is using kernel functions instead of dot product to identify the hyper-plane separation. SVM can be used for multi class classification.

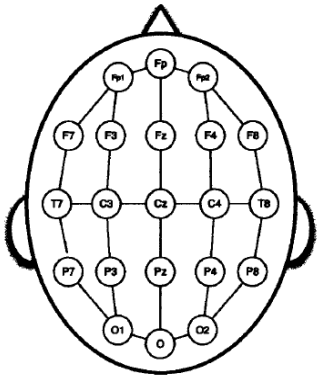

Figure 7: Electrodes position [14]

3.5.Algorithm Evaluation

In order to test the proposed algorithm, an EEG dataset which were previous recorded at Children's Hospital Boston (CHB) is used. The data set provides hours of EEG recordings for 24 different patients. During these recordings more than hundred of seizures took place. The

EEG signals were recorded by connecting electrodes the patients' scalps. The electrode configuration is shown in the Figure 7 [14].

It is important to note that the results will be evaluated based on 4 criteria which are accuracy, sensitivity, specificity and failure rate. The equations used for calculating these terms are shown below. Also all patients will be used except for patient 12 due to the inconsistency regarding the number and the positions of electrodes used.

$$\text{Accuracy} = \frac{\text{TPR} + \text{TNR}}{\text{TPR} + \text{FPR} + \text{TNR} + \text{FNR}} \quad (2)$$

$$\text{Sensitivity} = \frac{\text{TPR}}{\text{TPR} + \text{FNR}} \quad (3)$$

$$\text{Specificity} = \frac{\text{TNR}}{\text{FPR} + \text{TNR}} \quad (4)$$

$$\text{False Discovery Rare (FDR)} = \frac{\text{FPR}}{\text{TPR} + \text{FPR}} \quad (5)$$

Where TPR =true positive rate, TNR=True negative rate, FPR=false positive rate and FNR= false negative rate; such that

1. If the outcome from a prediction is p and the actual value is also p, then it is called a true positive (TP)
2. If the actual value is n and the prediction is p then it is said to be a false positive (FP).
3. A true negative (TN) has occurred when both the prediction outcome and the actual value are n,
4. False negative (FN) is when the prediction outcome is n while the actual value is p.

4. RESULTS AND DISCUSSIONS

This chapter presents the experimental results which were generated using an EEG dataset which was mentioned before in the methodology section under algorithm evaluation. The results presented in the chapter are organized as follows. In Section 4.1 several classical features which could be utilized in indentifying epileptic seizures are examined. Next the performance of the classifier is investigated with respect to two different organization methods and with respect to the number of channels utilized. In the last section, the results for 23 epileptic patients are presented. The results are evaluated in terms of accuracy, sensitivity, specificity and failure rate. The results were generated using different methods for comparison purposes.

4.1. Classical features identification

In order to identify the classical feature that can be used to differentiate between Seizure and Non-Seizure, a set of possible features was developed. These features were extracted from an EEG recording to check their performance. It is important to note that a sliding window of one second (256 points) will be utilized as mentioned before in methodology chapter in data fragmentation section. The list includes the following:

1. Mean per second:

   Mean is basically the average of values within the data set.

$$mean = X_{avg} = \frac{\sum X_i}{n} \quad (6)$$

2. Variance per second:

   Variance is related to the dispersion within the data set. Its value reflects how big the differences between individual values are.

$$variance = \frac{\sum (X_i - X_{avg})}{n} \quad (7)$$

3. Kurtosis per second:

   Kurtosis is related to probability distribution. It can be used in estimating the peakedness of the distribution and frequency of extreme values [15].

$$Kurtosis = n\frac{\sum_{i=1}^{n}(X_i - X_{avg})^4}{(\sum_{i=1}^{n}(X_i - X_{avg})^2)^2} \quad (8)$$

4. Skewness per second:

   Skewness is also related to probability distribution. It measures the degree of symmetry the probability distribution has [15].

$$Skewness = \sqrt{n}\,\frac{\sum_{i=1}^{n}(X_i - X_{avg})^3}{(\sum_{i=1}^{n}(X_i - X_{avg})^2)^{\frac{3}{2}}} \quad (9)$$

5. Average power per second:

   Power is related to energy. Total average power will be calculated for each second. Power will also be calculated for specific frequency bands which are delta band, theta band, alpha band, beta band and gamma band. These frequency bands were discussed in more details in the literature review chapter.

