Electrical and Biomedical 4BI6
Project Proposal

Statistical Pattern Recognition Methods Applied to Evoked Electroencephalogram Data in Depressed Patients

by

Jason O'Reilly(0648417)

Department of Electrical and Computer Engineering
Faculty Advisors: Dr. H. de Bruin and Dr. J. Reilly

Electrical and Biomedical Engineering Project Report
Submitted in partial fulfillment of the requirements
for the Bachelor of Engineering

McMaster University
Hamilton, Ontario, Canada
April 23, 2010

I. ABSTRACT

Currently there exist a great deal of medication to deal with various mental disorders. Many of these medications serve similar purposes though only a select few work for a given individual. It can take several weeks to assess if any given medication is even working effectively. The purpose of this project is to develop an objective approach to diagnosing and more accurately treating various mental disorders with medications. To accomplish this one can observe relationships between surface currents of the brain and the patients mental disorder through statistical pattern recognition methods and appropriately assign a specific treatment using data a psychologist could not observe. The task has high computational requirements and made use of the McMaster electrical engineering grid. A framework to manipulate gigabytes of EEG data was established. A method to obtain features necessary was coded into the framework. Conducting a literary review of the field showed many similar depression calculations. Based on these depression feature calculations, an EEG analysis framework was established to easily obtain a number of studied features. Feature selection was used to find features which discriminate between classes. These features were then input into an support vector machine creating a classifier specifically designed for depression separation. A test data set of normals was used to perform relevant depression calculations including band powers, inter-hemispheric power ratios and coherences between all channel among other prominent calculations common throughout the EEG depression field. Results of the system were then analyzed to ensure accuracy and meaningfulness.

II. ACKNOWLEDGMENTS

I would like to thank Dr. J. Reilly, Dr. H. de Bruin and Ahmad Khodaryari-Rostamabad for their contributions to this project. I have learnt a great deal from them. Without sharing their knowledge and experience I would not have known where to being this project. Dr. T. Greenlay also provided guidance teaching me how to use the McMaster ECE grid. The assistance was greatly appreciated.

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1. INTRODUCTION

Manic depressive disorder (MDD) among other mental disorders is a prevalent issue in our society. MDD specifically affects 7-12 percent of men and 20-25 percent of women [1] during the course their lives. Modern antidepressant drugs typically have 65 percent success rates requiring 2-6 week to identify a response [5]. There is currently an abundance of medical treatments available for major depression disorder (MDD). Many of these treatments such as electroconvulsive therapy and certain medications cause a great deal of collateral damage and have low success rates. Electroencephalography (EEG) is a method that uses electrodes placed in an a specific orientation on the patients head to determine the changing potentials transversing the surface of the brain. These potentials show show the joint electrical activity of many neurons. The electroencephalographer correlates the central nervous system (CNS) functions or dysfunctions with certain patterns in the EEG using an empirical approach. These extracellular potentials are field potentials. The extracellular potentials are related to intracellular neurons and glia cells which are located between the neurons and can be seen in the 1. The soma nucleus of the neuron serves several purposes. Many branches of dendrites and axons stem from the nucleus and branch into organs and other cells from in the network. These form inter-neuronal connections that contact by thousands of synapses [7]. When signals are sent between neurons there is depolarization of the subsynaptic membrane as seen in the figure below. If an action potentials run along nerve fibres which ends in an excitatory synapse, an excitatory postsynaptic

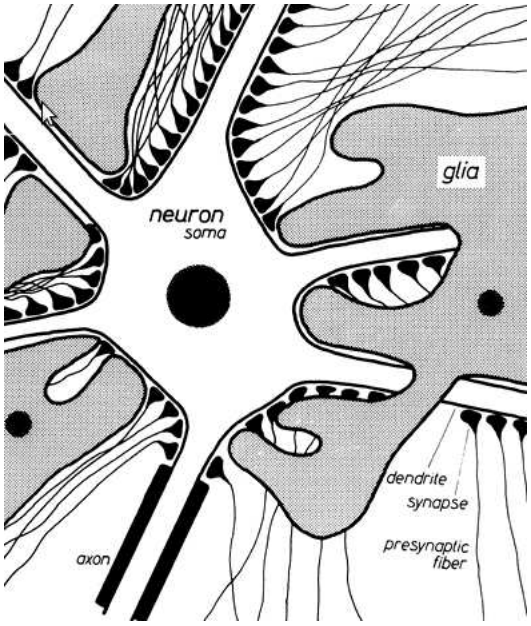

Fig. 1. The ion fluxes in the extracellular space are of paramount significance in the generation of field potentials [7]..

potential (EPSP is created. Hyperpolorization will occur if the action potential ends in a inhibitory synapse, causing an inhibitory postsynaptic potential (IPSP). These can both be seen in Figure 2 [7]. If two neurons travel in the same direction in a short period of time summation of EPSP triggering can cause an action potential on the postsynaptic neuron after reaching the membrane threshold. The potential gradient caused by an EPSP a flow of cations from the subsynaptic region to the extracellular space. The fields these gradients create are then measured by the EEG.

The potentials from the brain are sampled and stored on a computer for analysis by modalities of interest. Using Support Vector Machines (SVMs) classifiers can be made to distinguish between different groups of data. For a given learning task, with a given finite amount of training data in this case being 22 patients each with 6 trials the SVM defines a classifier. The best SVM performance is achieved by right balancing the accuracy attained on the training set, and capabilities of the hardware. Only under these circumstances can the the machine learn a training set without error. Burges describes this challenge elegantly A machine with too much capacity is like a botanist with a photographic memory who, when presented with a new tree, concludes that it is not a tree because it has a different number of leaves from anything she has seen before; a machine with too little capacity is like the botanists lazy brother, who declares that if its green, its a tree [3]. This remark describes how an SVM can actually be over-trained to the determent of classification. To classify, the SVM creates a hyperplane between the classes which optimally separates the classes by a gap, preferably as large as possible. When the classifer is given a new test data set, it is mapped out in the same feature space and will belong to a particular category based on which side of the

