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Progress Report

Efficient Epileptic Seizure Onset detection

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

TABLE OF CONTENTS

CHAPTER 0: ABSTRACT	1
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CHAPTER 1: PROJECT CONSTRAINTS	
SECTION 1.1: INTRODUCTION	2
SECTION 1.2: GOVERNMENTAL CONSTRAINTS	2
SECTION 1.3: ETHICAL CONSTRAINTS	2-3
SECTION 1.4: HEALTH AND SAFETY CONSTRAINTS	3
<hr/>	
CHAPTER 2: CUSTOMER NEEDS AND ETHNOGRAPHIC STUDY	
SECTION 2.1: INTRODUCTION	4
SECTION 2.2: HISTORICAL REVIEW	4-5
SECTION 2.3: CURRENT ETHNOGRAPHIC ANALYSIS	5-6
SECTION 2.4: FINDINGS AND CONCLUSIONS	6
<hr/>	
CHAPTER 3: BENCHMARKING	
SECTION 3.1: INTRODUCTION	7
SECTION 3.2: STUDY CONDUCTED	7-8
<hr/>	
CHAPTER 4: FUNCTIONAL MODELING	
SECTION 4.1: INTRODUCTION	9
SECTION 4.2: FUNCTIONAL MODELING	9
SECTION 4.3: EXPLANATION OF FUNCTION MODELING	10-11
<hr/>	
CHAPTER 5: CONCEPT GENERATION AND EVALUATION	
SECTION 5.1: INTRODUCTION	12
SECTION 5.2: CRITERIA RANKING	12
SUBSECTION 5.2.1: CRITERIA DESCRIPTION	13
SECTION 5.3: RELATIVE COMPARISON	14
SECTION 5.4: SCORING AND CONCLUSIONS	14

CHAPTER 6: DETAILED SYSTEM DESIGN

SECTION 6.1: PROJECT BUDGET	15-16
SECTION 6.2: PROJECT TIMELINE	17

CHAPTER 7: CONCLUSION AND PROGRESS

SECTION 7.1: PROGRESS	18
SECTION 7.2: CONCLUSION	18-19

CHAPTER 8: REFERENCES AND APPENDIX

SECTION 8.1: REFERENCES	20
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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 report is to give an overall view of our project and the accomplishments that have been done so far. Chapter one talks about some of the constraints that the project will face because of governmental, ethical, and health and safety challenges. The main focus of chapter one will be the inability to use the physical device because of these challenges. Chapter two of the paper talks about the customer needs and the ethnographic study that was conducted. Since it was hard to conduct such a study here in Qatar with the amount of confidentiality and permissions needed, a similar study done by Weill Cornell Medical College at Qatar (WCMC-Q) was used. Chapter three talks about the conducted benchmarking study where the algorithm that will be developed was compared with other algorithms that were researched. The comparison areas were latency, sensitivity, and number of false alarms per hour with reference to the length of data hours that were used.

Chapter four discusses the functional modeling and the theory to be followed in order to accomplish this project. The project is divided into two phases, the Feature Extraction stage and the Classification stage. The Wavelet Transform, neural synchrony, and the calculated energy of each signal are to take place in the feature extraction stage while the Support Vector Machine learning will take place in the classification stage. In chapter five, the concept behind choosing EEG signals among other methods to detect the seizures was discussed. The EEG method was chosen as it had the highest score in the scoring table. In chapter six, a detailed system design was discussed and the required finalized budget and timeline were stated. Chapter seven discusses the progress so far, the conclusion, and future work to be done in the project. Finally, all the references used for this report can be found in chapter eight.

