Texas A&M University at Qatar

Electrical and Computer Engineering Program

ECEN 404

Senior Design Lab

Semester: Spring 2017

Progress Report

Efficient Epileptic Seizure Onset detection

Team Members:	**Fatima Al-Ansari,**	**Electrical Engineering Student**
	Noor Al-Zeyara,	**Electrical Engineering Student**
	Omar Barhoumi,	**Electrical Engineering Student**
	Osama AlSaad,	**Electrical Engineering Student**
	Fatima Al-Malki	**Electrical Engineering Student**

Project Mentor: **Dr. Erchin Serpedin,** **Electrical Engineering Professor**

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"On my honor, as an Aggie, I have neither given nor received unauthorized aid on this academic work."

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CHAPTER 0: ABSTRACT

The Efficient Epileptic Seizure Onset Detection (ESD) Project aims to enhance the quality of life of epileptic patients by developing an efficient onset detection algorithm of seizures. The proposed algorithm is based on analyzing pre-recorded Electroencephalogram (EEG) brain signals of epileptic patients that have been bought and recorded anonymously. Our method of an efficient algorithm is based on combining the output of the neural synchrony phase with the output of the wavelet transform of the EEG signals phase in a process called fusion. By implementing this, we expect to have an enhanced system with low latency, low false alarms, high durability, and high sensitivity. A Support Vector Machine (SVM) tool, which uses Machine Learning techniques that is frequently used for signal processing, will be used to classify the output if whether it is a seizure event or not. The system will be first trained with the bought EEG data. Just like all machine-learning systems, the more pre-recorded data the system is fed, the better the performance.

The purpose of this progress report is to give an overall view of our project and the accomplishments that have been done so far. Chapter one talks about the customer needs study and our updated progress so far. Chapter two discusses the project design and development process. This chapter focuses on the design characteristics by providing detailed explanation of the functional modeling and the theory to be followed in order to accomplish this project. Benchmarking was also conducted in this chapter in which different researched algorithms along with our developed one were compared with each other. Chapter two also talks about the concept behind choosing EEG signals among other methods to detect the seizures and the EEG method was chosen as it had the highest score in the scoring table.

Chapter three discusses the detailed system design and development. This chapter provides a clear explanation of the code responsible for our project design. In this chapter, feature extraction, wavelet transform, channel selection and part of neural synchrony codes are explained. Chapter four deals with the experimental results found and talks about our current progress so far. Chapter five concludes the work so far including the required finalized budget and depicts our future work directions.

CHAPTER 1: LITERATURE REVIEW

1.1: Introduction: Literature/Historical Review

Historical review was needed to observe the desired need in the past and compare it to the present in order to insure effectiveness of design. The results of "Epidemiology and Etiology of Intractable Epilepsy in Qatar" by the Neurology section in Hamad Medical Corporation in the year 2004 was utilized in historical background [10].

During the year 2001, medical records of 1271 epileptic patients were observed to determine the incidence of epilepsy among adults in Qatar. The ratio of male to female was 2:1 with 807 males and 410 females with ages ranging from 13 to 85 years. These figures were extrapolated to an approximation of an incidence of 174 in 100,000 persons per year [10].

Country	Reference	Year	No. of patients	Incidence
China	Li et al[15]	1985	60	35
Ecuador	Placencia et al[3]	1992	137	190
England	Cockerell et al[16]	1996	06	23
Ethiopia	Tekle-Haimanot et al[17]	1997	139	64
France	Loiseau[18]	1990	271	24
Guam	Stanhope et al[19]	1972	30	35
Italy	Granieri et al[20]	1983	230	33
Qatar	Present study	2001	1217	174
Sweden*	Forsgren et al[21]	1990	107	34
	Forsgren et al[8]	1996	160	56
Tanzania	Rwiza et al[22*]	1992	122	73
USA	Hauser et al[10]	1993	880	44

* age > 17 years

Figure 1: Annual incidence rate of epilepsy per 100,000 persons for some developing and developed countries [10]

With such a relatively high number, the need of more research to enhance the life of epileptic patients is a must. Therefore, our project aim is to enhance the life of epileptic patients through the developing of an efficient on set detection algorithm.

1.2: Customer needs study/survey – Ethical, Health, safety constraints

- Interview

An interview was conducted with Dr. Naim Haddad from Weill Cornell-Medicine University at Qatar, an associate Professor of Clinical Neurology and a Consultant in Hamad Medical Corporation and a couple of senior students who had relevant research. Dr. Haddad's new study of mapping epilepsy in Qatar, "Epilepsy in Qatar: Causes, treatment and outcome" [9] was discussed. Dr. Haddad's research is considered to be the first detailed information about epilepsy in Qatar.

- Research analysis

Information was collected from 468 patients having epilepsy through the national health system adult neurology clinic. Patients' age, nationality and gender were considered. Forty countries of origin were divided into three group: Qatari, MENA (North Africans) and Asian. The final results showed that 60% of patients in Qatar were men. From figure 2, the age of people having epilepsy in Qatar is between 8 to 82 years and it can be noticed that people who are 21 to 40 years have the highest percentage of epilepsy of which is estimated to be 52% of the other ranges.

Comparison of demographic and clinical characteristics between patients according to the region of origin.

Variable	Qatari n (%)	MENA n (%)	Asian n (%)	p-Value
Age at last follow up (years)				
8–20	24 (13.3)	34 (28.8)	18 (11.7)	<0.001*
21–40	92 (51.1)	55 (46.6)	93 (60.4)	
41–60	38 (21.1)	25 (21.2)	40 (26.0)	
60–82	26 (14.4)	4 (3.4)	3 (1.9)	
Gender				
Male	90 (50.0)	66 (55.9)	116 (75.8)	<0.001*
Female	90 (50.0)	52 (44.1)	37 (24.2)	
Employment				
Yes	80 (47.3)	61 (54.5)	114 (77.6)	<0.001*
No	89 (52.7)	51 (45.5)	33 (22.4)	

Figure 2: Comparison of demographic and clinical characteristics between patients according to the region of origin [9]

P-value corresponds to the significance of the estimation
P-value≤0.05 is significant

From the studies that were mentioned, it was found that 20 to 30 percent of epileptic patients suffer from a condition called refractory epilepsy where they fail to respond to any form of medication. Early onset seizure detection can help patients to take the necessary precautions in the case of seizures. Using early seizure onset detection technique can improve these patients' quality of life.

- Constraints

    - Ethical and Governmental Constraints

The team was made aware at the beginning of the semester that pre recorded data will be provided instead of taking real time data using the device. The reason was simply because in order to use such a device on persons or "subject", a lot of steps were to be followed before getting the required governmental permission to use such a device. Aside from the governmental constraint that the team faced, an ethical constraint arisen. Through the discussions the team held with the project mentor, the team arrived at a conclusion that even if the governmental permissions were granted, it would be unethical to test the device on any subject in real-time. The reason being that if the device were to have any false alarms, the subjects might be negatively affected by this result.