$$Power = \frac{\sum {X_i}^2}{n} \quad (10)$$

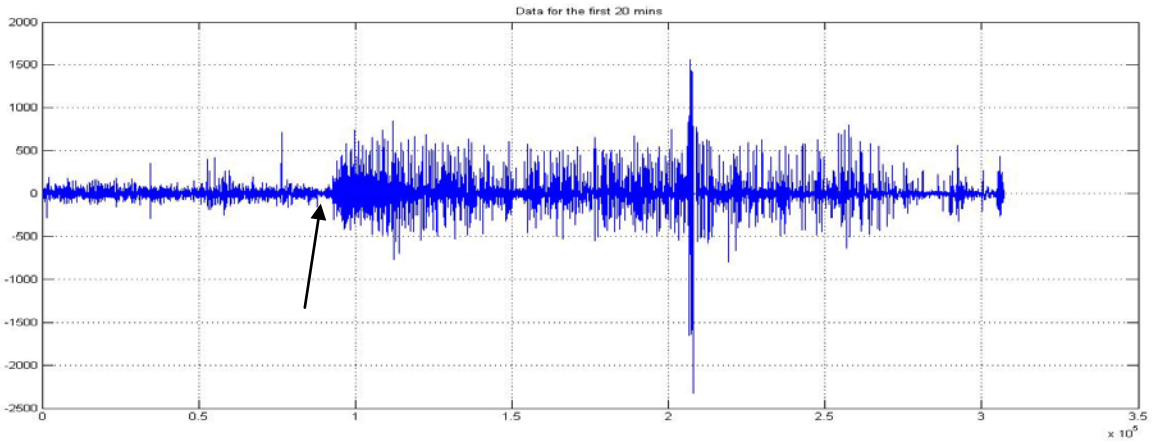

Figure 8: 20 Minutes Plot For Raw data

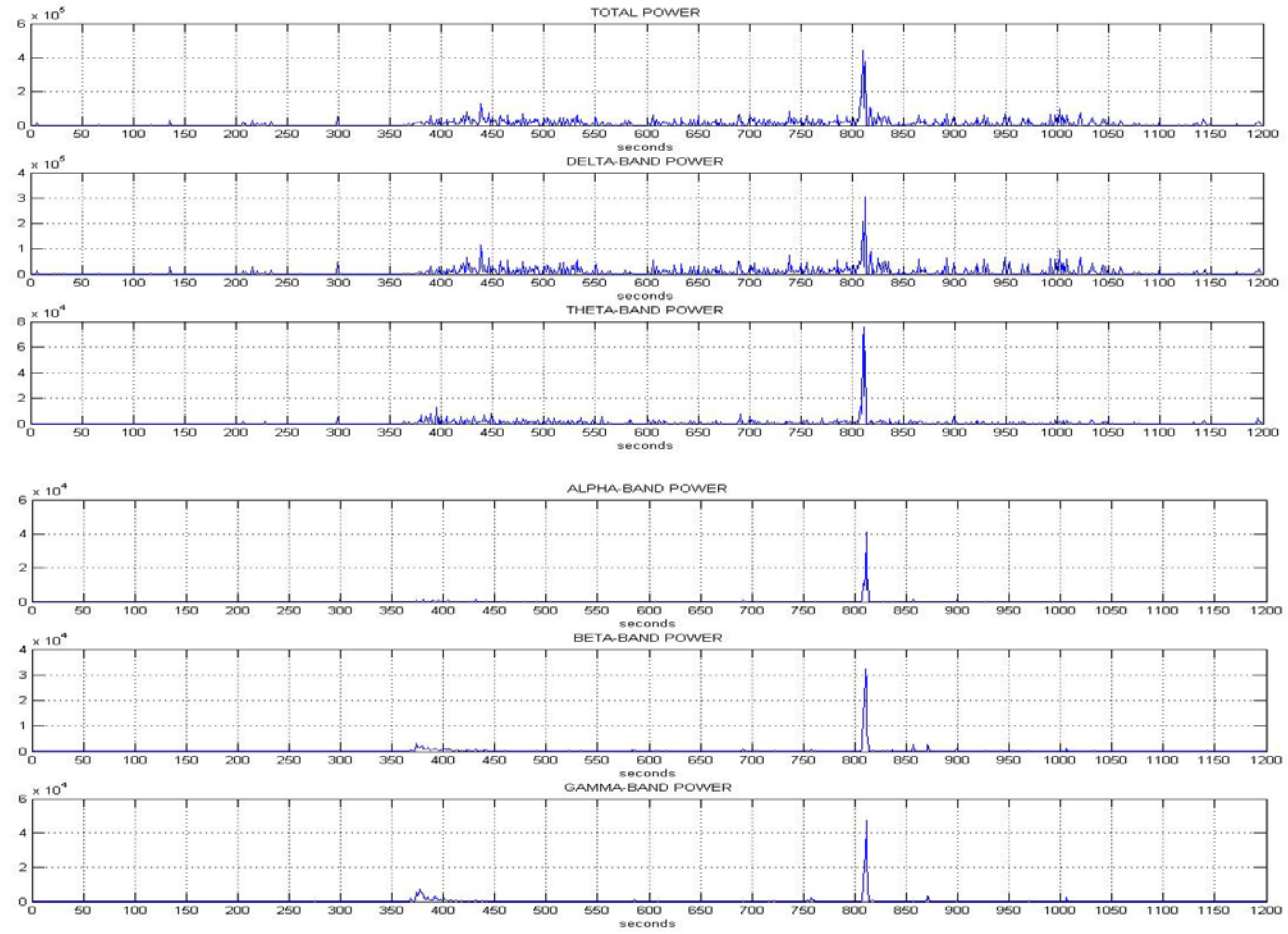

Figure 9: 20 Minutes Plot For Power, from top to bottom Total average power, Delta band average power, Theta band average power, Alpha band average power, Beta band average power, Gamma band average power