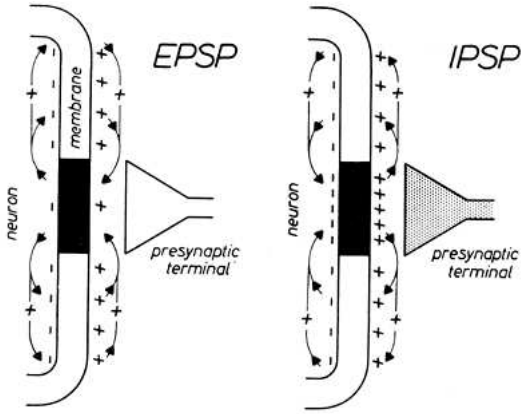

Fig. 2. During EPSP and IPSP, ionic current flows occur through as well as along the neuronal membrane, as shown by arrows. The density of + and - signs indicate the polarization of the subsynaptic (dark area) as well as that of the postsynaptic membrane during synaptic activation [7].

gap the are on. Another key factor is the selection of the features themselves that make up the mapping. Every feature cannot be selected, the mapping of the data to the feature space with massive dimensions would result in a machine with poor performance. This is because a set of hyperplanes for a given SVM are parameterized by the dimensions of the feature matrix [3]. Feature selection can be decomposed into two steps. The feature construction aspect, and the feature selection. The goal of this is ultimately data reduction to limit storage requirements and increase algorithm speed. The EEG data is the general data and is not within the scope of the project to be retrieve or alter the given general data set.

What can be significantly reduced is the feature sets, which can intern alter the following rounds of data collection to minimize the size of the general data set. For instance, if there are no significant features beyond 50 Hz, why sample at 205 Hz when the general data set could be halved with little information loss by changing the sampling rate to 100 Hz. The main component of feature reduction is to obtain higher accuracy and ensure the system is not over-trained. After prominent features have been found they can be assessed used for visualization and further understanding of the general data set. There are three main approaches to feature extraction, filters, wrappers and embedded methods [6]. To visualize how a feature could be removed the Figure 3 shows a 3 feature space mapping. The features x1 ans x2 are evidently not discerning. The feature selection algorithm would notice the separation that occurs on the x3 feature axis and extract this feature with higher ranking ideally. Given 24, each having around 43000 samples at 205 Hz there is an infinite amount of features one could extract. Such a wide range of data would require massive computational requirements to sift through every possible feature. Features had to be selected by carefully evaluating EEG papers on various subjects to find the most discerning features for the project. To find the appropriate features the

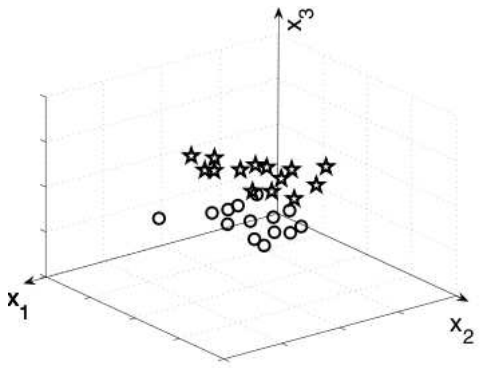

Fig. 3. Features x1 and x2 contain little information of class separation. Feature x3 shows clear separation of the classes [6].

brain must first be examined from a psychologist’s standpoint. One of the pioneers in the EEG depression field, Davidson [4] found that brain asymmetry is related to depression. Davidson’s finding showed a relationship depression and less activation power in the left frontal cortex when compared to the right frontal cortex. People found with this asymmetry were more likely to show signs of depression which was especially apparent in the alpha power band. Asymmetry studies are a common theme throughout depression papers, as such a two functions were developed in Matlab to distinguish power ratios of given frequency bands. Depression features are now being insistently researched because of the prevalence of depression in society and is detailed in the literature review.

2. Objectives

The original objective outlined my proposal at the beginning of the year was to use EEG data to achieve a more accurate and objective description of a patients depression status. In order to accomplish this, many software components had to be developed or selected to deal with the shear magnitude of data. The primary objective of the project is quite broad and sub-objectives were developed throughout the course of the term as a result of unforeseeable circumstances.

A. Handling the Data

Development of a framework to handle the data, allowing one to open and manipulate EEG data with relative ease was the first objective after literature review had been conducted. There are twenty-two patients, each having six trials with 24 channels sampled at 205 Hz with 43000 data points per channel. Functions needed to be created to easily access the data. For example a function had to be created to retrieve patient 12, trial number 3, channel number 5, etc. This component objective was vital for analysis of the EEG data. After this task was complete, analysis of the data was to be considered.

B. Storing the Data

After performing some analysis trials on the data, such as Fast Fourier Transforms and correlations the required computational requirements became clear and a new objective was created. It would be impossible to perform analysis in the desired time frame constantly performing FFTs and correlations because there were simply to many calculations. The next objective was deciding the most meaningful data to store to maximize computational speeds but not taking up ridiculous amounts of disk space at the same time. A balance needed to be established.

C. Functions

While sifting through the papers in the field, many calculations and measurements for depression and other EEG relationships were found. There were many equations describing similar attributes such as asymmetry. A base of functions had to be developed to implement the equations and allow for future additions was necessary.

D. Learning Machines

Once all the appropriate numbers were established from the analysis, the objective was to implement a learning machine. There are a great deal of statistical pattern recognition and learning machines available, many of which are open source. Research was conducted to find the learning machine most suitable for this project. Code for proper formatting had to be done on the data to be created for inputing to the learning machines.

E. Analysis

The task of analyzing the output of the learning machine and the analysis equations were the next concern. Individually evaluating which equations created the features that were optimal for classification. Selection of the correct features can drastically change the accuracy and speed.