Chapter 1: Project Constraints

1.1 Introduction

As any device to be released in the market, the device being designed in this course is governed by external factors such as economic, environmental, social, governmental, ethical, and health and safety ones. For our project, since EEG is the data set that will be used, economic factors are irrelevant because only the algorithm is changing but the device is not. The device has no effect on the environment as it does not have any emissions or other environmentally damaging factors. The device can be beneficial socially as it can offer privacy for the epileptic patient before experiencing a seizure and not cause a scene which would improve the quality of life of the patient. Resultantly, the following sections will focus on the effects of political, ethical, and health and safety factors as they are determined to have a contribution to the outcomes and constraints of this project.

1.2 Governmental Constraints

During the course of this semester, the senior design team was able to get a couple of epileptic patients to volunteer with the team and allow the team to analyze their EEG signals. The team was later on made aware that in order to use the device on any person, many governmental steps have to be followed in order to secure these permissions.

The process was done before by Texas A&M for certain projects. After the team consulted with the knowledgeable parties, the team was made aware that this process could take months. Resultantly, the team made a decision to not use the device on any subjects, which meant that the team was constrained to use pre-recorded data for this project.

1.3 Ethical Constraints

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.

1.4 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.

Chapter 2: Customer Needs and Ethnographic Study

2.1 Introduction

Performing an ethnographic study is an essential part in observing the need of societies. Since this project, early onset seizure detection technique is dedicated for epileptic patients; an ethnographic study should be based on gathering great number of epileptic patients, which created a sort challenge. The challenge presented is due to the fact of the unavailability of a significant data base of epilepsy patients due to confidently reasons. Therefore, two researches from Hamad Medical Corporation and Weil cornel University of medicine in Qatar [9,10] were successfully used in order to perform the costumer need and ethnographic study this project.

2.2 Historical Review

- Overview

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].

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]

- Analysis

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].

2.3 Current Ethnographic Analysis

- 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 groups: 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*

2.4 Findings and Conclusions

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 onset seizure onset detection technique can improve these patients' quality of life.

Chapter 3: Benchmarking

3.1 Introduction

The benchmarking study was conducted to view the results of other researchers that studied different approaches to EEG algorithms. This will be helpful as it will set minimum goals for the team's algorithm to meet. The different studies were compared in terms of sensitivity, false alarms, and latency in referral to the length of data that was acquired by each research. Each criterion is important to determine whether the algorithm is successful or not, while the length of data is important to determine if the research is viable or needs more testing before evaluating the data.

3.2 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 1: Study Conducted

Table 1 above shows the benchmarking study that was conducted. The study compared four different algorithms and approaches that were published in four different previous researches. The first algorithm was published in "Seizure Prediction Using Spike Rate Intracranial EEG," [1]. The study was based on the spike rate of the intracranial EEG probes that are attached to the human skull. As it can be inferred, a low sensitivity percentage and a low FA/hr rate were found. Although these numbers are low, the length of data is also low, which compromises the legitimacy of the results.

The Second study we looked at is the "Patient-specific seizure onset detection," [2]. This study was based on evaluating the patients separately based on their lifestyle and daily actions. The EEG diagram of each person was compared to the individual previous records and the results are shown.

The third study we looked at is "Seizure detection, seizure prediction and closed-loop warning systems in epilepsy", [3]. In this study, a closed loop feedback system was implemented in the algorithm. This resulted in a great sensitivity percentages and low latency and FA/hr values.

The fourth and the last study we looked at was "A review of channel selection algorithms for EEG" [4]. This study was based on increasing the number of channels for the purpose of detecting more EEG signals. Although this approach gave a good sensitivity results, the latency of the system increased latency. That was due to the fact that the number of channels increased dramatically which added more complexity to the system and to the neural synchrony stage.

Our goal for this project is to achieve higher sensitivity, and lower latency, FA/hr values than the studies we considered above. By looking at the functional modeling, we could see that this is achievable due to the fusion of the neural synchrony and the energy waveform of each EEG sub-band which is projected to result in a higher sensitivity and lower latency.

