BME 418: Introduction to Neuroengineering
University of Rochester

Project Title: Detection of epileptic seizure events from EEG signal

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Abstract:
Epilepsy is a neurological disorder that generates abnormal electrical activity in the brain and causes seizures. Electroencephalogram (EEG) is a commonly used tool for the detection of epileptic seizure events. However, it is a great challenge to visually reveal the subtle changes that differentiate between an epileptic and non-epileptic EEG. This is because, EEG signals vary among individuals as well as with the recording location and with the number of electrodes used. Therefore, the traditional approach of manual inspection of EEG data by neurologists is very time-consuming and is often prone to erroneous results. Automated detection of EEG signals can greatly reduce the workload of neurologists. In this paper, we have proposed an automated method for epileptic seizure event detection based on the delta and theta band power of the EEG signal. We then used support vector machine and k-nearest neighbor classifier. We performed ten-fold cross-validation on each subject and achieved an average cross-validation accuracy of 77.86%. Then, we trained the system with a composite training set including data from five subjects and independently tested it with another set of six subjects. The average results we obtained on those composite data is 76.92%.

Specific Aims:
Detection of seizure segments from EEG is a challenging task. Because the brain's electrical activity is composed of numerous classes with overlapping characteristics. Therefore, it is important to identify the features capable of separating seizure from other normal brain activities. Many of the features proposed in literature to detect seizure events do not characterize the brainwave activities that make the difference between seizure and non-seizure events. Rather, they focus on the mathematical properties of the sample values of the EEG signal. Besides, the proposed methods are tested on a limited number of subjects or on a single database. We aim to develop an automated system based on two features: delta and theta brainwave power. Our selected features match with cognitive and neurophysiological study on epilepsy confirming that the delta and the theta wave activities indeed mark the difference between seizure and non-seizure events of an epileptic patient. We also aim to test our method on several datasets to establish reliability and to gain more confidence. As part of preliminary work, we have tested our method on a single database and the primary results have indicated that the proposed features perform reliably in seizure event detection.

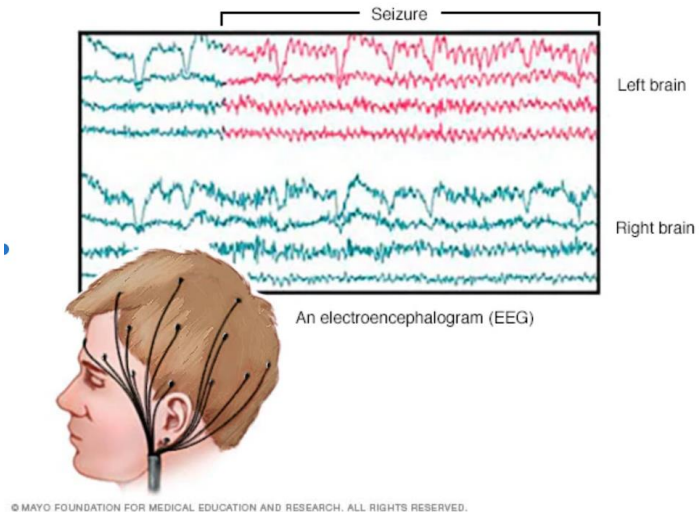
Introduction:
Epilepsy is a group of related disorders characterized by a tendency to develop recurrent seizures. At present, about 50 million people in the world are afflicted with epilepsy [1]. People of all ages-including children can fall victim to epilepsy. According to the American Epilepsy

Society, approximately 2.2 to 3 million people in US have epilepsy and the number is on the rise [2]. The number of children in US with the condition of epilepsy increased from 450,000 in 2007 to 470,000 in 2015 [3]. What is more afflicting is that in many parts of the world, people with epilepsy and their families often suffer from stigma and social dishonor because of the unwanted or somewhat abnormal behavior of the patients during seizure events**.** All these alarming statistics explain why people should learn more and care about epilepsy**.**

Neurons in our brain generate electrical and chemical signals, and they are responsible for all our actions including the way we talk, learn, think or act. In epilepsy, the normal pattern of neuronal activity becomes disrupted. The disruption can arise from an imbalance of nerve signaling chemicals called neurotransmitters or from alteration of behavior of various ion-channels in the neuron or from combination of these two and many other factors. During an epileptic seizure event, a surge of excessive electrical activity goes on in the brain causing involuntary body movements, unusual sensations, emotions and often, loss of awareness. Again, the symptoms widely vary between individuals. Some people simply stare blankly for a few seconds during a seizure, while others repeatedly jerk their arms or legs, and some other people may show psychic symptoms like fear or anxiety.