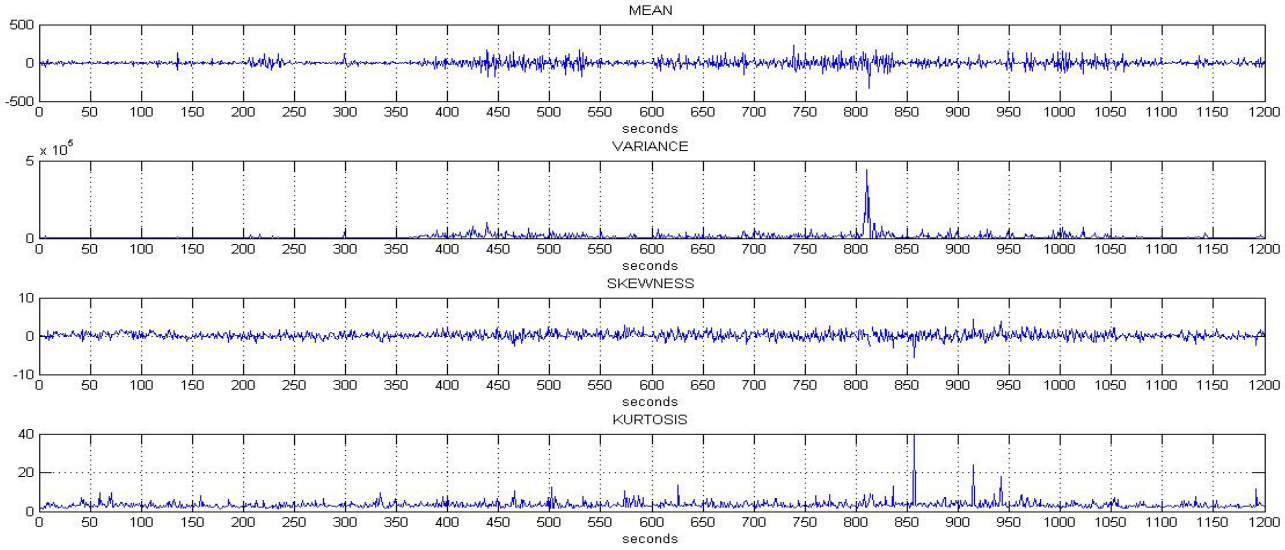

Figure 10: 20 Minutes Plot For Features: (from top to bottom) Mean, Variance, Skewness and Kurtosis

Figure 8 is a plot of the raw data before extracting any features. The arrow shows the start of the seizure which is after 362 seconds from the start of EEG recording. 362 second is equivalent to 92672 points.

Regarding the five average power features extracted, by analyzing Figure 9 we have arrived to the following conclusions. Only total power and delta band power show clearly the start of the seizure. Theta band power shows to some extent the seizure start, however compared with Total power and delta band power, it is still not clear. Alpha, beta and gamma band power does not show a clear difference between seizure and non-seizure state.

Regarding the last four features shown in Figure 10, by analyzing the figure, we have arrived to the conclusions that both mean and variance show the seizure clearly while there is no difference between seizure and non-seizure in both Kurtosis and Skewness.

So to conclude, the following classical features will be used which are total average power per second, delta band average power per second, mean per second, variance per second

4.2.Classifying factors

Two factors which could affect the accuracy of classification were checked. These factors are the way data are organized before classification and the number of channels used.

4.2.1. The data organization method

In order to check this factor, the data was organized in two methods.

a. Method 1 involves putting the data gathered from all channels in one vector i.e. if there are 4 channels then all channels' average power data are combined together and fed to the classifier as one feature vector. The advantage of this method is minimizing the number of feature vectors fed to the classifier.

b. Method 2 involves dealing with each channel data as a separate feature vector i.e. if there are 4 channels, then the average power from each channel will be put in a separate feature vector, which will result in a total of 4 feature vectors.

A sample of patients was chosen randomly, the four classical features were extracted and they were fed to a classifier to test the both method 1 and method 2. The results for correct classification (accuracy) are shown in the Table 3 below.

No.	**Patient No.**	**Percentage of Correct Classification**	
		Method 1	Method 2
1	Patient 3	94.68	97.43
2	Patient 5	89.31	94.94
3	Patient 7	83.69	92.53
4	Patient 10	72.34	91.63
6	Patient 17	84.39	93.41
7	Patient 19	79.36	85.15
8	Patient 21	73.19	84.98
-	Average	82.42	91.44

Table 3: Classification Results for both method 1 and method 2

As seen in the Table 3, method 2 achieves much better results compared with method 1. An average increase of 9 % is achieved. This may be due to the fact that in method 1, the classifier has to differentiate between all values regardless of the channels' location, however in method 2 the location is taken into consideration as the location affects the relative value extracted. The classifier became able to differentiae much better on channel basis compared with before. The extracted features are identified as spatial features as they depend on its channel's location.

4.2.2. The number of spatial features

The second factor that has to be checked is the effect of the number of spatial features or the number of channels on classification accuracy. The results for the average sample of patients were calculated using two methods

- Method 1: involves using only affected channels i.e. if the seizure took place in the frontal lobe then only frontal lobe channels will be used.
- Method 2: involves using all channels (all spatial features)

The results generated are for

- Using Classical Features only
- Using Singular values only
- Using both singular values and classical features

The results for both methods are shown in the Table 4 and Table 5 below.

No.	**Patient No.**	**Percentage of Correct Classification using only affected channels (**Method 1**)**		
		Using Classical Features Only	**Using Singular Values Only**	**Using Both Singular Values And Classical Features**
1	Patient 1	97.55	98.99	98.70
2	Patient 3	97.43	97.92	97.68
3	Patient 5	94.94	98.49	98.40
4	Patient 7	92.53	98.48	98.48
5	Patient 10	91.63	93.72	93.94
6	Patient 17	93.41	97.30	97.47
7	Patient 19	85.15	93.72	93.93
8	Patient 20	90.07	94.54	93.87
9	Patient 21	84.98	87.68	87.68

Table 4: Classification Results for both using only affected channels (method 1)

No.	Patient No.	Percentage of Correct Classification using all channels (Method 2)		
		Using Classical Features only	**Using Singular values only**	**Using both singular values and classical features**
1	Patient 1	98.42	98.85	98.85
2	Patient 3	98.90	98.53	98.78
3	Patient 5	98.58	99.02	99.023
4	Patient 7	95.27	98.62	98.48
5	Patient 10	92.84	92.84	94.93
6	Patient 17	98.31	96.79	98.65
7	Patient 19	86.40	94.98	94.56
8	Patient 20	90.56	96.36	96.19
9	Patient 21	92.36	88.67	92.86

Table 5: Classification Results for both using all channels (method 2)

To summarize the important observations from Table 4 and 5, the percentage of correctly classification for using both singular values and classical features increased for 8 out of 9 patients. The accuracy of the ninth patient did neither increase nor decrease, it remained the same. The percentage of correctly classification for using classical features only increased for all the patients. The increases reached more than 7% in one of the cases. The percentage of correctly classification For using singular values only increased with average accuracy 0.43 %. For method 2, the percentage of correctly classification for using both singular values and classical features is equal to or larger than that of using singular values only for 6 out of 9 cases. The average difference is positive 0.85 %, the increase reached more than 4 % in one of the cases while the maximum decrease is 0.4184 %.