Chapter 4: Functional Modeling

4.1 Introduction

In order to for members to successfully generate needed knowledge, a block diagram was built in order to specify the main and detailed functions and stages of the project. The functional model was built based on several theoretical research done by the students in order to retrieve the main stages. The mentor’s approval was pursued through meetings. The following sections illustrate the functional model block diagram and provide an explanation of each block.

4.2 Functional Modeling

The detailed functional modeling of the proposed project is shown in Figure 3. This diagram illustrates the main functional stages. The diagram consists of 5 main stages that are essential to represent the functions of the project, some of the stages in this diagram are parted into units such as feature extraction unit and classification unit. In the next section a detailed and separate explanation of each block will be given.

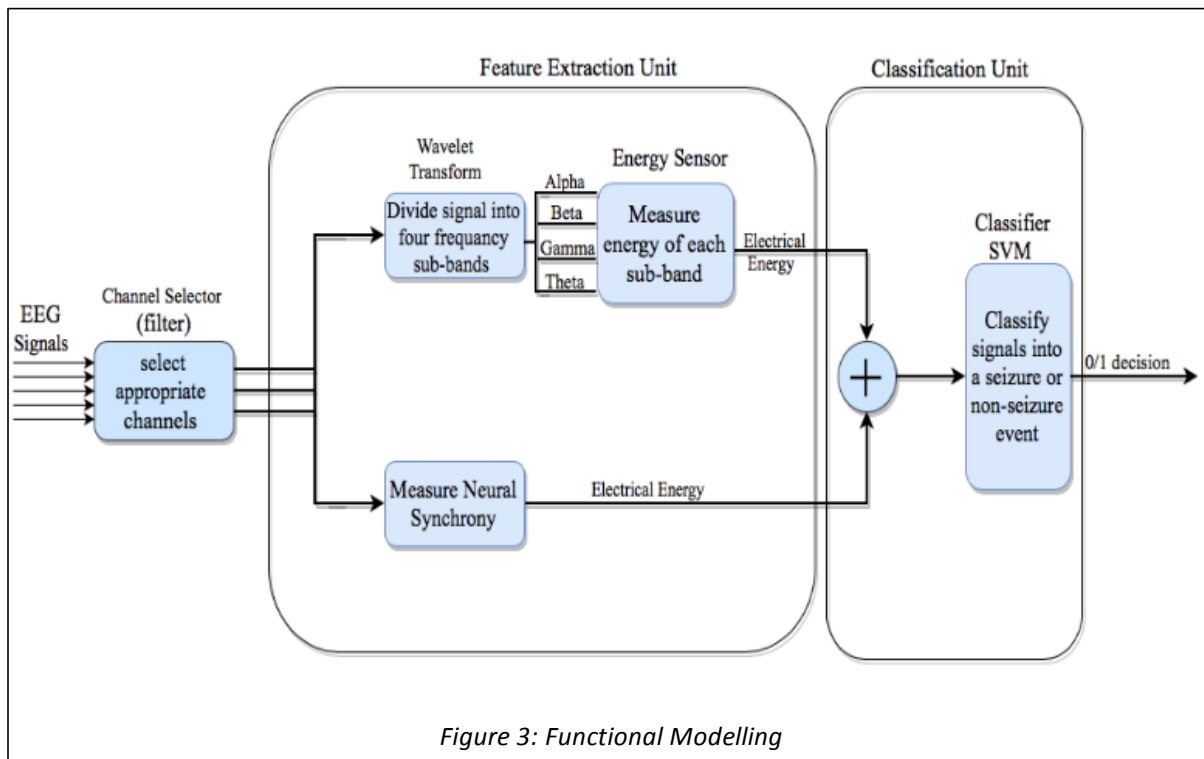


Figure 3: Functional Modelling

4.3 Explanation of the Functional Modeling

In order to construct an efficient algorithm, all functions in figure 3 must be performed successfully. The initial input of the ESD algorithm is EEG signal acquired from the patient's brain, while the final output is a detection that notifies the patients of an occurring seizure. A detailed explanation of the functional modeling is given below:

1) Channel selection:

This stage is going to take place after EEG signal acquisition, in this stage appropriate channels are going to be selected. Selecting specific channels from a larger channel range will allow a more accurate examination of channels. selecting channel will lower the number of channels used which positively affect the performance of the algorithm as lowering the number of channels can help to lower the amount of consumed energy. It will also lower the computation time which will decrease the latency rate [7]. Selection is dependent on the channels that are most active during a seizure, as there are many ways to preform channel selection, however the considered method is filtering based on variance as the selected channels will be selected based on the maximum variance value among them [4] and filtering is chosen as it proves its high speed and independency.

- Feature Extraction Unit:

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

2) Wavelet Transform:

Wavelet transform is going to be applied to the signals as it will help to convert them from real time domain signals into frequency domain signals. It will also breakdown the signals into four main frequency sub-bands (Alpha, Beta, Gamma, Theta) then, with the use of an energy sensor, the energies of those sub-bands are going to be measured. Wavelet transform is going to be performed by applying a compressed mother wavelet into the EEG signal waves and measuring peak values [13].

3) Neural Synchrony:

Signal are going to be 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[7] .Analyzation 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 indicated 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 is because it is a fast and simple method for extracting EEG signal [8].

- Classification unit:

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

4) 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 in 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.

5) The Classifier:

In order to classify events into 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 that is used to make decision based on where the observation lies with respect to the hyperplane [12].The extracted features of both energy and neural synchrony analysis will be fed into the support vector machine in order for it 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 [7].

Chapter 5: Concept Generation and Evaluation

5.1 Introduction

For this project, the main concept to be evaluated is which type of data set is to be used. Having accurate and meaningful calculations here is crucial in order to later on have optimal results. Having optimal results means that this project will offer considerable advancement in the field of detecting epileptic seizures.

5.2 Criteria Ranking

The data sets that were being considered are: EEG, ECG, accelerometry, video detection, mattress sensors, and baby monitors. To evaluate which of these concepts should be used, a number of criteria were developed for the Epileptic Seizure Detection device. These criteria were compared against each other to determine a ranking of importance and calculate a weighing factor that will later be used to determine which concepts are the most powerful. When the criteria are being compared against each other, the criteria can either get a value of 1, meaning that is more powerful, or 0, meaning that it is less powerful than what it is being compared to. To determine the weighing factor, the score of each criteria was summed and divided by the total sum of all of the scores of the criteria. Table 2 shows 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 2: Criteria-Ranking Matrix

Subsection 5.2.1: Criteria Description

This subsection serves to describe each criterion and what it means in reference to our project. The criteria that will be mentioned are sensitivity, latency, false alarms, durability, safety, and cost. Table 3 shows the descriptions of the criteria.

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 3: Criterion Description

5.3 Relative Comparison

After establishing the different criteria and calculating the weighing factors, the scoring of the different data sets will be calculated. Table 4 shows 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 4: Screening Table

5.4 Scoring and conclusions

Using the data from the past sections, it can be viewed that EEG signals are more prominent than any other proposed alternative. Table 5 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 5: Scoring Table

As it can be seen from the table above, EEG ranks better than all the other concepts. Resultantly, EEG was chosen as the data set that will be analyzed for this project.

Chapter 6: Detailed System Design:

6.1. 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 [11] 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 4 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 6 shows a complete breakdown of the budget.