The exact causes of epilepsy are unknown. It may be a result of some genetic disorders and malformation of brain, or it may be acquired as a result of brain injury, trauma or stress. But seizure does not necessarily identify a person to be an epileptic patient. Some seizures may be provoked by another medical problem and would not be sustained or recurrent. In these situations, the seizures are not considered epileptic**.** A person is not considered to have epilepsy until he has not faced two or more 'unprovoked' seizures with a gap of at least 24 hours [4]. An unprovoked seizure means it is not provoked by high fever, alcohol consumption, blood sugar or electrolyte level fluctuation. Epileptic patients are treated with medications. But before prescribing a specific dosage of a specific anti-epileptic drug, doctors need to confirm the severity of the disorder and the abnormality in the brain function of the suspected patient.

The most common way to diagnose the condition and detect the potential abnormal brain activity of a suspected epileptic patient is Electroencephalogram (EEG). In this diagnostic method, electrodes are attached to the patient's scalp to record the electrical activity of the brain. It is expected to have changes in normal pattern of EEG waves if the patient is epileptic, as soon as any seizure event shows up. Doctors monitor the patient on video while conducting EEG while the patient is awake or asleep to record any seizure he experiences.



Collected from: https://www.mayoclinic.org/diseases-conditions/epilepsy/diagnosis-treatment/drc-20350098
Figure 1: EEG recording in search of brain function abnormality in a suspected epileptic patient.

EEG recordings are then analyzed by neurologists to detect and categorize the data into seizure and non-seizure segments. The process is very laborious because analyzing big chunks of EEG data consumes lots of time and energy. It can take many hours or even days to examine several hours of data recorded from a patient. Visual inspection is also prone to human error. Some normal tracings can be read as abnormal while some revealing patterns can be missed out. As such, the analysis of EEG recordings puts a heavy burden on the neurologists. These limitations have motivated efforts to design and develop automated systems to assist neurologists in classifying epileptic and non-epileptic EEG signals. Because an automated system can analyze each and every sample of EEG data with equal importance. The purpose of such a system is not to replace the neurologists altogether, but to generate some sorts of flags or alarms calling for extra attention to the suspected region related to a seizure event. The system can therefore become a great assistance for neurologists. As a result, automated detection of epileptic seizure events from EEG signal is a common interest among the researchers.

<u>Literature Study:</u>
Over the last few decades, researchers have developed different methods to automatically identify the presence of epileptic seizure by analyzing the EEG patterns of suspected patients. Each of the methods focuses on reducing implantation time, complexity and increasing detection accuracy. The generic procedure is common for all: analysis of the EEG signal, extraction of features from the signal and application of those features into a classifier to differentiate between epileptic and normal EEG. One limitation of some of the methods we reviewed is high feature dimension. For example, Greene et. al 2008[5], used 19-time domain, frequency domain and entropy-based features. Polat and Gü Nes n.d.[6] identified epileptic seizure event from EEG signals by the use of Fast Fourier Transform (FFT) and decision-tree classifier. They extracted total 129 features from FFT based Welch spectral analysis. Problem

with such high feature dimension in machine learning is that they create redundant information and put heavy burden on the classifiers resulting in more execution time and more learning error.

Another common practice in literature is the use of statistical features. Seng et. al 2012[7] combined mean, coefficient of variation, dominant frequency, mean and variance of the power spectrum of EEG segments. These features depend on the EEG potentials recorded from each subject and do not guarantee consistency among different subjects. For example, if the classifier is trained with the mean value of EEG potentials of one subject, it is possible that the mean value is lower than the lowest potential value of another patients. Besides, how these parameters explain brainwave characteristics is not well understood.

Many researchers have relied on a threshold-based approach. For example, Mohseni et. el 2006[8], computed variance from each EEG segment and compared with a constant threshold. If the variance was greater than the threshold, the segment was considered as a seizure and vice versa. How this threshold was chosen and how a constant threshold can work for all different subjects are not well-understood from their work.