From these results we can reach the following generalization; as the number of channels used increases the percentage of correctly classification increases hence the accuracy will also increase.

4.3.Results

To conclude up till now, Only 4 classical features will be used which are Total power per second, Delta band power per second, Mean per second, Variance per second. These classical features will be used in addition to singular values. The features will be organized in spatial features vector manner. All channels will be utilized in calculations to increase the accuracy.

The results for 23 patients were generated using 4 methods

- Using Classical Features only
- Using Singular values only
- Using both singular values and classical features (proposed algorithm)
- A recent algorithm for comparison purposes. This algorithm was developed by Rafiuddin et. al. As explained before in the literature review, this algorithm uses four features which are energy, coefficient of variation, interquartile range and median absolute deviation. The first two features are extracted from the coefficients of 5 level decomposition using daubechies (db4) wavelet while the last two are calculated from raw data.

The results are evaluated in terms of accuracy, sensitivity, specificity and failure rate which were explained before in the methodology. The results are shown in the Figures 11-14 below. More detailed results are given in the appendix.

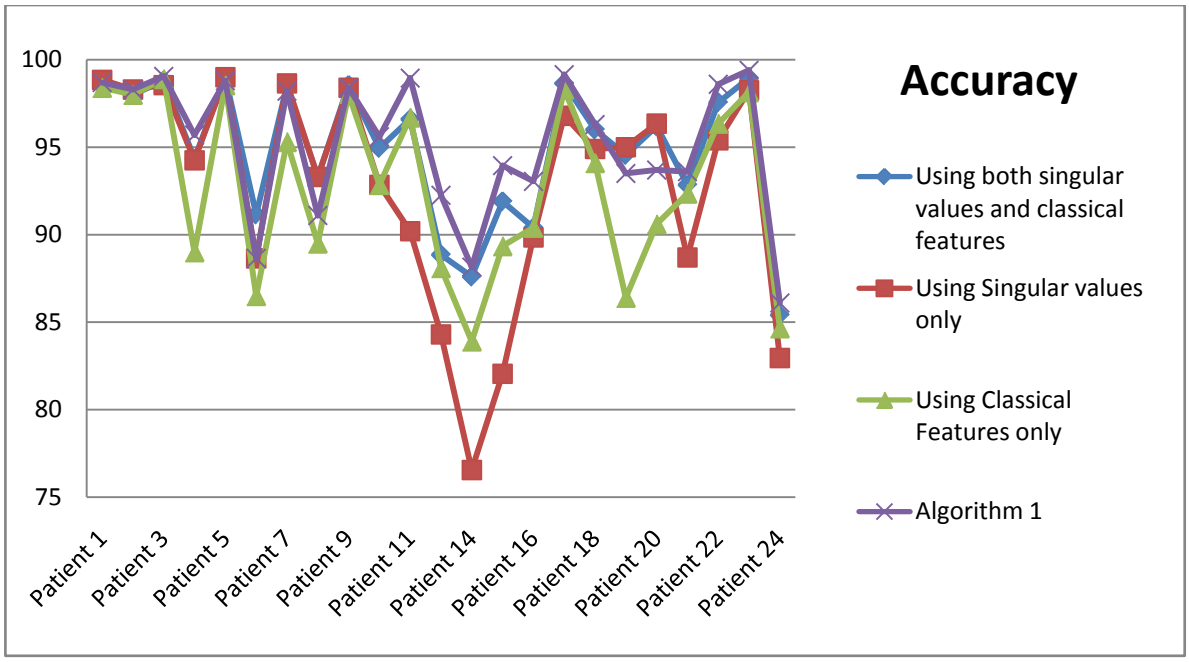

Figure 11: Accuracy for 23 patients

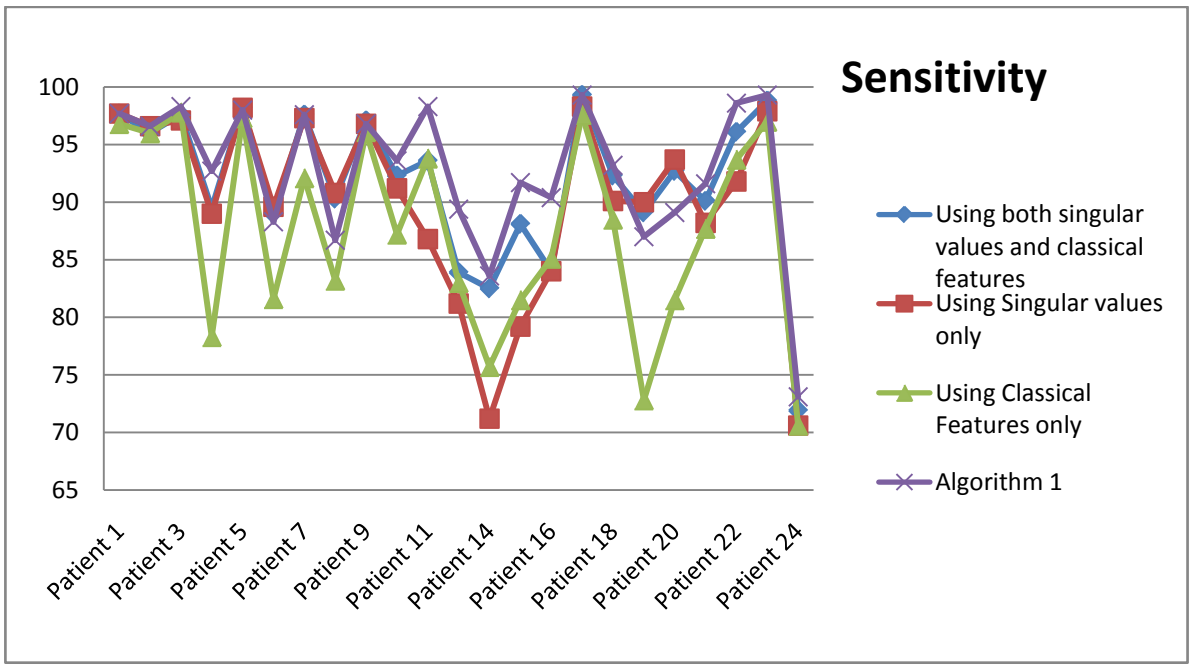

Figure 12: Sensitivity for 23 patients

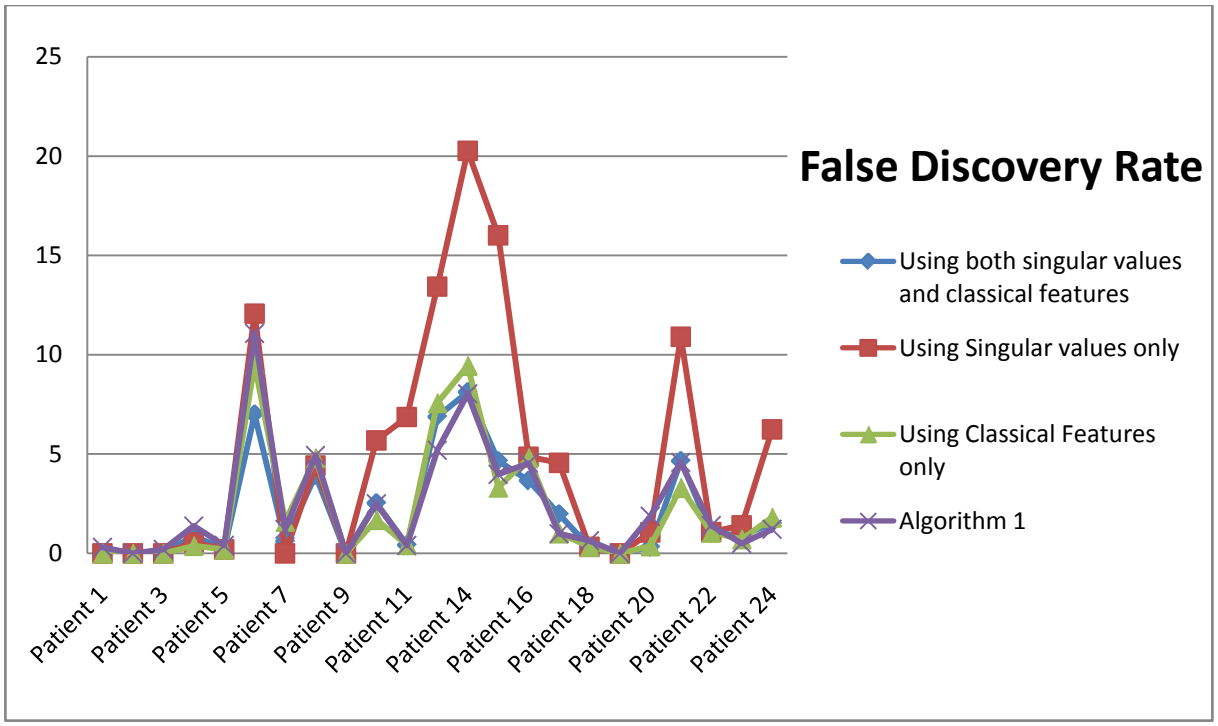

Figure 13: False Discovery Rate for 23 patients

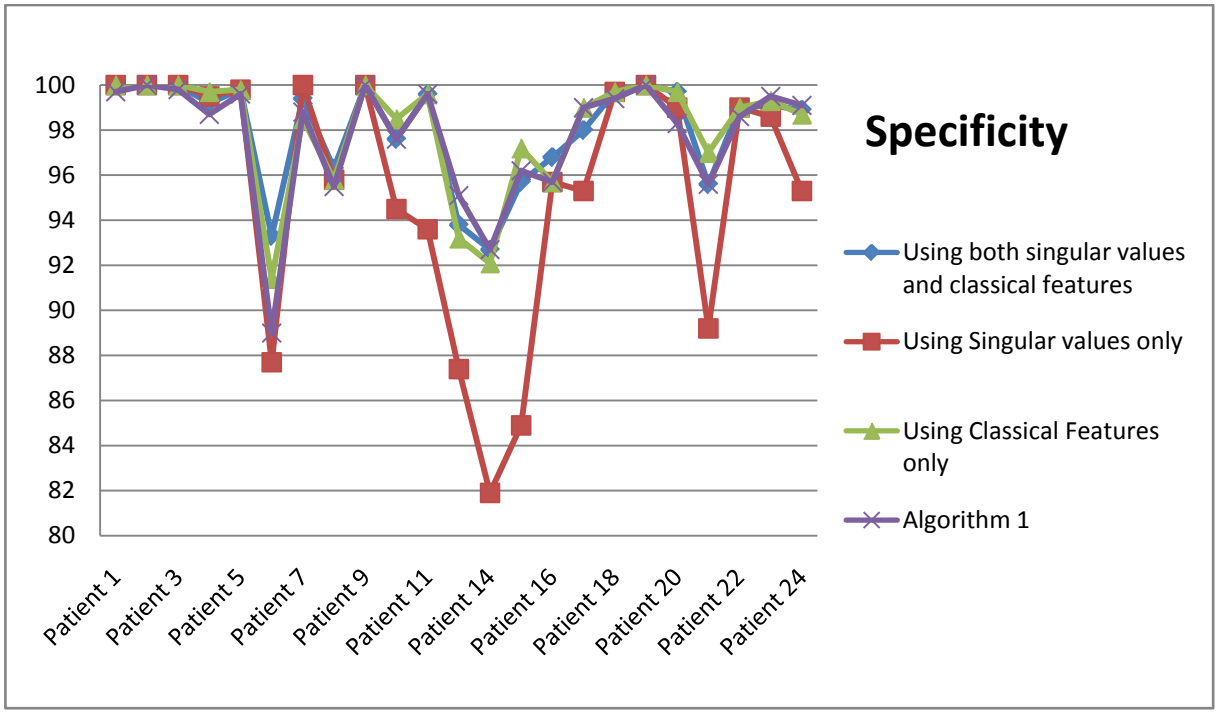

Figure 14: Specificity for 23 patients

From the results, we can observe that the proposed algorithm which is using both singular values and classical features have better results that using singular values alone or using classical features alone. The average results show an increase in terms of accuracy, sensitivity, specificity and failure rate for the proposed algorithm. Furthermore it is clear that the proposed algorithm has a balanced performance as it is not very high in one field and very low in another. Its performance is balanced all over the four criteria. Also by comparing the proposed algorithm with the recent one we can see a similar performance which proves that the proposed algorithm is successful in identifying epileptic seizures.