3. Literature Review

Another measure that was found to be a prominent indication of depression was the Frontal Brain Asymmetry (FBA) ratio . The formula is as follows [8]:

$$FBA = \frac{\frac{1}{P_{\alpha L}} - \frac{1}{P_{\alpha R}}}{\frac{1}{P_{\alpha L}} + \frac{1}{P_{\alpha R}}} = \frac{P_{\alpha R} - P_{\alpha L}}{P_{\alpha R} + P_{\alpha L}}$$

Where PL is the left alpha power PR is the right alpha power. The derivation of this formula is based on the results from a number of studies. The alpha power in the brain is inversely proportional to mental activity (Davidson, 1988). Thus, if a person is doing intense mental arithmetic a small alpha power is observed in that region of the brain, whereas if someone is mentally inactive in a given region, that region will tend to have higher alpha power. Thus, the formula is basically normalizing the left-right difference in brain activity for given left and right channels. A function was created to obtain this feature for two given channels. Inter-hemispheric coherence between FP1-FP2, T3-T4, P3-T4, and O1 and O2 in particularly alpha and theta bands were a common indicator of depression being studied in several papers. The formula used is for inter-hemispheric coherence was as follows:

$$C_{xy}(f_1, f_2) = \frac{\left(\sum_{f=f_1}^{f_2} s_{xy}\right)^2}{\sum_{f=f_1}^{f_2} s_{xx}(f) \cdot \sum_{f=f_1}^{f_2} s_{yy}(f)}$$

Sxy is the cross-spectral density of the two signals. Sxx and Xyy are the power spectral density of each signal by itself. The spectral asymmetry index (SASI) is another key calculation and is the relative difference in power of two EEG special frequency bands. It is calculated as follows:

$$W_{lmn} = \sum_{f=F1}^{F2} s_{mn}; \qquad W_{hmn} = \sum_{f=F3}^{F4} s_{mn}$$

Wlmn corresponds to the lower frequency density of channels m and n from frequency F1 to F2. Whmn are the higher frequency densities of channels m and n from frequency F3 to F4. Finally, these are used to calculate the SASI:

$$\mathrm{SASI}_{mn} = \frac{W_{hmn} - W_{lmn}}{W_{hmn} + W_{lmn}}$$

Evidently, the power asymmetry between two channels m and n are represented by the SASI [**?**]. To obtain a frequency bands ratio with respect to the entire frequency band, the following calculation is used:

$$W'_{Lmn} = \sum_{f=f_1}^{f_2} s_{Lmn} \Big/ \sum_{f=0.5\ \mathrm{Hz}}^{48\ \mathrm{Hz}} s_{Lmn};$$

$$W'_{Rmn} = \sum_{f=f_1}^{f_2} s_{Rmn} \Big/ \sum_{f=0.5\ \mathrm{Hz}}^{48\ \mathrm{Hz}} s_{Rmn},$$

interest with respect to the entire band of measured brain frequency. The normalized densities can then be used to calculate the inter-hemispheric asymmetry [**?**]:

$$A_{mn}(f_1, f_2) = \frac{W'_{Lmn} - W'_{Rmn}}{W'_{Lmn} + W'_{Rmn}} \cdot 100.$$

This is quite similar to the Frontal Brain Asymmetry calculation except the inverse of the power is not taken and this asymmetry is reflective only of power differences and not cognitive function at the time of measurement as in FBA. Several papers address the There are many methods currently being implemented to analyze EEG data. Many papers implement analyze data specifically for EEG purposes. Another segment of papers dealt with detection of early response to medications. The literature review revealed the broadness of the EEG depression field.

4. Design and Experimental Procedure

The basis of the overall design are the functions created to manipulate the data. After completion of each function several tests were performed to ensure it was functional and had meaningful output. The EEG data itself with no modifications is shown in 4. This shows figure basically a few arbitrary channels from the occipital, frontal and temporal lobes. This only displaying a few thousand samples of the 43000 at 205 Hz.

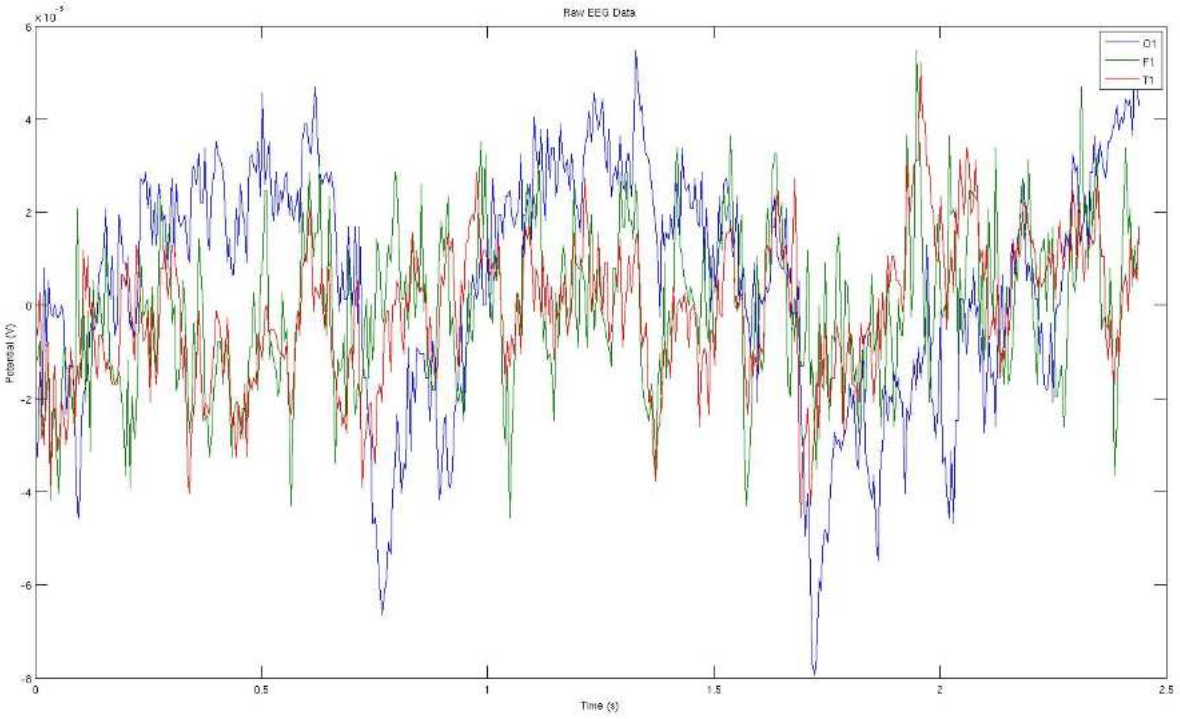

Fig. 4. Raw Data: Raw EEG data from channels O1, F1, and T1. Showing 1000 samples of 43000 sampled at 205 Hz.