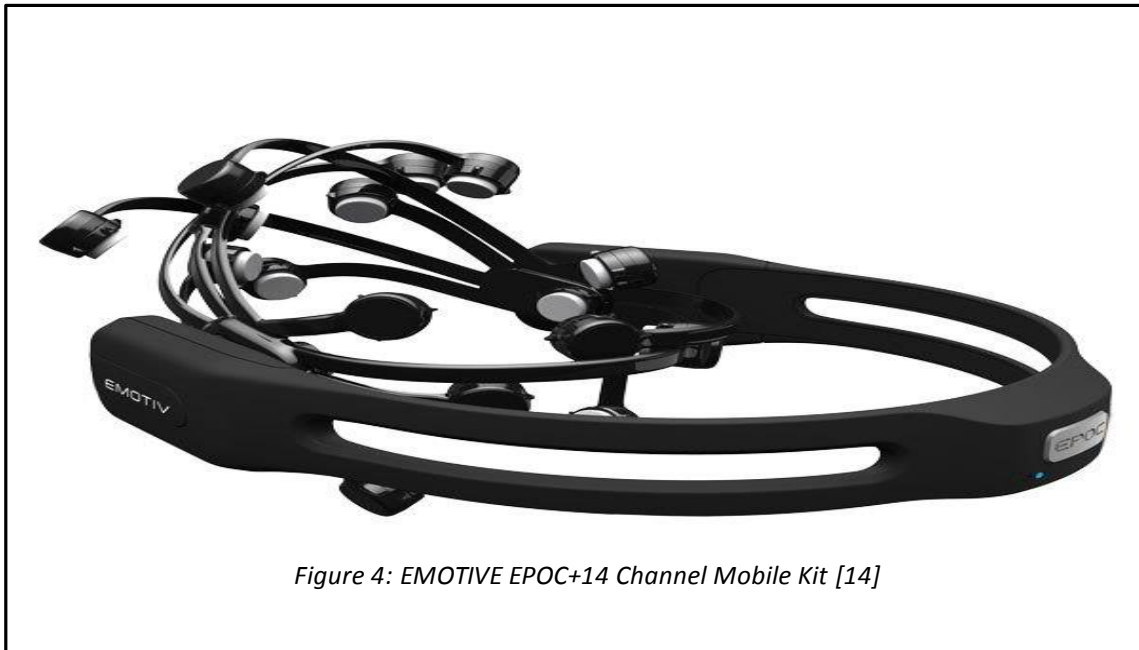


Figure 4: EMOTIVE EPOC+14 Channel Mobile Kit [14]

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 6: 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.

6.2 Timeline

The Timeline was constructed to keep track of the project work and deadlines. The timeline was planned at the beginning of the semester before starting the project, and was updated once a specific task was done. The Timeline is shown below in figure 5:

PROJECT TIMELINE 2016-2017

PROJECT PHASE I FALL 2016	STARTING	ENDING	PROJECT PHASE I FALL 2016	STARTING	ENDING
PROJECT PROPOSAL, INITIAL WEBSITE, TEAM AGREEMENT	28 - 8 - 2016	8 - 9 - 2016	PEER EVALUATION	-	4 - 12 - 2016
PROPOSAL PRESENTATION	17 - 9 - 2016	29 - 9 - 2016	FINAL PROGRESS REPORT	-	5 - 12 - 2016
CUSTOMER NEEDS STUDY	2 - 10 - 2016	6 - 10 - 2016	SEMINAR 2	24 - 11 - 2016	4 - 12 - 2016
BENCHMARKING	9 - 10 - 2016	13 - 10 - 2016	PROJECT VIDEO	-	4 - 12 - 2016
FUNCTIONAL MODELING + PROJECT STUDY VIDEO UPLOADED TO WEBSITE	16 - 10 - 2016	20 - 10 - 2016	PROJECT PHASE II SPRING 2017 (UPCOMING)	STARTING	ENDING
PROGRESS PRESENTATION	23 - 10 - 2016	3 - 11 - 2016	THEORETICAL BACKGROUND	15 OCT	TBA
CONCEPT SELECTION	6 - 11 - 2016	17 - 11 - 2016	FEATURE EXTRACTION STAGE	15- 1 - 2016	15-2-2016
INTELLECTUAL PROPERTY	20 - 11 - 2016	-	CLASSIFICATION STAGE	15-2-2016	1-3-2016
INITIAL PROJECT DESIGNING	20 - 11 - 2016	5 - 12 - 2016	TRAINING AND TESTING	1-3-2016	1-4-2016
FINAL PROGRESS PRESENTATION	22 - 11 - 2016	4 - 12 - 2016	ABSTRACT SUBMISSION TO QATAR ANNUAL RESEARCH CONFERENCE (ARC)	TBA	TBA