Researchers are constantly testing their methods with new features, dataset, classifiers, detection and machine learning algorithms. But transferring these methods to clinical practice requires to answer lot more questions. Because the methods are generally tested with a specific dataset. For example, Pan et al.[9] used spatiotemporal correlation along with the frequency-based features and used the Mutual Information model as a feature selection method, which led to 88.99% sensitivity rate using SVM as classifier. But their dataset contained EEG signals of only 7 epileptic patients with a duration of 30-50 minutes each. Kiranyaz et al. 2013[10] used 50 features based on Conditional Mutual Information Maximization (CMIM) and achieved 93.78% sensitivity and a specificity of 99.05%. But they analyzed EEG data of only four subjects from CHB-MIT database (the same database we are going to study in this paper) although this database contains data of 23 subjects. As a result, there are reliability and reproducibility issues regarding their performance on a different dataset. Therefore, it is still an open field of research to come up with solutions that will work on the EEG data of all patients throughout the world and undoubtedly, this is a challenging task.

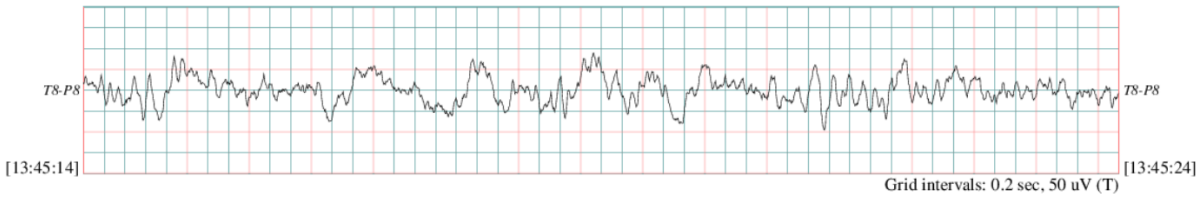
Proposal:

As a fundamental part of any cluster analysis or pattern recognition problems, researchers propose features- some defining or varying properties that will reliably differentiate among different classes involved in the problem. In our case, we must differentiate between two classes: Seizure and Non-seizure segments from our available EEG data. The features that will quantify the differences between the two target classes should generalize for all subjects. Therefore, the features should not include any set threshold value or any such parameters that cannot be explained in the context of brainwave activity. Rather, focus should be on those brainwave dynamics that change their characteristics between seizure and non-seizure events. Some neurophysiologic studies on epileptic EEG have shown that two such brainwave dynamics are delta and theta band power.

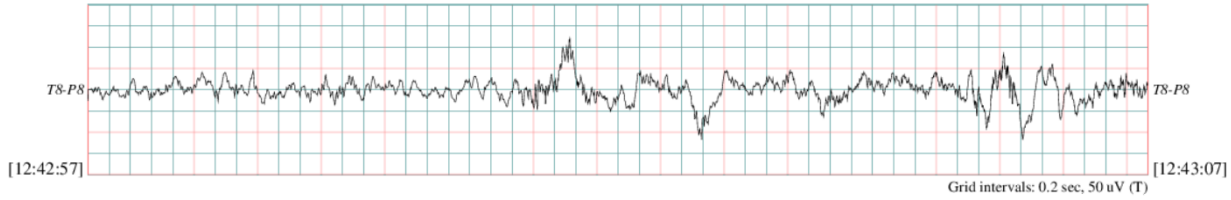
EEG waveforms are divided into four frequency bands [11]: delta is the frequency range up to 4Hz, theta is from 4 Hz to 8 Hz, alpha from 8 Hz to 14 Hz and beta is the frequency range from 14Hz to about 30Hz. Bancaud 1983[12] showed that epileptiform potentials are characterized by spikes and sharp waves, and these spikes and sharp waves predominantly lie in the delta and theta frequency region. Pellegrino et al. 2017[13] studied the EEG power spectral density of fifteen focal epileptic patients and fourteen healthy subjects during wakefulness and sleep. The comparison between the two groups revealed higher delta and theta power over the affected hemisphere of patients compared with control subjects. We can integrate this result to our machine learning system to detect seizure events: since delta and theta waves exhibit higher activities during seizure events, if we train our machine with the delta and theta band powers extracted from our EEG data at hand, we can expect that our machine will be able to tell us which segments contain seizure events and which segments do not. The rest of this paper demonstrates our procedures to test this hypothesis.