The ways in which a subject can be negatively affected are the following:

1) The subject will lose a sense of security and trust with such devices which can negatively impact his health
2) The subject may have increased levels of stress and paranoia on the basis that he or she will be experiencing a seizure event
3) The subject might have an increased heart pressure level which can negatively affect his or her health
4) The subject's perception that a seizure event is about to occur might induce the seizure

Therefore, from an ethical standpoint, it is vital to test the device on pre-recorded data and determining all these figures before considering testing on subjects.

    - Health and Safety Constraints

Although the short term usage of the device does not pose any health and safety concerns, the team has to acknowledge that the prolonged use of the device might have negative impacts on a subject's health. The team will not be using the device for the purpose of this year's project, but acknowledging the negative impacts on health might be useful for any team that pursues the continuation of this project. Prolonged usage of the device, mainly the connection of electrodes to the scalp, can cause skin abrasions. Minimal skin abrasions can cause lacerations and bleeding, while deeper, more severe abrasions can lead to the formation of scar tissue. Therefore, from a health and safety standpoint, it is highly recommended to research these effects more deeply before using the device on subjects.

1.3: Semester Plan – Team Working Agreement

We started planning this semester's task during the ECEN 403 lab and we distributed the tasks accordingly. Below is the initial plan that we started this semester with.

PROJECT TIMELINE 2016-2017

PROJECT PHASE I FALL 2016	STARTING	ENDING
PROJECT PROPOSAL, INITIAL WEBSITE, TEAM AGREEMENT	28 - 8 - 2016	8 - 9 - 2016
PROPOSAL PRESENTAION	17 - 9 - 2016	29 - 9 - 2016
CUSTOMER NEEDS STUDY	2 - 10 - 2016	6 - 10 - 2016
BENCHMARKING	9 - 10 - 2016	13 - 10 - 2016
FUNCTIONAL MODELING + PROJECT STUDY VIDEO UPLOADED TO WEBSITE	16 - 10 - 2016	20 - 10 - 2016
INITIAL PROJECT DESIGNING	20 - 11 - 2016	5 - 12 - 2016
FINAL PROGRESS PRESENTATION	22 - 11 - 2016	4 - 12 - 2016
FINAL PROGRESS REPORT	-	5 - 12 - 2016
PROJECT VIDEO	-	4 - 12 - 2016

PROJECT PHASE II SPRING 2017 (UPCOMING)	STARTING	ENDING
THEORITICAL BACKGROUND	15-10-2016	10-12-2016
PREPARE PATIENT RECORD	15- 1 - 2017	29-1-2017
CHANNEL SELECTION STAGE	15- 1 - 2017	5-2-2017
NEURAL SYNCHRONY	5-2-2017	28-2-2017
WAVELET TRANSFORM	5-2-2017	28-2-2017
CLASSIFICATION STAGE	29-2-2017	1-4-2017
TRAINING AND TESTING	29-2-2017	1-4-2017
ABSTRACT SUBMISSION TO QATAR ANNUAL RESEARCH CONFERENCE (ARC)	TBA	TBA

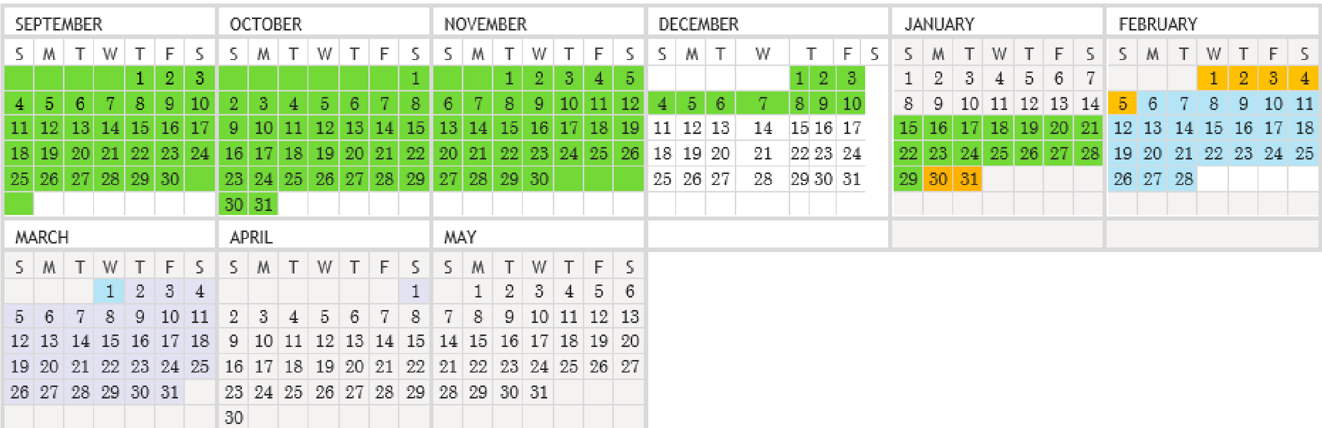

Figure 3: Timeline

After acknowledging the theoretical background during the past semester and the winter break, we started this semester with preparing the patients records by downloading them, and inserting them to MATLAB. We then worked on the channel selection code, and from that the work was divided into the two groups that worked on the neural synchrony and wavelet transform stages. After that we moved into training our support vector machine. As it could be inferred from the timeline above, we are currently in the training and testing stage.

The task distribution among the team members is shown below.

Team Member Name	Tasks Done	Current Tasks
Fatima Al-Ansari	403 Related tasks Channel Selection Code Wavelet Transform Support Vector Machine	Performance measurements
Fatima Al-Malki	403 Related tasks Wavelet Transform Code Wavelet Transform Support Vector Machine	Performance measurements
Noor Al-Zeyara	403 Related tasks Neural Synchrony Code	Performances code Neural Synchrony Support Vector Machine
Omar Barhoumi	403 Related tasks Wavelet Transform Code	Performances code Neural Synchrony Support Vector Machine
Osama AlSaad	403 Related tasks Prepared Patient Records Wavelet Transform Support Vector machine	Performance measurements

Table 1: Task Distribution

CHAPTER 2: PROJECT DESIGN AND DEVELOPMENT PROCESS

2.1: Benchmarking

2.1.1: Introduction

A study was taken to compare the project in relation to other previous studies in the area. It was vital in providing the goals and objectives of the project. Some of the criteria used aimed at ascertaining the sensitivity, latency in reference to data length and cases of false alarms as shown in the previous studies. The approach was quite crucial in that it tested the significance and intended success of the project. Likewise, the length of the data proved critical in determining the viability of the research and the related contingencies.