5. CONCLUSION

When brain cells exchanges messages, they generate electric signals which can be captured by electroencephalogram (EEG). The EEG recording has been used to check for epileptic seizures. Epileptic seizures can be defined as brain dysfunction. There are several types of epileptic seizures which may have different symptoms.

There has been a need to develop an efficient and an accurate way to analyze EEG recordings in order to identify epileptic seizures. This project aims at developing an algorithm which is capable of extracting specific features within EEG recording, analyzing them and determining whether an epileptic seizure took place or not.

An algorithm has been proposed to identify epileptic seizure by using both classical features and singular values. Ten classical features were examined by extracting them from one patient and analyzing them. Only four features were selected and used which are total average power per second, delta band average power per second, mean per second and variance per second. Two more factors were examined to check their effect on the accuracy of the algorithm. The first factor is the way of data organizing. It was proven that the accuracy increases when data are organized in vectors on channel basis (spatial feature vector). The second factor is the number of spatial features utilized and the results showed that the accuracy is directly proportional with number of channels used.

The results were generated for 23 patients using four different methods which are using classical feature alone, using singular values alone, using both classical feature and singular values (proposed algorithm) and finally using a recent algorithm for comparison. The results were evaluated based on terms of accuracy, sensitivity, specificity and failure rate. The results showed that the proposed algorithm achieved better results than using singular values alone or using classical features alone. Furthermore the proposed algorithm performance is balanced with regard to the four criteria mentioned before. Last but not least, the similarity in the performance between the proposed algorithm and the recent one proves that the proposed algorithm is

successful in identifying epileptic seizures. The proposed algorithm successfully achieved an average accuracy of 94.82%.

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7. APPENDIX

No	Patient No	Using both singular values and classical features							
		True Positive Rate (Seizure)	False Positive	True Negative Rate (Non Seizure)	False Negative	Accuracy	Sensitivity	Specificity	False Discovery Rate
1	Patient 1	0.98	0.00	1.00	0.02	98.85	97.70	100.00	0.00
2	Patient 2	0.96	0.00	1.00	0.04	98.00	96.00	100.00	0.00
3	Patient 3	0.98	0.00	1.00	0.02	98.80	97.60	100.00	0.00
4	Patient 4	0.90	0.01	0.99	0.11	94.35	89.50	99.20	0.89
5	Patient 5	0.98	0.00	1.00	0.02	99.00	98.20	99.80	0.20
6	Patient 6	0.89	0.07	0.93	0.11	91.15	89.00	93.30	7.00
7	Patient 7	0.98	0.01	0.99	0.02	98.50	97.60	99.40	0.61
8	Patient 8	0.90	0.04	0.96	0.10	93.30	90.30	96.30	3.94
9	Patient 9	0.97	0.00	1.00	0.03	98.55	97.10	100.00	0.00
10	Patient 10	0.92	0.02	0.98	0.08	94.95	92.30	97.60	2.53
11	Patient 11	0.94	0.00	1.00	0.06	96.60	93.60	99.60	0.43
12	Patient 13	0.84	0.06	0.94	0.16	88.85	83.90	93.80	6.88
13	Patient 14	0.83	0.07	0.93	0.18	87.60	82.50	92.70	8.13
14	Patient 15	0.88	0.04	0.96	0.12	91.90	88.10	95.70	4.65
15	Patient 16	0.84	0.03	0.97	0.16	90.40	84.00	96.80	3.67
16	Patient 17	0.99	0.02	0.98	0.01	98.65	99.30	98.00	1.97
17	Patient 18	0.92	0.00	1.00	0.08	96.00	92.30	99.70	0.32
18	Patient 19	0.89	0.00	1.00	0.11	94.55	89.10	100.00	0.00
19	Patient 20	0.93	0.00	1.00	0.07	96.20	92.70	99.70	0.32
20	Patient 21	0.90	0.04	0.96	0.10	92.85	90.10	95.60	4.66
21	Patient 22	0.96	0.01	0.99	0.04	97.55	96.10	99.00	1.03
22	Patient 23	0.99	0.01	0.99	0.01	98.95	98.80	99.10	0.90
23	Patient 24	0.72	0.01	0.99	0.28	85.40	71.90	98.90	1.51
_	Average					94.82	91.64	98.01	2.16