The potentials are on the order of microvolts which is expected for EEG signals. The temporal and frontal lobe can be seen to follow each other more closely given their proximity. The occipital lobe at the back of the heads potential is quite different. This is the raw data the design of the project is based on. The main functions designed to manipulate the EEG data are now listed.

A. Coherence

function [Xcoh freq] = getCoherence(x1,x2) Inputs: 2 1xN column vectors of EEG data Outputs: Normalized correlation of channels with size 1x(N-1) and corresponding frequencies

Method: Firstly, the cross correlation of the channels is taken using the function xcorr. The cross correlation is then normalized so the maximum value is one. The size of the FFT is zero padded to the next value that can be taken derived from an exponential with base of two to speed up the FFT process. The frequencies are determinable given the sampling frequency of the EEG acquisition system of 200 Hz. The crosse correlation between highly positionally proximal channels is shown in 4-A.

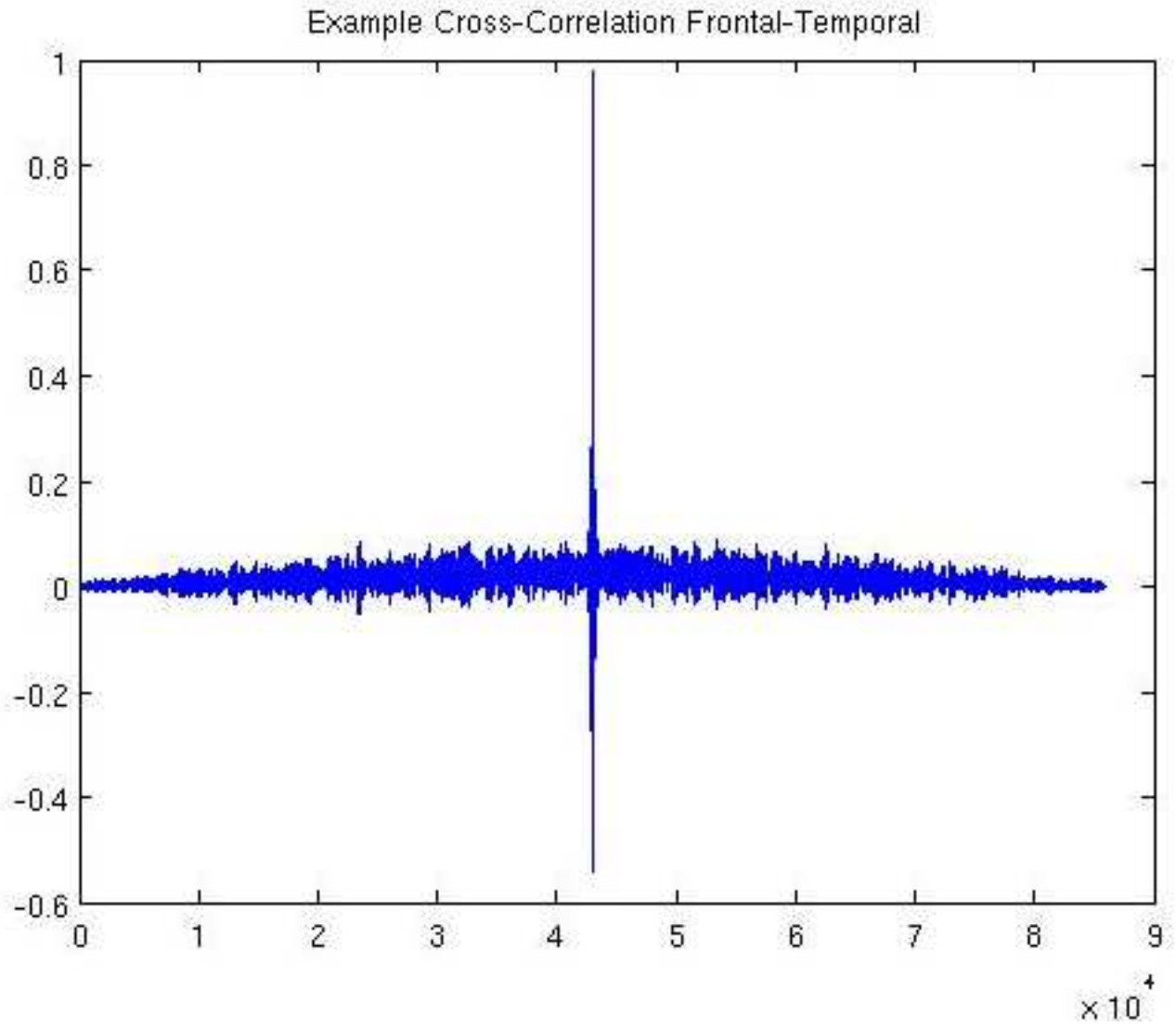

Fig. 5. Cross-Correlation: Cross-correlation of proximal EEG channels shows near 1 correlation at tau equals 0.

The frontal and temporal lobes show almost a perfect correlation at time is zero. This quickly

drops off steeply after. The correlation is normalized. Taking the FFT of the normalized correlation using this function yielded the following output:

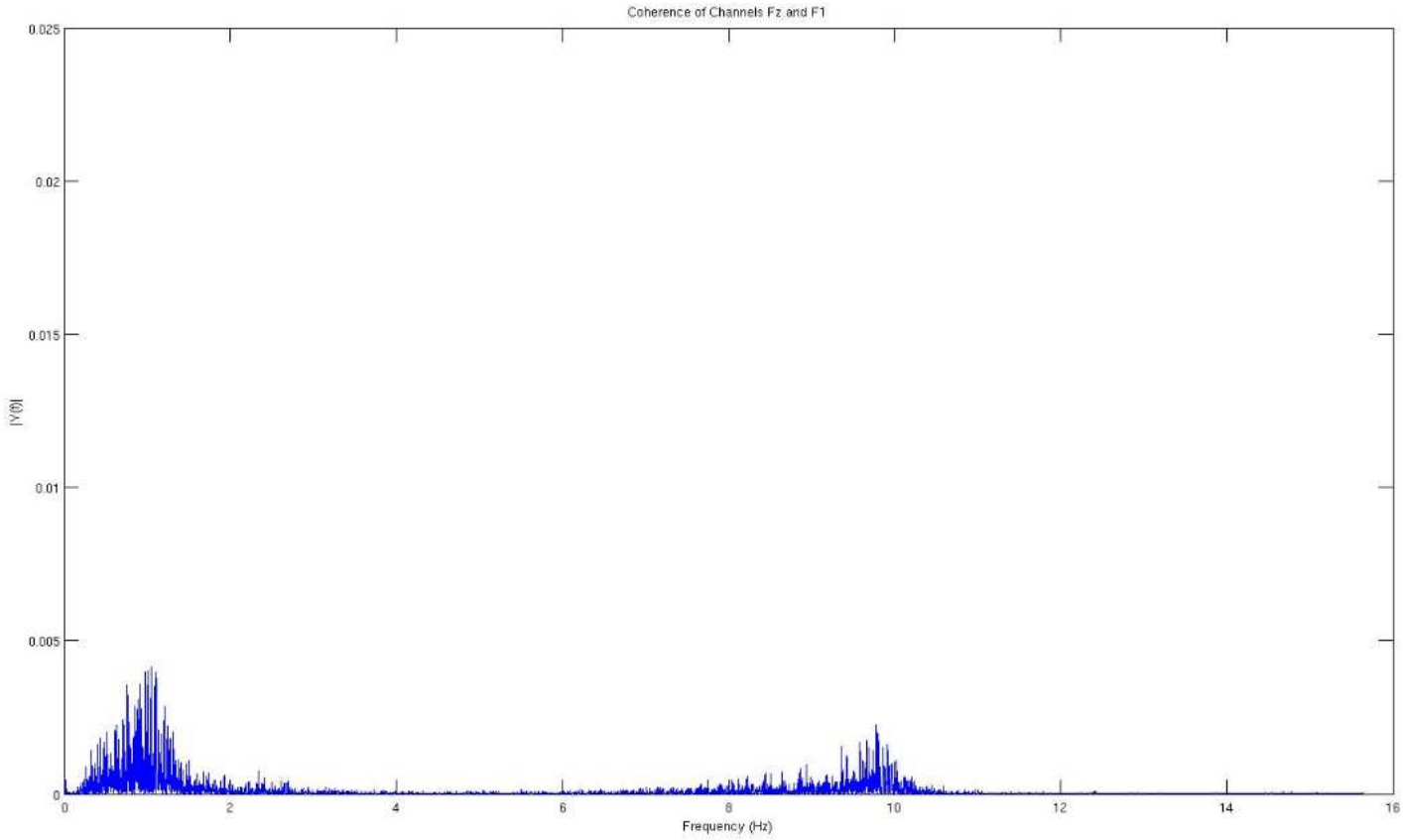

Fig. 6. Coherence: Coherence calculations between proixmal channels Fz and F1 share delta and alpha power.

Image 4-A shows the coherence between proximal channels Fz and F1. The FFT can show data up to around 100 Hz, half the sampling frequency. This coherence shows only the first 20 or so hertz. A strong delta power can be seen between 0.5-4 Hz. In addition to this alpha band activity can be seen in the 8-14 Hz range. Beta and theta bands appear relatively inactive in this segment. The fact that there was a physiological meaning of the data indicated the coherence was working properly.

B. Coherence Averaging

function [AVGcoh freq] = getAveragedCoherence(patient,x1,x2) Inputs: The number corresponding to the patients of interest and channels containing EEG data Outputs: Averaged cor-

relation size 1x(N-1) and corresponding frequencies. Method: Opens all six EEG data files including EO/EC and retrieves desired channels x1 and x2. It calls function (1) six times and averages the results. Purpose: This is an important step to minimize error. Notes: There was also a similar function with similar output created except it uses the saved average frequencies as the input to decrease computational time.

C. Power Averaging

function AvgPow = getSavedAvgPower(patient,x1,x2,freq0,freq1) Inputs: The patient number from 1-22 and the channels of interest. Freq0 and freq1 represent the upper and lower bounds of the frequencies that average power is calculated over. Method: Opens the saved coherence data which can be also interpreted as the power spectral density functions (PSDs) between the two channels. The power is then just the integral from freq0 to freq1. Since the data points are discrete an approximation had to be made to calculate the area under the curve. A fast way to solve for the area was to take each discrete data points magnitude within the range freq0 to freq1 and multiple it by on frequency interval and sum the result. Using this method there will clearly be some overlap over the boundaries by half a frequency interval on each side in the band, but the size of a frequency increment negligible compared to the range between freq0 and freq1. This yields a relatively accurate method of efficiently calculating the power. After using this estimate it became apparent that one could just as well sum all the data points and multiply it by one frequency interval which could simplify the process. Another realization was then made that multiplying by some arbitrary constant every time was also useless because it does not change the relative relationship between the values and the feature selection algorithm would treat it the same without multiplying the discrete points by the frequency interval. Finally, it was decided just to sum the magnitude of the data points because to the support vector machine it is all the same so long as all eigenvalue values are proportional. Purpose: Power was shown to be an important feature in many applications during the literature review. It can be used to find powers of the alpha, beta, theta and gamma brain waves. It can also be used in calculation of power ratios.

D. Power Ratios

function PowRatio = getPowRatio(patient,x1,x2,bands) Inputs: The patient and channels of interest in addition to a 2x2 bands matrix containing the upper and lower bounds of the powers necessary. Outputs: The power of band 1 found in column one of the bands matrix over the power of band 2 in column 2 of the bands matrix. Purpose: Imbalance in power ratios in certain bands have been linked to depression making power ratios an important feature to be considered. The Average power was tested over several coherences.

TABLE I

FREQUENCY BAND AVERAGE POWERS

	Frequency Range (Hz)	Average Power
Delta	0.5-4	1.62E-001
Theta	4-8	4.82E-002
Alpha	4-14	9.09E-002
Beta	14-30	3.70E-002

Example outputs for the coherence shown in Figure 4-A. Looking at the plot, these values seem proportional to the observed powers. The delta band clearly shows the most power in the plot, followed by the alpha bands. Smaller powers are seen in the theta and beta because of the EEG conditions.