2.1.2: Study Conducted

Detector Type	Sensitivity (%)	Latency (sec)	FA/hr	Length of Data (hrs)
"Seizure Prediction Using Spike Rate Intracranial EEG," [1]	75.8	10	0.09	95
"Patient-specific seizure onset detection,"	89.8	9.2	0.125	1419
"Seizure detection, seizure prediction, and closed-loop warning systems in epilepsy", [3]	97	5	0.6	428
"A review of channel selection algorithms for EEG" [4]	94.2	8±3.2	0.25	875

Table 2: Study Conducted

Table 2 represents the benchmarking study. It is a comparison of the indicated algorithms and approaches already published in other researches. As shown, the first algorithm appeared in *Seizure Prediction Using Spike Rate Intracranial EEG* research based on the spike rate of the intracranial EEG probes attached to the human skull. It concludes low sensitivity percentage and a low FA/hr rate. The length of the data is low as shown by the figures thus depicting the legitimacy of the results.

The second parameter observed was *Patient-specific seizure onset detection* by separately evaluating the patients based on their lifestyles and daily actions. The EEG result of each was compared to their previous records as indicated.

In the third category, *Seizure detection, seizure prediction and closed-loop warning systems in epilepsy*, a closed loop feedback system was implemented in the algorithm and indicated higher sensitivity percentages, low latency, and FA/hr values.

The fourth and last category involved *a review of channel selection algorithms for EEG* and involved an elevation of the number of channels in order to detect more EEG signals. Despite the fact that it provided better sensitivity results, it increased the latency of the system. This was as a result of the number of channels added increasing the complexity of the system in the neural synchrony stage.

The goal of the project is to achieve higher sensitivity, lower latency, and lower FA/hr values as compared to other case studies. Based on functional modeling, it is clear that the project is viable typically because of the fusion of the neural synchrony and the energy waveform of each EEG sub-band aimed at increasing sensitivity and lowering latency.

2.2: Functional Modeling

2.2.1: Introduction

The block diagram employed specifies the main functions and stages of the project. The functional model was based on a number of theoretical researches for purposes of retrieving the main stages. It was likewise facilitated through meetings and provides elaborative explanations as per the blocks.

2.2.2: Functional Modeling

Figure 4 represents detailed functional modeling of the proposed project. It illustrates the main functional stages and consists of 5 main stages essential in representing the functions of the project. Some of the stages in the diagram were divided into units such as feature extraction unit and classification unit.

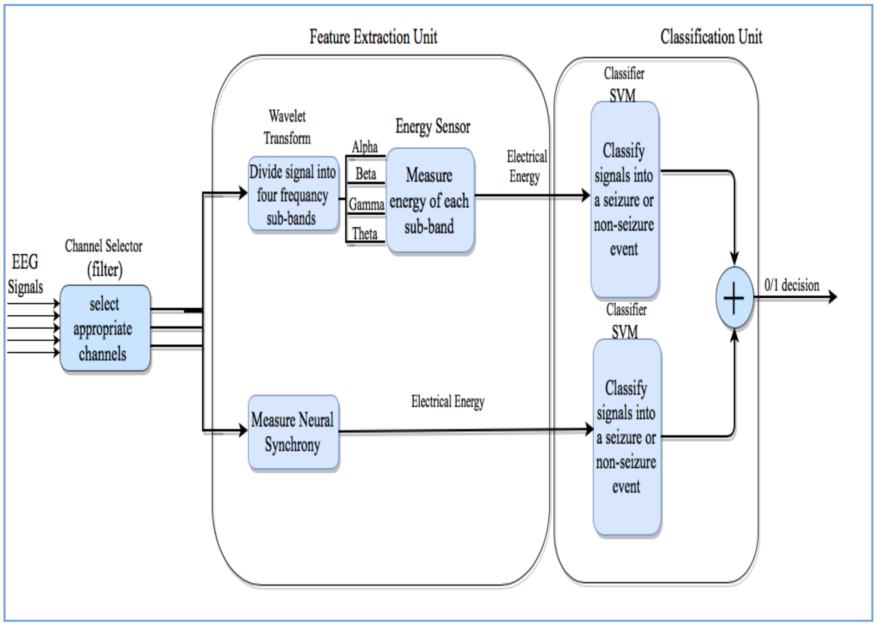

Figure 4: Functional Modeling

Figure 4 explains that when EEG signals are sent to the channel selector they are divided into two. One section divides the signal into four frequency sub bands and the other section measures neural synchrony. The four frequency sub bands are passed to the energy sensor and then to the SVM classifier. The other section goes directly to SVM classifier. In both SVM classifiers the signals are classified between seizure or non-seizure then joined together to make decision.

2.2.3: Explanation of the Functional Modeling

To create an efficient algorithm, all functions have to perform successfully. The initial input of the ESD algorithm is EEG signal acquired from the patient's brain and the final output is a detection that notifies the patients of an occurring seizure. Further elaboration of the functional modeling is shown below:

i. Channel selection:

The stage begins after the acquisition of the EEG signal then followed by a selection of appropriate channels. Selection of specific channels from larger channel range allows an accurate examination of channels. Selecting channel lowers the number of channels used positively affecting the performance of the algorithm as lowering the number of channels can help to lower the amount of consumed energy. It likewise lowers the computation time hence decreasing the latency rate. Selection is strongly dependent on channels active during a seizure considering that there are many ways of performing channel selection. Nevertheless, the considerable method is based on the maximum variance value and it is chosen based on its speed and independence.

- Feature Extraction Unit:

In the extraction unit signal, features are extracted using various signal-processing techniques in order to detect the seizure onset event. In this unit, two things take place:

ii. Wavelet Transform:

The wavelet transform is applied to the signals, as it helps to convert them from real time domain signals into frequency domain signals. It also breaks down the signals into four main frequency sub-bands i.e. Alpha, Beta, Gamma, &Theta). It then uses energy sensor where the energies of those sub-bands are measured. The wavelet transforms performed by applying a compressed mother wavelet into the EEG signal waves and measuring peak values.

iii. Neural Synchrony:

Signals are analyzed for parts where synchronization among them appears. Whenever synchronization is in place, it means that neurons in the brain are firing at the same time and a seizure is currently happening. The analysis is going to be based on the degree of correlation among the signals and the extraction of a condition number from channels at a particular time to indicate the level of synchrony. The calculation of a condition number is going to be based on the EEG matrix at a certain time. The reason behind choosing the condition number calculation as it is a fast and simple method for extracting EEG signal.

- Classification unit:

In the classification unit, the extracted signal is going to be observed in order to classify the occurring events into a seizure and non-seizure events:

iv. The Fusion Component:

The fusion component is a part of the classification unit as it will provide more efficacy to the detection processes as the energy readings of the signals are going to be combined with the neural synchrony analyzation. At the same time, notice will be taken at this stage as if fusion will increase the consumed energy and the computation time then the neural synchrony might be dismissed or replaced by another extraction method.

v. The Classifier:

In order to classify events into a seizure or non-seizure events, a support vector machine (SVM) is going to be used. A Support Vector Machine (SVM) is a classifier that is defined by a separator hyperplane used to make a decision based on where the observation lies with respect to the hyperplane. The extracted features of both energy and neural synchrony analysis will be fed into the support vector machine to classify events, but first, the SVM classifier must be trained in order to distinguish between the two different types of events. The machine will be trained offline by feeding it with the previously recorded seizure readings of patients after the machine is trained, a new (unknown to the SVM) record is going to be fed into the machine and the machine will be able to classify seizure and non-seizure events based on the training done.