Table 6: Results for 23 patients using proposed algorithm

No	Patient No	Using Singular values only							
		True Positive Rate (Seizure)	False Positive	True Negative Rate (Non Seizure)	False Negative	Accuracy	Sensitivity	Specificity	False Discovery Rate
1	Patient 1	0.98	0.00	1.00	0.02	98.85	97.70	100.00	0.00
2	Patient 2	0.97	0.00	1.00	0.03	98.30	96.60	100.00	0.00
3	Patient 3	0.97	0.00	1.00	0.03	98.55	97.10	100.00	0.00
4	Patient 4	0.89	0.01	1.00	0.11	94.25	89.00	99.50	0.56
5	Patient 5	0.98	0.00	1.00	0.02	99.00	98.20	99.80	0.20
6	Patient 6	0.90	0.12	0.88	0.10	88.65	89.60	87.70	12.07
7	Patient 7	0.97	0.00	1.00	0.03	98.65	97.30	100.00	0.00
8	Patient 8	0.91	0.04	0.96	0.09	93.30	90.80	95.80	4.42
9	Patient 9	0.97	0.00	1.00	0.03	98.40	96.80	100.00	0.00
10	Patient 10	0.91	0.06	0.95	0.09	92.85	91.20	94.50	5.69
11	Patient 11	0.87	0.06	0.94	0.13	90.20	86.80	93.60	6.87
12	Patient 13	0.81	0.13	0.87	0.19	84.30	81.20	87.40	13.43
13	Patient 14	0.71	0.18	0.82	0.29	76.55	71.20	81.90	20.27
14	Patient 15	0.79	0.15	0.85	0.21	82.05	79.20	84.90	16.01
15	Patient 16	0.84	0.04	0.96	0.16	89.85	84.00	95.70	4.87
16	Patient 17	0.98	0.05	0.95	0.02	96.80	98.30	95.30	4.56
17	Patient 18	0.90	0.00	1.00	0.10	94.90	90.10	99.70	0.33
18	Patient 19	0.90	0.00	1.00	0.10	95.00	90.00	100.00	0.00
19	Patient 20	0.94	0.01	0.99	0.06	96.35	93.70	99.00	1.06
20	Patient 21	0.88	0.11	0.89	0.12	88.70	88.20	89.20	10.91
21	Patient 22	0.92	0.01	0.99	0.08	95.40	91.80	99.00	1.08
22	Patient 23	0.98	0.01	0.99	0.02	98.25	97.90	98.60	1.41
23	Patient 24	0.71	0.05	0.95	0.29	82.95	70.60	95.30	6.24
_	Average					92.70	89.88	95.52	4.78

Table 7: Results for 23 patients using Singular values only

No	Patient No	Using Classical Features only							
		True Positive Rate (Seizure)	False Positive	True Negative Rate (Non Seizure)	False Negative	Accuracy	Sensitivity	Specificity	False Discovery Rate
1	Patient 1	0.97	0.00	1.00	0.03	98.40	96.80	100.00	0.00
2	Patient 2	0.96	0.00	1.00	0.04	98.00	96.00	100.00	0.00
3	Patient 3	0.98	0.00	1.00	0.02	98.90	97.80	100.00	0.00
4	Patient 4	0.78	0.00	1.00	0.22	89.00	78.30	99.70	0.38
5	Patient 5	0.97	0.00	1.00	0.03	98.55	97.30	99.80	0.21
6	Patient 6	0.82	0.09	0.91	0.18	86.50	81.60	91.40	9.53
7	Patient 7	0.92	0.02	0.99	0.08	95.30	92.10	98.50	1.60
8	Patient 8	0.83	0.04	0.96	0.17	89.50	83.20	95.80	4.81
9	Patient 9	0.96	0.00	1.00	0.04	98.05	96.10	100.00	0.00
10	Patient 10	0.87	0.02	0.99	0.13	92.85	87.20	98.50	1.69
11	Patient 11	0.94	0.00	1.00	0.06	96.70	93.80	99.60	0.42
12	Patient 13	0.83	0.07	0.93	0.17	88.10	83.00	93.20	7.57
13	Patient 14	0.76	0.08	0.92	0.24	83.90	75.70	92.10	9.45
14	Patient 15	0.82	0.03	0.97	0.19	89.35	81.50	97.20	3.32
15	Patient 16	0.85	0.04	0.96	0.15	90.40	85.10	95.70	4.81
16	Patient 17	0.98	0.01	0.99	0.02	98.30	97.60	99.00	1.01
17	Patient 18	0.89	0.00	1.00	0.12	94.10	88.50	99.70	0.34
18	Patient 19	0.73	0.00	1.00	0.27	86.40	72.80	100.00	0.00
19	Patient 20	0.82	0.00	1.00	0.19	90.60	81.50	99.70	0.37
20	Patient 21	0.88	0.03	0.97	0.12	92.35	87.70	97.00	3.31
21	Patient 22	0.94	0.01	0.99	0.06	96.35	93.70	99.00	1.06
22	Patient 23	0.97	0.01	0.99	0.03	98.15	97.00	99.30	0.72
23	Patient 24	0.71	0.01	0.99	0.29	84.65	70.60	98.70	1.81
_	Average					92.80	87.60	98.00	2.28

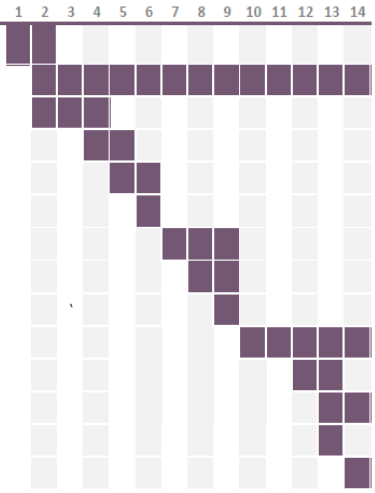
Table 8: Results for 23 patients using Classical features only