The Dataset:

We have used CHB-MIT scalp EEG database [14]. It is a publicly accessible dataset and is being widely used in seizure detection research works over the past few years. The EEG dataset was recorded from pediatric subjects with intractable seizures at Children's Hospital Boston. This database contains 23 subjects (17 females, ages 1.5–19; 6 males, ages 3–22). The International 10-20 system of EEG electrode positions and nomenclature was used to collect these EEG recordings. All signals were sampled at 256 samples per second. Patients were monitored for up to several days and the EEG data of each hour is stored as EDF files. (European Data Format- a standard file format to store long time-series data). As a result, a patient monitored for 42 hours, has 42 separate EDF files in his record. In this database, epileptic seizure segment of EEG signal has been marked as "seizure" by experts along with the seizure start and end time and all other segments out of the seizure duration are considered as "seizure-free" or "normal".
The following is a segment of EEG data taken from the dataset, duration of 10 seconds and recorded from a single channel. It contains one seizure event of 10 seconds duration. So, it is a seizure frame.

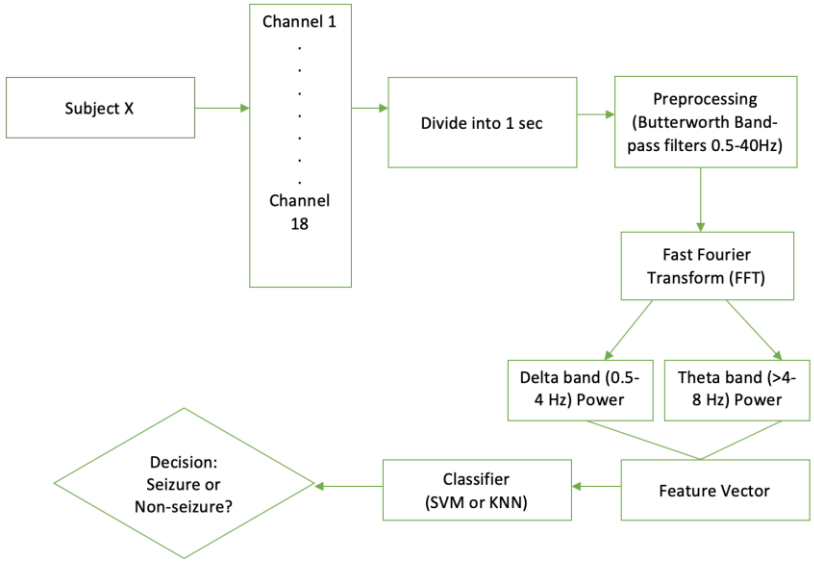


Below is another 10 seconds EEG data frame collected from same patient and same EEG channel, but it contains no seizure event. So, it is a non-seizure data frame.



The two raw EEG signals look the same but a lot more information is hidden behind the patterns and needs to be brought out. As stated in the hypothesis section, one way to bring out the differences between the two is to focus on their delta and theta wave.

Block Diagram of the proposed method:



Our proposed method has five major parts: Preprocessing, Fourier transform, Feature extraction, Classifier and Results.

1. Preprocessing: Raw EEG data are usually not clean, and they contain noise resulting from electromagnetic interference between the electrodes and other electronics involved in the setup. For EEG analysis, the frequency range of interest is 0.5 Hz to 30 Hz since this range contains all of the four brain waves-delta: 0.5-4 Hz, theta: 4-8 Hz, alpha: 8-12 Hz and beta: 12-30 Hz. The raw EEG data is therefore filtered by a 5-th order Butterworth bandpass filter with passband 0.5 Hz to 30 Hz. With this passband frequency, the 60Hz power noise is automatically removed and no extra notch filter is required. Butterworth filter is chosen because it has the flattest, ripple free passband which makes it very good at simulating the passband of an ideal filter. One disadvantage of this filter is that it goes to zero at a slower rate providing path to some part of the stopband into the passband. But an easy fix to this problem is to increase the order of the filter. So, a 5-th order Butterworth filter is designed.