2.3: Concept Generation and Evaluation

2.3.1: Introduction

The project will mainly dwell on the kind of dataset to be employed. It is thus critical to get accurate calculations to obtain optimal results. This will imply that the project will be viable in advancing research in detection of epileptic seizure onset.

2.3.2: Criteria Ranking

The datasets considered included the EEG, ECG, accelerometry, video detection, mattress sensors, and baby monitors. In evaluating the concept to be used, vast options were catered in developing the Epileptic Seizure Detection device and compared accordingly to select the best. The rest are as indicated in the table below indicating the criteria ranking matrix.

Criterion		A	B	C	D	E	F	G	Total	Rank	Weight
A	Sensitivity	/	1	1	1	1	1	1	6	1	0.28
B	Latency	0	/	1	1	1	1	1	5	2	0.23
C	False Alarms	0	0	/	1	1	1	1	4	3	0.19
D	Durability	0	0	0	/	1	1	1	3	4	0.15
E	Safety	0	0	0	0	/	1	1	2	5	0.10
F	Cost	0	0	0	0	0	/	1	1	6	0.05
G	Factor	0	0	0	0	0	0	/	0	7	0.00
										Total	1.00

Table 3: Criteria-Ranking Matrix

2.3.3: Criteria Description

The table below represents the criteria used and their appropriate descriptions. They include such factors like sensitivity, latency, false alarms, durability, safety, and cost.

Criterion	Description
Sensitivity	Percentage of seizures correctly identified by the device
Latency	Delay between the seizure onset and the detection
False Alarms	Number of times the device detects a seizure in the absence of an actual event
Safety	Is the device safe for usage
Durability	How long can the device keep on running
Cost	Development cost of the device
Sensitivity	Percentage of seizures correctly identified by the device

Table 4: Criterion Description

2.3.4: Relative Comparison

After selection of different criterion and calculating the weighing factors, the scoring of the different data sets is calculated. Table 4 indicates a summary of the individual scores for every criterion.

Criteria	Sensitivity	Latency	False Alarms	Durability	Safety	Cost
Weighing Factor	**0.28**	**0.23**	**0.19**	**0.15**	**0.10**	**0.05**
Concepts						
EEG	30	30	25	20	15	20
ECG	20	35	25	20	25	20
Accelerometry	20	10	20	15	5	10
Video Detection	10	5	15	10	15	10
Mattress Sensor	15	10	5	15	20	20
Baby Monitors	5	10	10	20	20	20
Total	100	100	100	100	100	100

Table 5: Screening Table

2.4: Scoring and conclusions

Applying data from previous sections it can be shown that the EEG signals are more prominent as compared to other alternatives. The table below shows the values that each data set had. To determine the scores, the value given to each criterion was multiplied by the weighing factor of that criterion and summed to the rest of the values for each data set.

Concepts	Scores	Rank
EEG	25.50	1
ECG	24.90	2
Accelerometry	14.95	3
Mattress Sensor	12.70	4
Baby Monitors	11.60	5
Video Detection	11.05	6

Table 6: Scoring Table

Based on the results, it was evident that EEG ranks better as compared to other concepts. Thus, EEG was chosen as the data set that will be analyzed for this project.

CHAPTER 3: DETAILED SYSTEM DESIGN AND DEVELOPMENT

3.1: System design and modeling

The following is a breakdown of the code done so far in this project, it is followed by a detailed explanation of each section of the code:

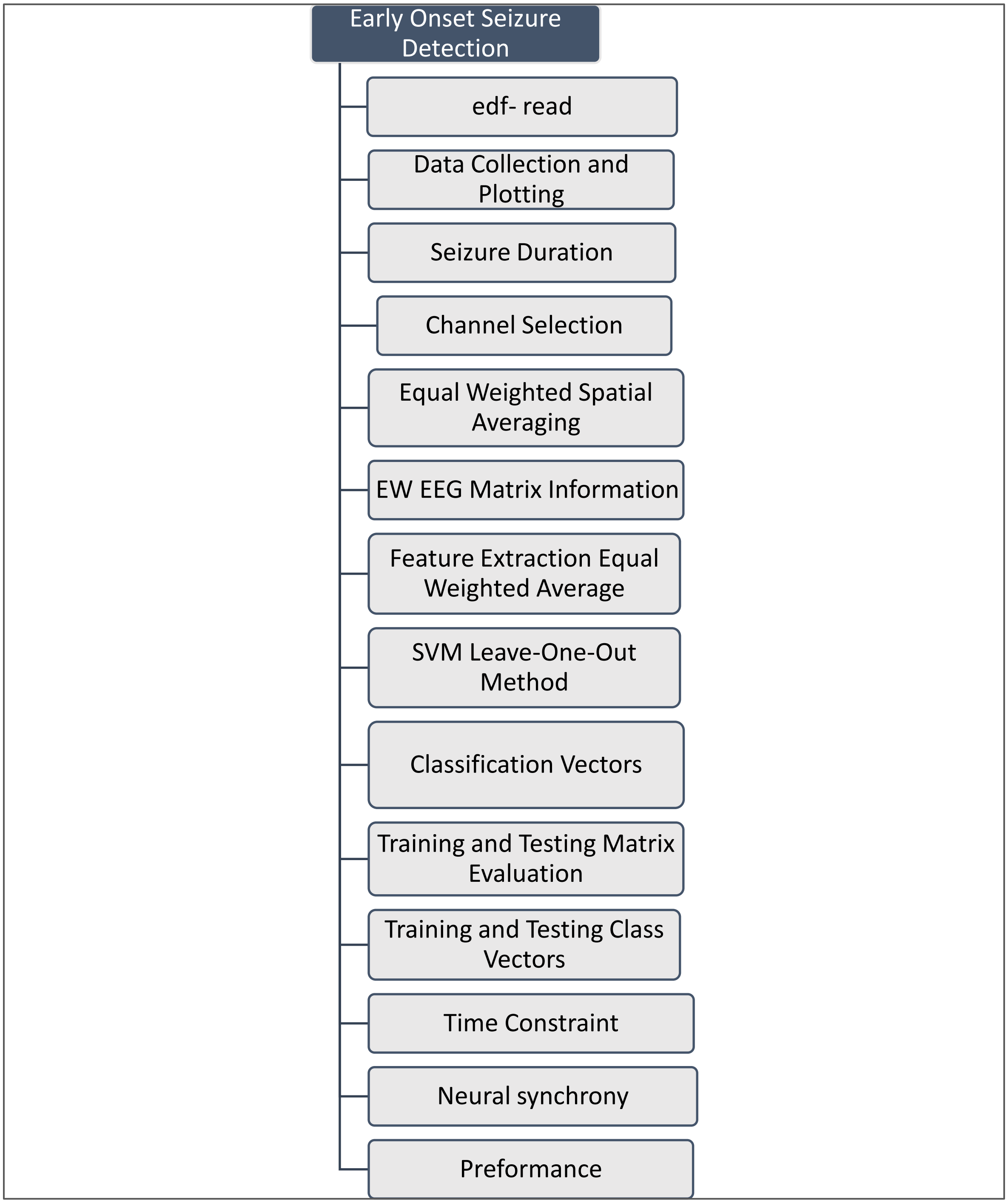

Figure 5: Code Flowchart

3.2: Code Breakdown

3.2.1: Edf read:

Records obtained from patients were in the EDF (European data format) format and needed to be translated into a MATLAB readable format. A suitable translation code (EDFREAD) was found downloaded from the European data format website http://www.edfplus.info/ in order to perform the needed conversion.

```
[hdr1, record01] = edfread('chb01_03.edf');
[hdr1, record02] = edfread('chb01_04.edf');
[hdr1, record03] = edfread('chb01_15.edf');
[hdr1, record04] = edfread('chb01_16.edf');
[hdr1, record05] = edfread('chb01_18.edf');
[hdr1, record06] = edfread('chb01_21.edf');
```

Figure 6: EDFREAD implementation

3.2.2: Data Collection and Plotting:

Specific records were imported into MATLAB and converted to a MATLAB readable file using the EDFREAD command. Those specific records were marked by the doctors as files with seizures seen in figure 7. Sampling frequency was found as recommend by the European data format to be 256 micro- hertz while sampling time was obtained by dividing (1/sampling frequency). For further observation, the records were plotted as amplitude in micro Volts Vs. time in seconds using the MATLAB code provided in figure 7. Since each record consists of 23 separate channels, 23 plots were obtained for each record. The reason behind plotting the records is to make sure that the EDF code is preforming perfectly and to observe the peaks in energies during a seizure. An example plot is shown in figure 8, and as it can be observed from the plot of EEG signal obtained from patients, spikes indicate a sudden change in the signal's energy which can indicate a possibility of a seizure. However, not all sudden changes are seizures, some are standard brain activity. The mentioned issue proves the need to construct a support vector machine that will help to distinguish between seizure or non-seizure events and will be explained in the following sections.

```
Fs = 256;
Ts = 1/Fs;

% Plotting the EEG data.

N = size(record01,2);                    % number of samples

for i = 1:23 %plotting each channel
figure(i)
plot((0:N-1) * Ts, record01(i,:).')
xlabel('time(sec)')
ylabel('EEG Amplitude (\mu volt)')
grid on
end
```

Figure 7: Data Plotting

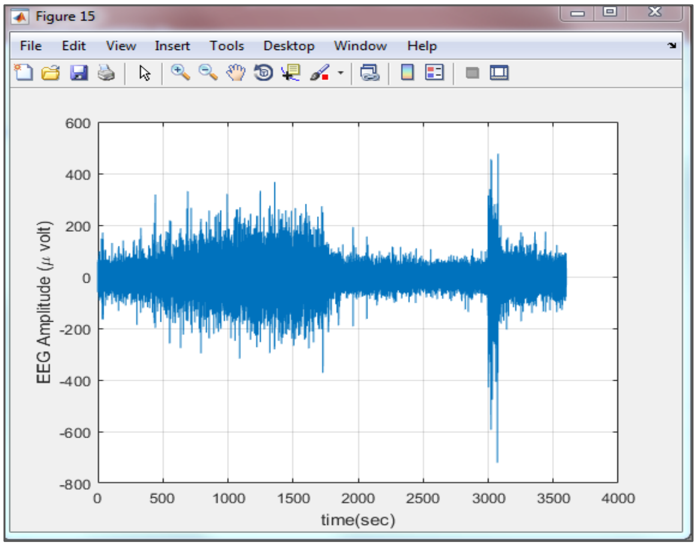

Figure 8: example plot

3.2.3: Channel Selection:

Another major issue proposes itself when trading energy consumption and efficiency as seizures does not occur at all parts of the brain, so a selective algorithm function called channel selection function was built in order to limit the number of channel from 23 channels to 4 active channels during one seizure. Channel selection will allow a minimization of both the consumed energy and computational complexity.

The channel selection function or CS was created as a function file in MATLAB shown in figure 9. Doing so will allow the easy mobility of the channel selection to work on multiple records at a very short period implementation and. In figure 9, it can be seen that the channel selecting process was based on maximum variances among all the channel's variances, and the 4 maximum values among these variances were arranged in a descending way, with their channel number (index number).

```
function [selected_channels] = SC(Fs,matrix,NC)

numberChannels = size(matrix,1);     % number of  EEG channels
N = size(matrix,2);                  % number of samples
L = N/Fs;
v = zeros (numberChannels,1);
for i=1:23

    v(i) = var(matrix(i,:));


end
% max_variance = max(v(i))

[Asorted CH] = sort(v,'descend')
selected_channels= CH(1:NC)'
selected_channels= CH(1:NC)
end
```

Figure 9 : Channel selection

```
NC = 4;
[selected_channels01] = SC(Fs,record01,NC);
[selected_channels02] = SC(Fs,record02,NC);
[selected_channels03] = SC(Fs,record03,NC);
[selected_channels04] = SC(Fs,record04,NC);
[selected_channels05] = SC(Fs,record05,NC);
[selected_channels06] = SC(Fs,record06,NC);
```

Figure 10: Channel selection implementation

3.2.4: Seizure Duration:

The doctor observation identifies the starting and ending time of each seizure that presents itself in a patient record. Starting and ending times enables the possibility of finding the duration of each seizure. Figure 11 shows the starting and ending time of the seizures as well as their duration implemented in the original code. Application wise, adding those identifications of time is extremely helpful in training the support vector machine or SVM and will be clarified in the following sections.

```
% Seizure Start and End
%ss == seizure start    se == seizure end

ss01 = 2996;
se01 = 3036;

ss02 = 1467;
se02 = 1494;

ss03 = 1732;
se03 = 1772;

ss04 = 1015;
se04 = 1066;

ss05 = 1720;
se05 = 1810;

ss06 = 327;
se06 = 420;

s_start = [ss01; ss02; ss03; ss04; ss05; ss06];
s_end = [se01; se02; se03; se04; se05; se06];
s_duration = [se01-ss01+1;se02-ss02+1; se03-ss03+1; se04-ss04+1;...
    se05-ss05+1; se06-ss06+1];
```

Figure 11: Seizure duration

3.2.5 Feature Extraction Unit

1. Equal Weighted Spatial Averaging:

In this section, data of all the 23 EEG channels will be inputted. Later, the voltages will be averaged in order to have a single value for the voltage of that specific records as seen in figure 12. When the channel selection function is implemented, it will average voltages of the selected channels only as seen in figure 13

```
%% Equal Weighted Spatial Averaging

record01_ew = mean(record01);
record02_ew = mean(record02);
record03_ew = mean(record03);
record04_ew = mean(record04);
record05_ew = mean(record05);
record06_ew = mean(record06);
```

Figure 12: Equal Weighted Spatial Averaging

```
% Equal Weighted Spatial Averaging

record01_ew = mean(record01(selected_channels01,:));
record02_ew = mean(record02(selected_channels02,:));
record03_ew = mean(record03(selected_channels03,:));
record04_ew = mean(record04(selected_channels04,:));
record05_ew = mean(record05(selected_channels05,:));
record06_ew = mean(record06(selected_channels06,:));
```

Figure 13: Equal Weighted Spatial Averaging of selected channels.