E. Coherence Storage

saveCoherences.m Inputs: All EEG data. Outputs: 20x20 EEG averaged coherence compressed matrices Method: Loops through two loops of 20 channels taking the averaged autocorrelation/cross correlation across every possible channel combination. Matrices are saved in compressed format. This is done by repeatedly calling function (2). Purpose: Calling function (2) is computationally expensive. Averaged coherence is used for a wide variety of features and needs to be accessed constantly. Thus, to minimize computational expense the matrices were saved so they could be acquired quickly. This was at the cost of approximately 8 gigabytes of storage. This function took several days to run and the output was stored on the McMaster ECE grid taking up about 10 gigabytes of space in a compressed format. Over 6000 coherence matrices were stored.

F. Frequency Feature Matrix

function m = freqFeatMat(x1,x2,freqs) Inputs: Arrays of channels and frequencies of interest. Outputs: A coherence frequency feature matrix with rows sized number of size nChannels*nFrequencies of interest and 22 columns, one for each patient. Method: Loops through each channel combination in arrays x1 and x2. Select frequencies in the freqs array are taken from the coherence of each channel combination and stored under the patients column. Each patient is looped until all 22 columns are filled with coherence frequency data. Purpose: Creates a feature matrix of selected frequencies and channels to be input into a feature matrix or feature selection algorithm. Certain brain frequencies can be correlated to depression among other things. This function was the basis of creating other feature matrices but was not used itself in practice because at each discrete frequency point is subject to too much noise. Averaging over large frequencies tends to be a more accurate representation. In addition, with 43000 data points each with an individual frequency feature per channel, a frequency feature matrix containing all possible frequencies could not be implemented giving the volume of data. The feature matrix would be to massive for practical use though it would be possible with more computational power. With infinite computational power this would likely give the most discerning features but because computational power is limited other forms of feature matrices must be designed to meet the requirements.

G. Power Feature Matrix

function m = powFeatMat(x1,x2) Inputs: Arrays of channels of interest. The frequency band input was restricted to alpha, beta, theta and gamma brain power calculations. Outputs: A power feature matrix with rows sized number of size nChannels*4 and 22 columns. Four brain wave bands are considered. Method: Goes through each channel array opening the saved coherence values. Calculates the power in the brain wave bands for each channel and saves it into the patients column and corresponding feature row. This process is repeated for each patient. Purpose: Creates a feature matrix of brain wave powers. These have shown to be important features to analyze throughout the literature review.

H. Power Ratio Feature Matrix

function m = powRatioFeatMat(x1,x2, bands) Inputs: Arrays of channels of interest. In this case frequencies bands can be modified by the user. Only two bands can be input in the bands array which is a 2x2 matrix containing the upper and lower bounds of the bands. Outputs: A matrix of size nChannels x nPatients. A the power for each band is calculated an the power of first band in column 1 of the input band matrix is divided by the power in the column 2 band. Method: Opens saved coherence values and calls the getPowRatio function to obtain the values of the feature matrix. Purpose: Power ratios features have been shown to relate to depression.

5. Results and Discussion

Previously in Figure 4-A the coherence between proximal channels were shown. The alpha and delta powers were most prominent in this scenario. To further test the system and the accuracy of the data distant coherences were also measured. Coherence between F1 and O2 are shown in the Figure 5.

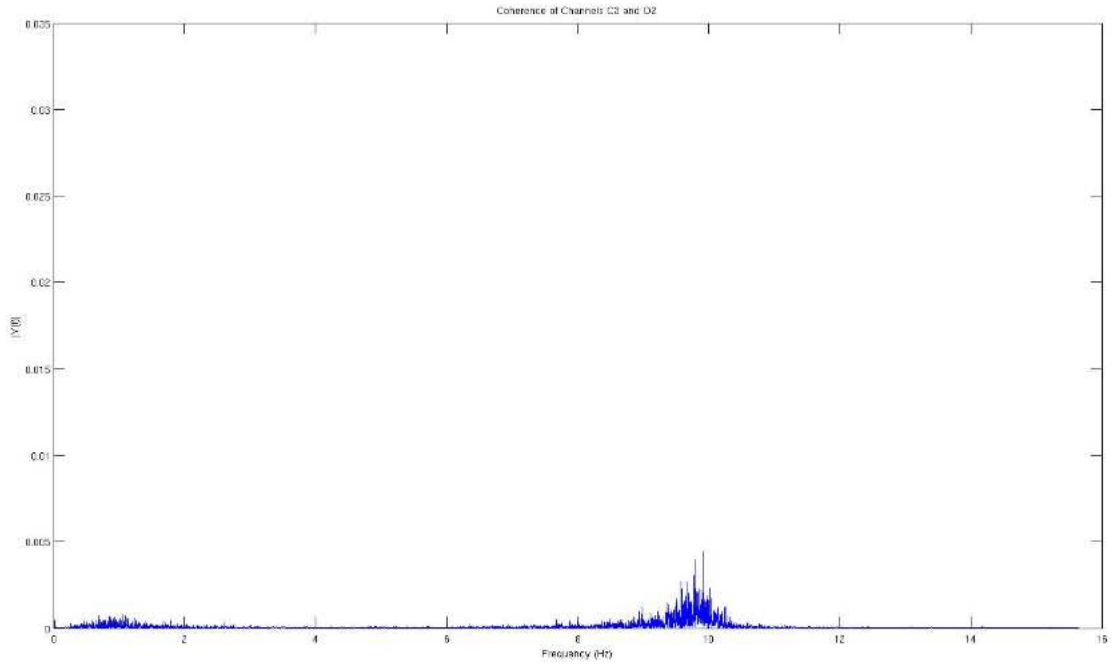

Fig. 7. Distant Coherence: Coherence calculations between distant channels.

Far less activation in the delta bands is apparent. Some relationship can still be seen in the alpha band however. This may be an indication that alpha waves are being transmitted throughout the brain to a greater extent than the delta waves. Once again the other theta and beta bands are not active at all. Running a few more trials the coherence getCoherence function was working for all patients and channels with an exception in patient 13 where there was a data fault that caused the program to crash.

The average coherence function was also tested for its reliability. The output of this function for proximal channels Fz and F1 are can be seen below in Figure 5.