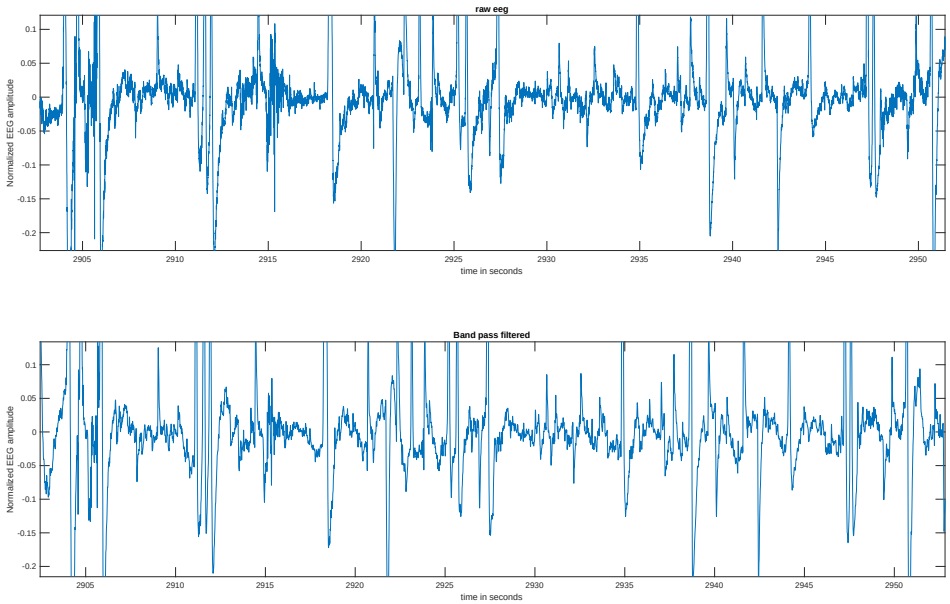


Figure: The upper figure shows the raw EEG data from patient chb01 and the bottom figure shows the EEG data from the same patient after filtering. Filtering has cleaned up noise from the EEG signal.

2. Fast Fourier Transform:

Fast Fourier Transform (FFT) performed on the EEG signal provides the four frequency band characteristics of the signal. The power of each frequency band is plotted in the following figure:

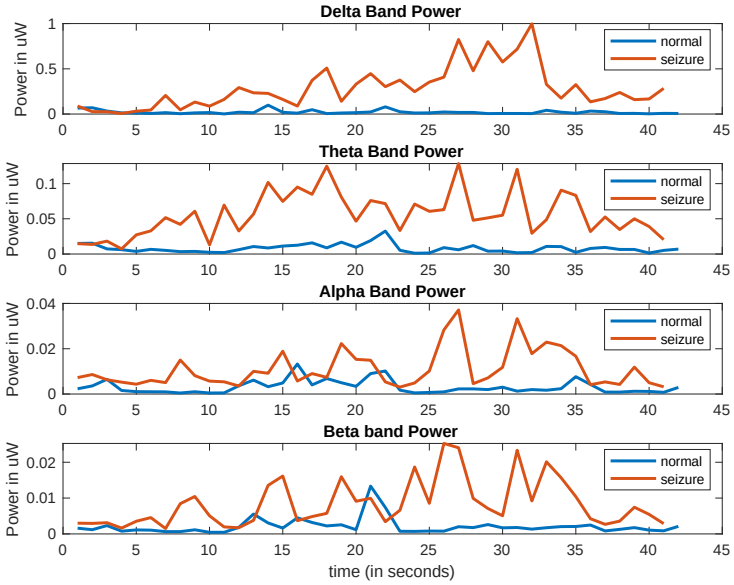


Figure: Comparison between various frequency band powers coming from 41 seconds of seizure and 41 seconds of non-seizure segment of a patient. The powers of seizure segments

are higher than those of the non-seizures, but the least overlap between seizure and non-seizure is found among the delta and theta band power, showing their characteristic change between seizure and non-seizure events. At the onset of seizure, delta and theta power start from their normal (non-seizure) values, but as time goes on during a seizure event, delta and theta power diverge to much higher values. The power values also rise up in the cases of alpha and beta band, but the y-axes show that their amplitudes are much lower than those of delta and theta bands. The highest amplitude of delta and theta powers are 1uW and 0.15uW respectively, whereas alpha and beta powers lie in the range of 0.04uW and 0.025uW respectively. That is why, delta and theta bands are more preferable.