No	Patient No	Algorithm 1							
		True Positive Rate (Seizure)	False Positive	True Negative Rate (Non Seizure)	False Negative	Accuracy	Sensitivity	Specificity	False Discovery Rate
1	Patient 1	0.98	0.00	1.00	0.02	98.70	97.70	99.70	0.31
2	Patient 2	0.97	0.00	1.00	0.03	98.30	96.60	100.00	0.00
3	Patient 3	0.98	0.00	1.00	0.02	99.05	98.30	99.80	0.20
4	Patient 4	0.93	0.01	0.99	0.07	95.70	92.70	98.70	1.38
5	Patient 5	0.98	0.00	1.00	0.02	98.80	98.00	99.60	0.41
6	Patient 6	0.88	0.11	0.89	0.12	88.65	88.30	89.00	11.08
7	Patient 7	0.98	0.01	0.99	0.02	98.20	97.60	98.80	1.21
8	Patient 8	0.87	0.05	0.96	0.13	91.10	86.70	95.50	4.93
9	Patient 9	0.97	0.00	1.00	0.03	98.40	96.80	100.00	0.00
10	Patient 10	0.94	0.02	0.98	0.06	95.60	93.60	97.60	2.50
11	Patient 11	0.98	0.00	1.00	0.02	98.95	98.30	99.60	0.41
12	Patient 13	0.89	0.05	0.95	0.11	92.25	89.40	95.10	5.20
13	Patient 14	0.84	0.07	0.93	0.16	88.15	83.60	92.70	8.03
14	Patient 15	0.92	0.04	0.96	0.08	93.95	91.70	96.20	3.98
15	Patient 16	0.90	0.04	0.96	0.10	93.05	90.40	95.70	4.54
16	Patient 17	0.99	0.01	0.99	0.01	99.15	99.30	99.00	1.00
17	Patient 18	0.93	0.01	0.99	0.07	96.30	93.20	99.40	0.64
18	Patient 19	0.87	0.00	1.00	0.13	93.50	87.00	100.00	0.00
19	Patient 20	0.89	0.02	0.98	0.11	93.70	89.10	98.30	1.87
20	Patient 21	0.92	0.04	0.96	0.08	93.60	91.60	95.60	4.58
21	Patient 22	0.99	0.01	0.99	0.01	98.60	98.60	98.60	1.40
22	Patient 23	0.99	0.01	1.00	0.01	99.40	99.30	99.50	0.50
23	Patient 24	0.73	0.01	0.99	0.27	86.10	73.10	99.10	1.22
_	Average					95.60	93.54	97.65	2.46

Table 9: Results for 23 patients using the recent algorithm

FYP 1 Planner

ACTIVITY	PLAN START	PLAN DURATION
Selection of Project Topic	1	2
Meeting With Supervisor	2	13
Preliminary Research about brain activty and EEG	2	3
Research about Epilpitic Seizures	4	2
Write Proposal	5	2
Submission of Proposal	6	1
Research about Classical features	6	2
Proposal Defence Preparation	8	2
Proposal Defence	9	1
Developing a code to identify epliptic seizure using classical feature	8	6
Write Interim Report	12	2
Research about singular values	13	2
Interim Report Draft Submission	13	1
Interim Report Submission	14	1

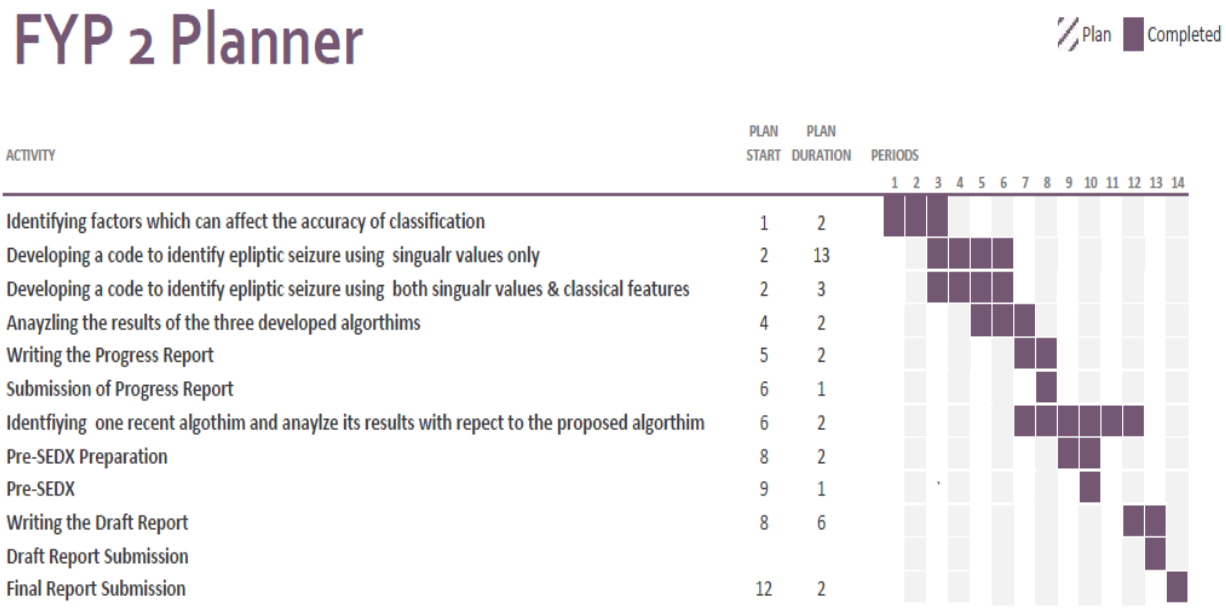


The key millstones for FYP1

1. To research and collect enough information about both brain activity and EEG recordings
2. To research and collect enough information about epileptic seizures
3. To research and identify possible classical features that can be used in identifying epileptic seizure.
4. To develop a code to identify epileptic seizure using classical features and to test it using a classifier.
5. To research and collect enough information about Singular value decomposition.

For milestones 1, 2 and 5, the success will be determined by the supervisor through submitting a summary of the readings and research carried.

However for milestones 3 and 4, the success will be based on the results which are posted in the results and discussion section.



The key millstones for FYP2

1. To determine the main factors which could affect the accuracy of classification
2. To develop a code to identify epileptic seizures using singular values
3. To develop a code to identify epileptic seizures using using both singualr values and classical features
4. To develop codes for a recent proposed algorithm and compare the results with the results of the proposed algorithm

For milestone 1, the success will be determined by the supervisor through submitting a summary of the steps and the work carried out.

However for milestones 2, 3 and 4, the success will be based on the results which are posted in the results and discussion section.