As one might expect. Averaging reduces the magnitude to a considerable degree. This is as

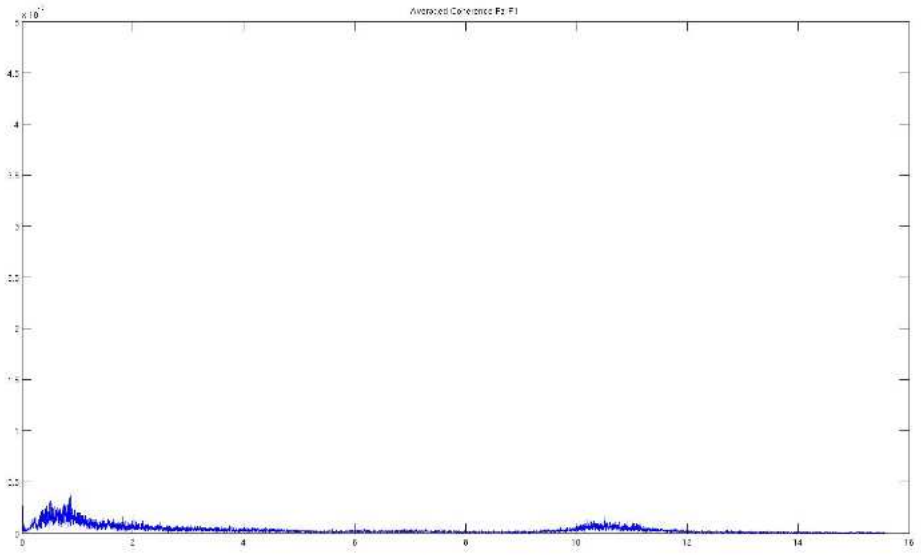

Fig. 8. Average Coherence: Coherence calculations between proximal channels Fz and F1. The coherence is averaged over 6 trials, three eyes open and three eyes closed.

a result of the high frequencies components being averaged out or smoothed. The averaging appears to have a similar effect to a lowpass filter that removes high frequency components to some degree. The averaging is done across six trials with three samples of eyes open and three eyes closed. There is no discrimination between these cases in the software framework currently because no papers regarding depression covered the topic and it was assumed not significant. If a paper was published that found differences in classification of depressed patients when their eyes are open versus when their eyes are closed this would need to be considered and would require minor changes to the coding. The output of this function appears to make physiological sense and after several trial appeared to be working smoothly.

To test the system several calculations seen commonly throughout the papers were implemented with the software framework established. First powers in the left hemisphere were measured. These are seen below in Figure **??**. Nine channels were measured in four frequency bands. The last two bands of the last channel are not shown.

The powers all appear around the E-4 and E-5 level which is roughly speaking the order of magnitude to be expected. The first row measuring channel X1 seems to be similar across all 11 patients in terms of magnitude. Many other rows show a wide variety of values containing