3. Feature Vector Construction:

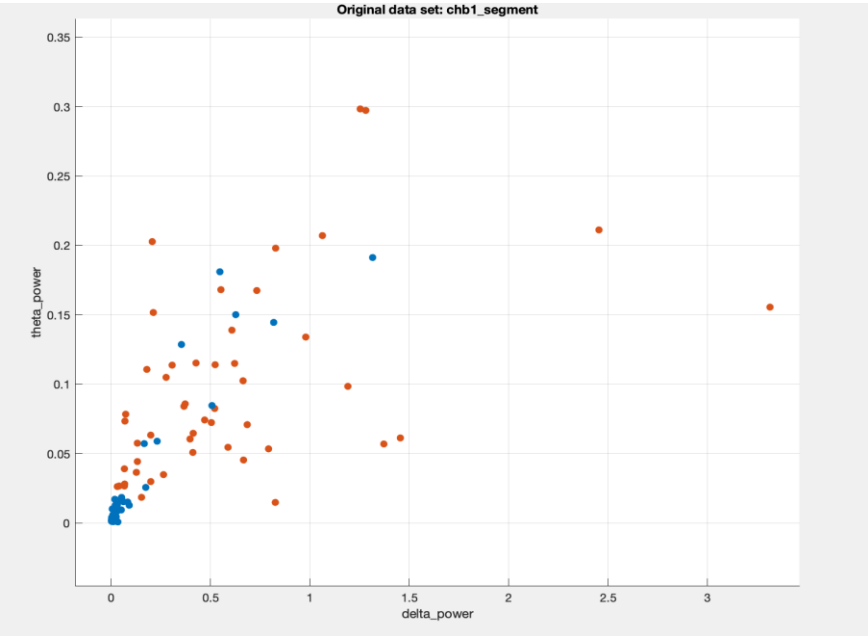
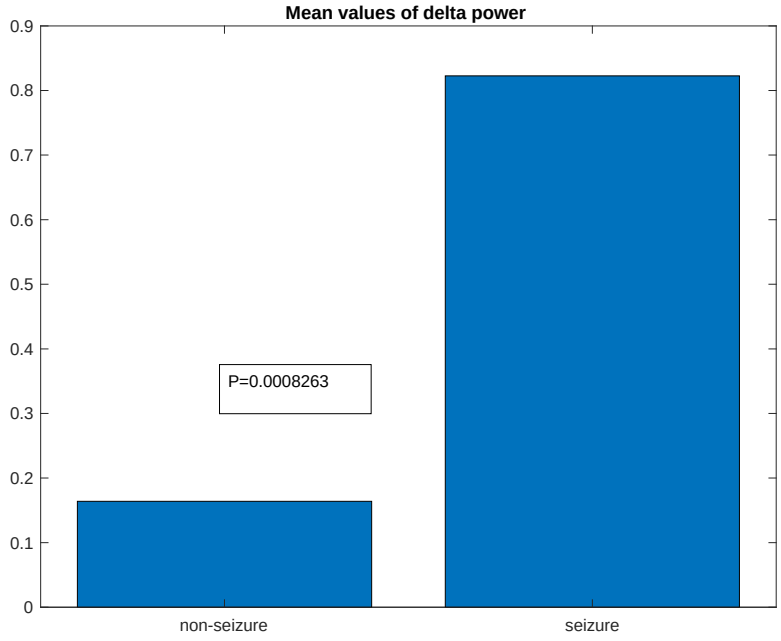


Figure: Scatter diagram of the feature vectors constructed from 40 seizure segments and 40 non-seizure segments from a subject. Blue and red dots correspond to non-seizure and seizure values respectively. Non-seizure features are clustered around the lower valued region and the seizure features are mostly located in the higher valued region. Note that there are some blue dots in the red region and some red dots in the blue region (which is why we did not achieve 100% accuracy), it is still possible to separate the two target classes with a line or plane.

A two-sample t-test is performed to find out if the difference between the seizure and non-seizure features are statistically significant or not. The result is reported below for subject Chb1. This patient experienced 449 seconds (seven minutes) of seizure events. To keep same number of samples in both groups, we have randomly chosen 449 seconds of non-seizure feature data to perform the t-test.