2. EW EEG Matrix Information:

This part of the code seen in figure 14 gives general information about the EEG matrix created. The thing that need to be highlighted here, is the epoch length, where each two seconds of the EEG signal was classified as an epoch. The epoch was used as a sliding window to slide over the real time and obtain the EEG information.

```
% EW EEG Matrix Information

numberChannels = size(record01_ew,1);     % number of  EEG channels
N = size(record01_ew,2);                  % number of samples
L = N/Fs;                             % length of channels (in seconds)
numberEpochs = L-1;                   % total number of epochs
epochLength = 2;                      % 2 second long epochs
windowStep = 1;
```

Figure 14: EW EEG Matrix Information

3. Feature Extraction Equal Weighted Average:

A function called feature _extraction shown in figure 15 was created to preform wavelet decomposition and energy extraction from each frequency sub-band. Then the coefficients were extracted into seven different detail coefficients where the last four (d4, d5, d6, d7) represent the amplitudes of the alpha, beta, gamma, and theta sub-bands. The squared sum was taken to obtain the energies of these sub-bands.

```
function x = feature_extraction(epoch, level, waveletName)

%% Wavelet Decomposition

[D,B]=wavedec(epoch, level, waveletName);  %wavelet decomposition --

%% Extract the detail coefficients

d1=detcoef(D,B,1);
d2=detcoef(D,B,2);
d3=detcoef(D,B,3);
d4=detcoef(D,B,4);
d5=detcoef(D,B,5);
d6=detcoef(D,B,6);
d7=detcoef(D,B,7);


%% Calculating the energy contained in each detail (freq band)
%absolute value of energies (not dB values)

x4 = sum(d4.^2);
x5 = sum(d5.^2);
x6 = sum(d6.^2);
x7 = sum(d7.^2);

x = [x4 x5 x6 x7]';

end
```

Figure 15: feature extraction function

In figure 16 the FE_matrix was created in order to preform online detection through shifting and to finally find the energies in dB.

```
function [feature_matrix feature_matrix_dB] = FE_matrix(Fs, matrix)

numberChannels = size(matrix,1);    % number of  EEG channels
N = size(matrix,2);                 % number of samples
L = N/Fs;                           % length of channels (in seconds)
numberEpochs = L-1;                 % total number of epochs
epochLength = 2;                    % 2 second long epochs
windowStep = 1;

waveletName = 'db4';
level = 7;


feature_matrix = [];

for indexEpoch = 0:numberEpochs-1

    disp(['Epoch Index: ' num2str(indexEpoch)]);  %displays what epoch number we are on

    feature = [];
    for indexChannel = 1:numberChannels
        epoch = matrix(indexChannel,[1:epochLength*Fs]+indexEpoch*windowStep*Fs);
        feature = [feature; feature_extraction(epoch, level, waveletName)];
    end

    feature_matrix = [feature_matrix feature];

end

feature_matrix = feature_matrix.';
feature_matrix_dB = 10*log10(feature_matrix);  % features in dB

end
```

Figure 16: FE matrix function

3.2.6: Classification unit

1. Support Vector Machine (SVM):

The leave one-out method was used in order to train the system to have the ability to recognize the event as seizure or non-seizure. This method works on creating two different matrices for training and testing by keeping all the values in the first matrix the same except for one as seen in figure 17. The SVM uses circular shift to shift between the index values of the training and testing matrices. The main reason behind choosing this method is due to the low number of available patient records where the leave-one-out method allows shifting of records, creating a new but different matrix for each test and train session.

```
%% SVM Leave-One-Out Method

NumberOfRecords = 6;

I = [1; 1; 1; 1; 1; 0]; % shifting index for training matrix
T = [0; 0; 0; 0; 0; 1]; % shifting index for testing matrix

% Classification vectors (1 = non-seizure, -1 = seizure)
class_vec_01(1:ss01-1) = 1;
class_vec_01(ss01:se01) = -1;
class_vec_01(se01+1:3599) = 1;
class_vec_01 = class_vec_01';

class_vec_02(1:ss02-1) = 1;
class_vec_02(ss02:se02) = -1;
class_vec_02(se02+1:3599) = 1;
class_vec_02 = class_vec_02';

class_vec_03(1:ss03-1) = 1;
class_vec_03(ss03:se03) = -1;
class_vec_03(se03+1:3599) = 1;
class_vec_03 = class_vec_03';

class_vec_04(1:ss04-1) = 1;
class_vec_04(ss04:se04) = -1;
class_vec_04(se04+1:3599) = 1;
class_vec_04 = class_vec_04';

class_vec_05(1:ss05-1) = 1;
class_vec_05(ss05:se05) = -1;
class_vec_05(se05+1:3599) = 1;
class_vec_05 = class_vec_05';

class_vec_06(1:ss06-1) = 1;
class_vec_06(ss06:se06) = -1;
class_vec_06(se06+1:3599) = 1;
class_vec_06 = class_vec_06';
```

Figure 17: Support Vector Machine (SVM)

```
% leave-one-out method

for i = 1:NumberOfRecords

    I = circshift(I,1);    % training indeces
    T = circshift(T,1);    % test index
```

Figure 18: Circular-Shift Implementation

```
% SVM

svmStruct=svmtrain(training_matrix, training_class_vec, 'kernel_function', 'rbf');

results = svmclassify(svmStruct,test_matrix);
```

Figure 19: SVM final statement

2. Allocation of the Output Vectors:

In this section, performance criterions: false alarm, latency and sensitivity are set initially to zero.

```
% Allocation of the output vectors

false_alarm = zeros(1,NumberOfRecords);
EOL_epoch = zeros(1,NumberOfRecords);
EOL_sec = zeros(1,NumberOfRecords);
Sensitivity = zeros(1,NumberOfRecords);
```

Figure 20: Allocation of the output vectors

3. Training Matrix Evaluation:

In this part shown in figure 21, training of the SVM is going to take place, where all the records except for one are going to be used as training references for the machine. As an example for the first run, all records except I06 was fed into the machine, In other words the training matrix can be represented as [111110], where ones represent the records I01 through I05 to be fed to the machine and zero represent I06 that will be used in testing.

```
%TRAINING MATRIX EVALUATION

I01 = FE_01_ew_dB*I(1);
I02 = FE_02_ew_dB*I(2);
I03 = FE_03_ew_dB*I(3);
I04 = FE_04_ew_dB*I(4);
I05 = FE_05_ew_dB*I(5);
I06 = FE_06_ew_dB*I(6);

A = [I01; I02; I03; I04; I05; I06];
B = nonzeros(A');
C = vec2mat(B,4);

training_matrix = C;
```