SEPTEMBER							OCTOBER							NOVEMBER							DECEMBER							JANUARY							FEBRUARY						
S	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S
				1	2	3						1			1	2	3	4	5				1	2	3	1	2	3	4	5	6	7									
4	5	6	7	8	9	10	2	3	4	5	6	7	8	6	7	8	9	10	11	12	4	5	6	7	8	9	10	8	9	10	11	12	13	14	5	6	7	8	9	10	11
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19	20	21	22	23	24	25	16	17	18	19	20	21	22	21	22	23	24	25	26	27																					
26	27	28	29	30	31	23	24	25	26	27	28	29	28	29	30	31																									

Figure 5: Project Timeline

It can be seen from the figure, the team members have successfully finished the required tasks for this semester, which are marked in green. The tasks for the upcoming semester (404) are planned above with set deadlines. A more detailed plan of the 404 phase will be given in the next semester.

Chapter 7: Conclusion

7.1 Progress

There is a current focus on developing 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.

7.2 Conclusion

The ESD is an improvement of an algorithm that can be used to detect the onset of epileptic seizures. By using the EEG signals that are already available at Texas A&M Qatar – as purchased from Campus Technologies Freiburg in Germany, the ESD will be capable of detecting and reading signals much faster. The system that is available currently runs 4 – 5 tests per patient to try to detect the signals that can identify the onset of seizures. These tests, on average, take 45 minutes to complete and often the data collected is insufficient. The ESD will be able to run less tests, in a shorter timeframe and produce results that are more accurate. This will not only save patient's time, but will also ensure that researchers are able to read the information in a timely manner and can then develop procedures that will prevent the occurring of future seizures.

There are five main stages to the functional modeling. First, channel selection, which is done directly after the acquisition of the EEG signal. The ESD filters the signals based on variance method, which will lower the number of channels used. This is beneficial in minimizing the amount of consumed energy as well as lowering the computation time, which will decrease the latency rate. Second, wavelet transform which breaks down the signals into four frequency sub-bands (Alpha, Beta, Gamma, Theta). Third, neural synchrony – measures the rate at which neurons are firing and is able to analyze multiple signals at the same time. Fourth, fusion unit, where energy readings of signals are going to be combined with the neural synchrony analysis to achieve more accuracy. Finally, classification, where SVM classifiers will be used which will allow capability to distinguish between seizure and non-seizure events. This training can take place offline by feeding it with previously recorded seizure readings.

The data sets that were being considered are EEG, ECG, accelerometry, video detection, mattress sensors, and baby monitors. After numerous tests were conducted on the variety of available data models – as mentioned in the criteria ranking above, the data collected from the EEG was determined as the most reliable and was therefore selected as the basis of this study. Using the functionality of the EEG, this project then has developed a more accurate algorithm, which detects differences in the signals at a much sooner rate. The ESD algorithm will prove to be more accurate than the most accurate measure currently available, which will make it a very viable and popular product.

Epilepsy is a serious condition that can severely hinder the daily lives of people that suffer from this condition. Early detection of seizures is vital to these people in order for them to lead normal lives and function well in society. Through the development of the ESD algorithm, the onset of seizures can be

detected much earlier which will allow sufferers the opportunity to prevent such seizures through the administering of medication. This will provide countless members of society the opportunity to lead fully functioning lives and participate in regular activities, which may have previously been considered too risky for epilepsy sufferers to partake in.

Until now, the group is performing and working based on the provided timeline, by the end of this semester a final meeting should be done to ensure a complete understanding of the project and to introduce tasks that are to be completed next semester.

Chapter 8: References

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