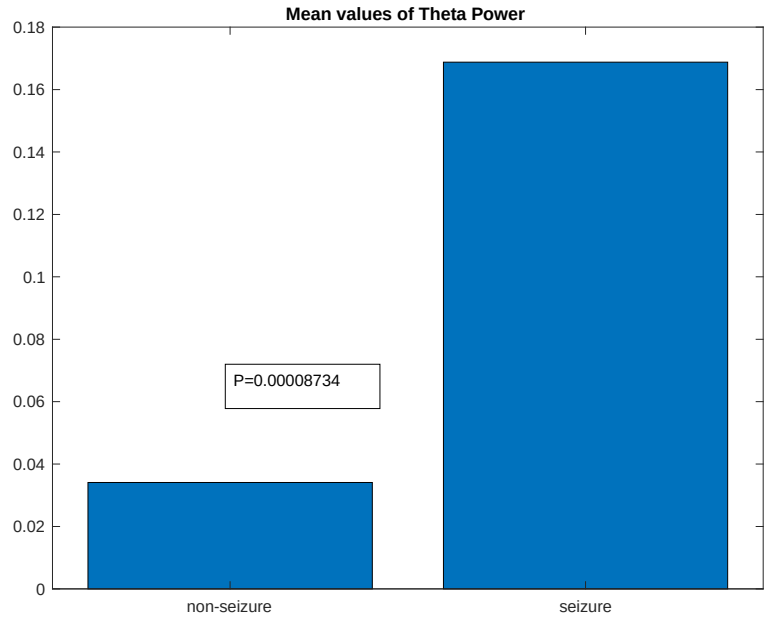


Figure: The mean of the feature values obtained from the two target classes are plotted. The p values indicate that the two-sample t-test rejected the null hypothesis and that the difference between the means of the two groups is statistically significant.

4. Classifier:

We have used two different classifiers to classify between seizure and non-seizure segments: Support Vector Machine (SVM) and K nearest neighbor (KNN). Both of the classifiers depend on supervised learning method. Given labeled training data, support vector machine builds up an optimal hyperplane which maximizes the margin between the target classes. In two-dimensional space, this hyperplane is a line dividing a plane in two parts where each class lie in either side. KNN, on the other hand, computes a distance function between the data to be classified and every item in the training set, and picks the k closest data points. Then it looks for the most frequently occurring class and assign that class to the test data.

5. Result:

a) Cross-validation Result:

We performed 10-fold cross validation separately on each subject to determine how well our proposed model fits to the data of each subject. In 10-fold cross validation, the original sample is randomly partitioned into 10 subsets. Each subset is called a fold. 9 out of the 10 folds are kept as training set and the remaining one is used as the validation set. The trial is repeated 10 times. The accuracy of the model is estimated by averaging the accuracies derived in all 10 trials. The cross-validation results for all 23 subjects in the dataset are reported below in terms of sensitivity, specificity and accuracy. Where:

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

$$\text{Specificity}=\frac{TN}{TN+FP}$$

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN}$$

TP= True Positive (Seizure segment correctly declared as seizure)
TN=True Negative (Non-seizure segment correctly declared as non-seizure)
FP= False Positive (Non-seizure segment incorrectly declared as seizure)
FN= False Negative (Seizure segment incorrectly declared as non-seizure)

	Support Vector Machine			K-Nearest Neighbor		
Subject	Sensitivity(%)	Specificity(%)	Accuracy(%)	Sensitivity(%)	Specificity(%)	Accuracy(%)
Chb1	83.4	93.11	87.64	82.6	86.94	84.63
Chb2	85.26	91.88	88.29	85.87	89.76	87.71
Chb3	80.56	90.51	84.84	83	83.78	83.38
Chb4	83.28	86	88.27	76.71	78.59	78.27
Chb5	92.32	86.45	89.17	94.66	86.45	90.14
Chb6	51.96	53.1	52.4	53.79	51.96	53.77
Chb7	82.51	82.16	82.34	79.57	80.22	79.89
Chb8	76.54	80.82	78.52	74.54	77.11	75.76
Chb9	96.53	91.88	94.08	95.3	93.55	94.41
Chb10	85.35	82.8	84.03	85.19	81.93	83.48
Chb11	92.11	92.32	92.21	92.45	91.01	91.72
Chb12	53.33	52.07	52.55	55.76	54.83	55.26