Figure 21: Training Matrix Evaluation

4. Testing Matrix Evaluation:

In this part shown in figure 22, the machine will be tested in order for it to distinguish seizure or non-seizure events by feeding I06 to the system so the training matrix will be [000001] as 1 represent I06 the record to be tested in this stage.

```
% TESTING MATRIX EVALUATION

T01 = FE_01_ew_dB*T(1);
T02 = FE_02_ew_dB*T(2);
T03 = FE_03_ew_dB*T(3);
T04 = FE_04_ew_dB*T(4);
T05 = FE_05_ew_dB*T(5);
T06 = FE_06_ew_dB*T(6);

AA = [T01; T02; T03; T04; T05; T06];
BB = nonzeros(AA');
CC = vec2mat(BB,4);

test_matrix = CC;
```

Figure 22: Testing Matrix Evaluation

5. Training and Testing Class Vectors:

Is this section of the code shown on the two figures bellow, the classification vectors obtained before will be multiplied by I(1) through I(6) using the same theory used in the training and testing matrix evaluation. It will allow the machine to distinguish between the different duration of seizure in each record.

```
% TRAINING CLASS VECTORS

C01 = class_vec_01*I(1);
C02 = class_vec_02*I(2);
C03 = class_vec_03*I(3);
C04 = class_vec_04*I(4);
C05 = class_vec_05*I(5);
C06 = class_vec_06*I(6);

class_vec_I = [C01; C02; C03; C04; C05; C06];
training_class_vec = nonzeros(class_vec_I);
```

Figure 23: Training class vectors

```
% TESTING CLASS VECTOR

CT01 = class_vec_01*T(1);
CT02 = class_vec_02*T(2);
CT03 = class_vec_03*T(3);
CT04 = class_vec_04*T(4);
CT05 = class_vec_05*T(5);
CT06 = class_vec_06*T(6);

class_vec_T = [CT01; CT02; CT03; CT04; CT05; CT06];
test_class_vec = nonzeros(class_vec_T);
```

Figure 24: Testing class vectors

6. Time Constraint:

The time constraint code shown in figure 25 works on the principle that if a spike of energies occurs only in one second then it is classified as a non-seizure event. On the other hand, by experiment it was noticed that if a spike that takes up to three seconds is noticed, then it will be classified as a seizure.

```
%Time-Constraint (T_C = 3)

T_C = [-1 -1 -1].' ;
row=size(results,1);
declare=zeros(row-2,1);
for j = 1:row-2
    if results(1+(j-1):3+(j-1),:) == T_C
        declare(j,:) = -1;  %declare seizure
    else declare(j,:) = 1;  %declare non-seizure
    end
end

% We do a similar operation for the true values of the TEST record so that when we
% do the performance analysis, we receive true results that are not off by
% two digits due to the timing-constraint we put (T=3)

T_C = [-1 -1 -1].' ;
row2=size(test_class_vec,1);
true=zeros(row2-2,1);
for j = 1:row-2
    if test_class_vec(1+(j-1):3+(j-1),:) == T_C
        true(j,:) = -1;  %declare seizure
    else true(j,:) = 1;  %declare non-seizure
    end
end
```

Figure 25: Time Constraint

3.2.7: Neural synchrony:

Neural synchrony part along with its support vector machine is combined with our system to ensure that output of the wavelet transform part is correct. It is calculated by taking the condition number CN of the recorded EEG matrix at a particular time. The EEG matrix corresponds to the (epoch1) shown in the figure 26. Epoch1 works as a sliding window of the time. Whenever 2 seconds of the epoch are read, epoch the sliding window (EEG matrix of time) will be shifted to the next 2 seconds. The condition number then is calculated by taking the maximum to the minimum singular values of the epoch

```
numberChannels = size(record01,1);    % number of  EEG channels
N = size(record01,2);                 % number of samples
L = N/Fs;                            % length of channels (in seconds)
numberEpochs = L-1;                  % total number of epochs
epochLength = 2;                     % 2 second long epochs
windowStep = 1;

for indexEpoch = 0:numberEpochs-1
    disp(['Epoch Index: ' num2str(indexEpoch)]);
    epoch1 = [];


    for indexChannel = 1:numberChannels
        epoch =record01(indexChannel,[1:epochLength*Fs]+indexEpoch*windowStep*Fs);
        epoch1 = [epoch1; epoch];
    end
end
minsing=min(epoch1)  %minimum value of singular XT
maxsing=max(epoch1)   %maximum value of singular XT
CN=maxsing/minsing   %condition number
```

Figure 26: Neural Synchrony

3.2.8 Performance:

In this section the system's performance is tested with and without the channel selection which will be implemented later in the course. The testing is based on the number of false alarms, electrographic seizure onset detection latency, and sensitivity.

1. Number of False Alarms:

   The section of the code shown in figure 27, works as a counter to detect the number of false alarms before and after the seizure in case the system alert for a seizure event when there is no real seizure.

```
    % Number of False Alarms

Number_of_FA_bs = 0; %reset before seizure FA counter
r = 0;
while r < s_start(i) - 1

    r = r+1;

    if declare(r) == 1
        Number_of_FA_bs = Number_of_FA_bs + 0;
    else Number_of_FA_bs = Number_of_FA_bs + 1;
        r = r + RP;
    end

end

Number_of_FA_as = 0; %reset after seizure FA counter
k = s_end(i);
while k < length(declare)

    k = k+1;

    if declare(k) ==1
        Number_of_FA_as = Number_of_FA_as + 0;
    else Number_of_FA_as = Number_of_FA_as + 1;
        k = k + RP;
    end

end

false_alarm(1,i) = Number_of_FA_bs + Number_of_FA_as;
```

Figure 27: Number of False Alarms

2. Electrographic seizure onset detection latency:

   Shown in figure 28 is the electrographic seizure onset detection latency (EOL) if will find the latency in both seconds and epochs.

```
% Electrographic Seizure Onset Detection Latency (EOL)

matching_seizure = true(s_start(i):s_end(i)-2) == declare(s_start(i):s_end(i)-2);
EOL_epoch(1,i) = find(matching_seizure,1) - 1;  % in epochs
EOL_sec(1,i) = epochLength*(find(matching_seizure, 1) - 1);  % in seconds
```

Figure 28: Electrographic seizure onset detection latency

3. Sensitivity:

The section of the code shown in figure 29, will calculate sensitivity by dividing the true positive (when a real seizure is detected) by the number of seizures in the record and multiplies it by 100.

```
% Sensitivity (S)
% S = TP/P
% TP: True Positive (detector detects a Seizure when there really is a seizure)

P = 1; % number of seizures in the record

if sum(matching_seizure) > 1
    TP = 1;
else TP = 0;
end

Sensitivity(1,i) = (TP/P)*100; % sensitivity = sum(true positive)/sum(actual positives)
```

Figure 29: Sensitivity

CHAPTER 4: EXPERIMENTAL RESULTS

4.1: Completed Results

Up until this point in the project, the team has completed the channel selection code, the wavelet transform code, the neural synchrony code, and the SVM for the wavelet transform. The results that the team has acquired are on the performance of wavelet transform while having four, five, six, seven, or all twenty-three channels operating. When changing the number of channels or the patient, the code has to be adjusted and reflect that change. When all channels were operating, the team collected data on patients one, two, three, five, eight, and eleven. When four channels were being tested, the team collected data on patients one, three, five, and eight. For the rest, data was collected on patients one and five. The reason a channel selection algorithm was added is because each channel consumes 300 micro-watts, and the goal of the project is to ensure, amongst other things, that the algorithm is energy efficient.