Table 1: Cross-validation results

	Support Vector Machine			K-Nearest Neighbor		
Subject	Sensitivity(%)	Specificity(%)	Accuracy(%)	Sensitivity(%)	Specificity(%)	Accuracy(%)
Chb13	75.42	81.46	78.12	80	77.76	78.83
Chb14	66.67	66.45	66.56	70.18	61.86	64.94
Chb15	60.02	66.04	62.34	62.79	59.03	60.59
Chb16	68.72	69.23	69.04	65	59.38	61.54
Chb17	69.92	80.69	74.16	71.06	73.31	72.13
Chb18	71.01	65.68	67.96	65.22	63.11	64.09
Chb19	89.47	80.67	84.52	93.26	79.3	84.94
Chb20	83.95	72.85	77.32	80	71.19	74.83
Chb21	69.67	79.63	73.65	68.45	69	68.72
Chb22	77.59	85.16	80.92	78.16	77.88	78.02
Chb23	78.83	85.59	81.85	79.35	79.12	79.23

Table 2: Cross-validation results (contd.)

Average cross-validation results over all the 23 subjects:
Sensitivity=77.14%, Specificity=78.98%, Accuracy= 77.86%

b) Testing on composite dataset:

The results in part (a) show that our proposed model has provided promising results when tested on individual subjects. In real life, it is expected that the health care centers will have a database where they will store the EEG data of all the patients they encounter. Then the database will be used to train the system and whenever a new patient comes, his entire EEG record will be fed into the system as a test set. With that in mind, we have built up a training dataset that combined data from multiple patients. We randomly chose 5 subjects for training purposes with their delta and theta EEG powers as feature vectors. Then, we randomly selected another 6 subjects for testing. In this part, we have used support vector machine since support vector machine is faster than K-nearest neighbor classifier with large data. The results are shown below:

	Support Vector Machine		
Subject	Sensitivity(%)	Specificity(%)	Accuracy(%)
Chb1	70.16	83.3	76.73
Chb2	85.14	72	78.57
Chb8	69.81	81.6	75.71
Chb19	62.76	76.99	69.87
Chb22	75.85	82.13	78.99
Chb23	75.81	87.5	81.65
Average:	73.255	80.58	76.92

Table 3: Classification result of six subjects. Subjects selected for training are Chb10, Chb11, Chb12, Chb13 and Chb15.

Performance Comparison to another method:

Greene et. al 2008[5] extracted 19 features from EEG data of 17 neonates with seizure. The features used in his studies were divided into three categories: frequency domain features like bandwidth, peak frequency, peak power etc., time domain features as zero crossings, RMS amplitude etc., and entropy-based features such as Shannon entropy, Spectral entropy, so on. They used a linear discriminant classifier and cross-fold validation to obtain results. Their reported results are: Sensitivity 81.08%, Specificity 82.23% and Accuracy 81.75%.

Whereas our method, with only two features, obtained average cross-validation sensitivity of 77.14%, specificity of 78.98% and accuracy of 77.86%, which show that our results are close enough.

Limitations and scopes for future work:

So far, we have tested our method on only one database since it was available for free. This database includes only pediatric subjects. To establish reliability, we must extend our work to different datasets including different population dynamics. Besides, we did not experiment much with the classifiers as we were more focused on our features: delta and theta power. Without giving much power to the classifiers, we were interested to see if these features can yield satisfactory results on their own. Therefore, we did not fine tune our classifier parameters. We hope that trying out different classifiers such as naive bayes, decision tree or deep neural networks and tuning their related parameters will further improve our detection accuracy.

Conclusion:

We proposed an automated method in this paper that will classify between seizure and non-seizure segments of long-term EEG data from epileptic patients. The greatest benefit of our proposed method is its simplicity. It does not require any expertise in sophisticated machine learning algorithms, or any computational complexity and the labeling of training data can be derived from information that is routinely supplied as part of clinical care or patient databases. Instead of extracting dozens of features, we have shown that only two features-closely resembling the electrophysiologic property of the brain during any seizure event can yield promising results. The biggest contribution of this project is that it has demonstrated that in a machine learning system, no matter how small the feature dimension is, if the features themselves have the capability to detect patterns in the data in consideration, we can hope for good results. Therefore, identifying a good feature set that closely resembles the problem domain should be the primary focus instead of fine tuning a thousand parameters in the machine learning models.

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