The tables below will show the average sensitivity, the average false alarms, as well as the energy consumed by that algorithm. Table 7 shows the results when four channels are selected. Table 8 shows the results when five channels are selected. Table 9 shows the results when six channels are selected. Table 10 shows the results when seven channels are selected. Table 11 shows the results when all channels are used.

	Avg. False alarm	**Avg. Sensitivity**	**Latency**	**Energy Consumed**
Patient 1	22.8333	100	11.3333	1200 Micro-Watts
Patient 3	29.5714	100	20.5714	1200 Micro-Watts
Patient 5	10.8000	100	8.4000	1200 Micro-Watts
Patient 8	16.6000	100	12.8000	1200 Micro-Watts
Total Average for Patients	19.95	100	13.2716	1200 Micro-Watts

Table 7: Four Channels Selected

	Avg. False alarm	**Avg. Sensitivity**	**Latency**	**Energy Consumed**
Patient 1	20.8333	100	6.3333	1500 Micro-Watts
Patient 5	11.2000	100	2.4000	1500 Micro-Watts
Total Average for Patients	16.0166	100	4.3666	1500 Micro-Watts

Table 8: Five Channels Selected

	Avg. False alarm	Avg. Sensitivity	Latency	Energy Consumed
Patient 1	18.3333	100	5.3333	1800 Micro-Watts
Patient 5	8.6000	100	5.6000	1800 Micro-Watts
Total Average for Patients	13.4665	100	5.4665	1800 Micro-Watts

Table 9: Six Channels Selected

	Avg. False alarm	Avg. Sensitivity	Latency	Energy Consumed
Patient 1	19.1667	100	5.3333	2100 Micro-Watts
Patient 5	10.6000	100	4.4000	2100 Micro-Watts
Total Average for Patients	14.8834	100	4.85	2100 Micro-Watts

Table 10: Seven Channels Selected

	Avg. False alarm	Avg. Sensitivity	Latency	Energy Consumed
Patient 1	14.5000	100	3.333	6900 Micro-Watts
Patient 2	6	100	0	6900 Micro-Watts
Patient 3	16.4286	100	18.28	6900 Micro-Watts
Patient 5	8.2000	100	16	6900 Micro-Watts
Patient 8	12.6000	100	14	6900 Micro-Watts
Patient 11	3	100	15.333	6900 Micro-Watts
Total Average for Patients	10.1213	100	11.157	6900 Micro-Watts

Table 11: All Channels Used

4.2: Planned Progress

As it can be viewed from the tables, the false alarm rate is high. The team expects that it will drop significantly after adding the fusion algorithm to neural synchrony. The algorithm currently detects any increase in energy which includes all seizures but also includes a lot of times where stress may be induced. When referencing the outcome of the wavelet transform with the neural synchrony, the code has to determine that a seizure happened from both functions before recognizing the occurrence of a seizure. The main plan is to complete the neural synchrony algorithm and test the theory by having a performance check on neural synchrony running alone, then having both wavelet transform and neural synchrony running together. At that point, the team will have three sets of results, each set of results is divided into multiple parts depending on how many channels are selected. After obtaining all the data, the team will determine which path is most optimal for the purpose of the project.

Chapter 5: Conclusion

5.1 Discussion

Our target is to develop a system that achieves better accuracy rates, at less energy consumption and error rate. Work is also done to improve an efficient seizure onset detection algorithm that uses the electroencephalograph signals (EEG) to detect the onset of seizures. For now, the code is nearly complete for feature extraction, wavelet transform, channel selection and neural synchrony. The support vector machine of the neural synchrony and fusion unit algorithm are under progress.

5.2 Verification

Currently, our theory of building an efficient system that detects seizures is almost proved. Appropriate channels responsible for seizures can now be successfully selected based on their maximum variance. Wavelet transform and channel selection of the feature extraction unit is verified according to the averaging responsible for false alarm, sensitivity, latency and energy consumed tables discussed earlier above.

5.3 Future recommendations

The final code is not done for the moment, a few tasks have to be accomplished in the future. The neural synchrony averaging table has to be finalized soon in order to insure its validity compared to the wavelet transform averaging table. The support vector machine of the neural synchrony is now in process and later has to be adjusted with the main neural synchrony part of the code. The performance of the neural synchrony has to be tested and compared along with the performance of the wavelet transform. The fusion unit responsible for fusing both outputs from wavelet transform and neural synchrony has to be accomplished.

5.4 Improvements and optimization

Improvements of the system is always taking place while writing the code. The results must accurately be consistent with the records having seizures.

5.5 Cost and budget

To build an efficient algorithm, two key items are needed:

1) Computers with MATLAB software being installed
2) EEG data of epileptic seizures to train the system

The computers and MATLAB are provided by TAMUQ in laboratories such as 241G. Patients' records of 10 patients were previously purchased by Dr. Erchin from Technologies Freiburg Campus in Germany for similar research he has been working on. The records were purchased, rather than being collected using the EEG detection kit, because EEG signals cannot be acquired directly from the epileptic patients here in Qatar for safety and confidentiality issues.

Despite the fact that EEG signals cannot be acquired in real time for the project, a 14-channel EEG signal acquisition kit shown in figure below was previously purchased by Dr. Erchin in order for the students to learn more about real time EEG extraction and to be used in future projects. It was deduced that the total "expected" budget is $2078.80; Table 11 shows a complete breakdown of the budget.

Figure 30: EEG Detection Kit

Product	Quantity	Price
EMOTIVE EPOC+14 Channel Mobile Kit [14]	1	$799.00
10 Patients Scalp EEG Data Set [11]	1	$1279.80
Total		$2078.80

Table 12: Budget Breakdown

The Channel Mobile Kit is needed for this project to push for the continuity of this project and ensure that the team's results will be built-on later and achieve advancement in this field. The records of the patients are needed to test the algorithm or use machine learning techniques to train the SVM.

Although the budget is mentioned to be $2078.80, it is important to emphasize that the team asked for $0 for the completion of this project. The data and the Channel Mobile Kit were already acquired by the university before the team began working on this project. The budget breakdown is provided only as a reference.

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