	1	2	3	4	5	6	7	8	9	10	11
1	2.1583e-04	2.1694e-04	1.9731e-04	2.1503e-04	2.0344e-04	2.1141e-04	1.7531e-04	2.4824e-04	2.2166e-04	1.8047e-04	2.0332e-04
2	1.0106e-05	2.0028e-05	1.3228e-05	1.3244e-05	1.0349e-05	2.2772e-05	1.0589e-05	7.8706e-06	9.1311e-06	1.1473e-05	1.2759e-05
3	2.9585e-06	3.3151e-06	3.0340e-06	2.3659e-06	3.0562e-06	5.1541e-06	3.5434e-06	2.6613e-06	2.4658e-06	9.1909e-06	4.7867e-06
4	6.8186e-07	1.5747e-06	9.8324e-07	2.7174e-06	2.1768e-06	1.6362e-06	2.2671e-06	1.5548e-06	5.0269e-07	4.8200e-06	1.3145e-06
5	2.5334e-05	1.2089e-04	1.3968e-04	1.0370e-04	6.6575e-05	9.7300e-05	7.7128e-05	8.0588e-05	1.0944e-04	6.0888e-05	5.1599e-05
6	1.1337e-05	2.4885e-05	3.8290e-05	1.0263e-05	1.7530e-05	3.2610e-05	2.6641e-05	2.1691e-05	2.6517e-05	3.7161e-05	4.4030e-05
7	1.9597e-05	1.6833e-05	2.6788e-05	7.0823e-06	1.5040e-05	2.3672e-05	2.7907e-05	4.1508e-05	4.8295e-05	6.9312e-05	5.5129e-05
8	1.5103e-05	6.7239e-06	6.4980e-06	5.6996e-06	1.0778e-05	1.5426e-05	8.9487e-06	1.5752e-05	6.1303e-06	1.1703e-05	1.1529e-05
9	9.7549e-05	9.8536e-05	1.7811e-04	1.2160e-04	1.0357e-04	1.3185e-04	1.5065e-04	1.4309e-04	1.8145e-04	1.0001e-04	9.0575e-05
10	2.4716e-05	1.9030e-05	3.7326e-05	1.1767e-05	1.4352e-05	3.8699e-05	3.1220e-05	1.9810e-05	2.1997e-05	3.4773e-05	4.7141e-05
11	3.6197e-05	8.3120e-06	1.7612e-05	7.5780e-06	9.8252e-06	2.3289e-05	2.0532e-05	1.9977e-05	3.1211e-05	4.8725e-05	4.4082e-05
12	7.8100e-06	4.5521e-06	4.6104e-06	6.7814e-06	8.2219e-06	8.9523e-06	5.4030e-06	8.0876e-06	3.8198e-06	1.1446e-05	7.6815e-06
13	2.9119e-05	8.1170e-05	1.1622e-04	1.1188e-04	8.1543e-05	6.4020e-05	7.3572e-05	8.1512e-05	6.9633e-05	4.4887e-05	3.1849e-05
14	1.4757e-05	1.9517e-05	3.4869e-05	1.4301e-05	2.6951e-05	3.0966e-05	3.3994e-05	2.4701e-05	2.0530e-05	2.8629e-05	7.9873e-05
15	5.4176e-05	1.8939e-05	3.7910e-05	9.2579e-06	2.1292e-05	2.5786e-05	5.7993e-05	5.0282e-05	9.4495e-05	8.1064e-05	8.7824e-05
16	9.9358e-06	8.5168e-06	9.3279e-06	6.0249e-06	1.1260e-05	1.8500e-05	7.1511e-06	1.8581e-05	5.7551e-06	1.5450e-05	7.2080e-06
17	1.5960e-04	1.6305e-04	2.0847e-04	1.8582e-04	1.7042e-04	1.6757e-04	1.1967e-04	1.9423e-04	2.2102e-04	1.0882e-04	1.2469e-04
18	1.8573e-05	4.8820e-05	2.6224e-05	1.5431e-05	1.5678e-05	3.8641e-05	2.8835e-05	1.2871e-05	1.5370e-05	2.4376e-05	4.1982e-05
19	2.1968e-05	1.4244e-05	1.0749e-05	4.1586e-06	8.9031e-06	1.6017e-05	2.5014e-05	1.0952e-05	1.7863e-05	4.6599e-05	3.0585e-05
20	6.1359e-06	7.2725e-06	3.1462e-06	4.7009e-06	6.3216e-06	7.1142e-06	8.4032e-06	6.7364e-06	2.0454e-06	1.1906e-05	6.8312e-06
21	9.7413e-05	1.1091e-04	1.5548e-04	1.1946e-04	1.3407e-04	1.2512e-04	1.1420e-04	1.6104e-04	1.7617e-04	8.4245e-05	8.7931e-05
22	3.1214e-05	4.4582e-05	3.4436e-05	1.4693e-05	1.9273e-05	3.7863e-05	4.0475e-05	2.0344e-05	2.4486e-05	2.9015e-05	4.4425e-05
23	4.3866e-05	1.4752e-05	1.6036e-05	5.5973e-06	1.1615e-05	1.7610e-05	3.5851e-05	1.7109e-05	4.0842e-05	5.4554e-05	3.2347e-05
24	7.1479e-06	6.9638e-06	7.8967e-06	6.8598e-06	8.7389e-06	9.8130e-06	6.5858e-06	9.0709e-06	4.4625e-06	1.4675e-05	9.8660e-06
25	7.6682e-05	9.6547e-05	1.5028e-04	1.0973e-04	8.4642e-05	1.2788e-04	8.8167e-05	1.1364e-04	1.0763e-04	5.9469e-05	5.3193e-05
26	3.4120e-05	4.0538e-05	5.2707e-05	1.4610e-05	2.0439e-05	4.8194e-05	3.9597e-05	2.6500e-05	2.6284e-05	3.4679e-05	5.2197e-05
27	5.2433e-05	1.8354e-05	2.8035e-05	8.4671e-06	1.4285e-05	2.2264e-05	4.9560e-05	3.3136e-05	7.1505e-05	7.2539e-05	6.0112e-05
28	8.3251e-06	7.8525e-06	6.8487e-06	8.0007e-06	1.1607e-05	1.1641e-05	5.8902e-06	1.4214e-05	6.6795e-06	1.6210e-05	9.8005e-06
29	6.1640e-05	1.2096e-04	1.3897e-04	1.3120e-04	9.7792e-05	1.1194e-04	7.8760e-05	8.9057e-05	7.7813e-05	5.3759e-05	3.7378e-05
30	2.7400e-05	4.3331e-05	4.3830e-05	1.9042e-05	2.3853e-05	4.3066e-05	3.5159e-05	2.4393e-05	2.3614e-05	2.8436e-05	5.3500e-05
31	6.0684e-05	3.4353e-05	4.0616e-05	1.2438e-05	1.9736e-05	2.7560e-05	7.7173e-05	5.4359e-05	9.7964e-05	8.4674e-05	1.1258e-04
32	8.8071e-06	9.0718e-06	6.9952e-06	6.3006e-06	1.0840e-05	1.5603e-05	4.9884e-06	1.7648e-05	5.8337e-06	1.6247e-05	5.5468e-06
33	4.6636e-05	1.0757e-04	1.3387e-04	1.3176e-04	1.0308e-04	1.1366e-04	6.9452e-05	8.8209e-05	5.6884e-05	4.4211e-05	2.2438e-05
34	1.9998e-05	3.0921e-05	3.9691e-05	1.9224e-05	2.6940e-05	3.6585e-05	3.0410e-05	2.4012e-05	1.9089e-05	2.6806e-05	5.9191e-05

Fig. 9. Left Hemispheric Power: Left hemisphere channel powers in delta, theta, alpha and beta bands. Four rows contains one channel of information. The last two bands of the last channel, rows 35 and 36 are not shown. The first 11 patients can be seen. Power spectral densities of channels X1, T3, F7, T5, F3, C3, P3, and O1 are shown.

desired features that could potentially seperate depressed patients from normals. There appears to be no large sources of high magnitude noise anywhere throughout the power feature matrix indicating the general data set was accurately obtained. This matrix can now be compared to the same bands and channels on the right side of the hemisphere seen in Figure 5.

Comparing the values between the charts some relationships are immediately apparent. Magnitudes in differing rows tend to vary to a similar degree. In addition, the variances on the rows appear similar in both hemispheres which makes physiological sense. For example, comparing the first rows of left and right hemispheres, the first rows magnitude slightly changes overall between hemispheres, showing more power generally in the left. These are normal patients, yet the magnitudes in the left hemisphere appears slightly greater indicating asymmetry in normal patients. It is a possibility that the left side of the brain shows slightly more activity even in normal patients on average. In creating a system that identifies depression such natural asymmetries would need to be accounted for. This magnitude differences may have also been introduced in

	1	2	3	4	5	6	7	8	9	10	11
1	1.8636e-04	1.2789e-04	1.9071e-04	1.2237e-04	1.5433e-04	1.8694e-04	1.9097e-04	1.3772e-04	2.0035e-04	1.5875e-04	1.4756e-0
2	1.9223e-05	3.2018e-05	3.0144e-05	2.2298e-05	1.9219e-05	1.8001e-05	2.3967e-05	1.9246e-05	1.3827e-05	1.6934e-05	2.4790e-0
3	2.0422e-05	1.6607e-05	1.0149e-05	1.7652e-05	8.8877e-06	1.2190e-05	9.8774e-06	1.7677e-05	7.5458e-06	9.4318e-06	2.6839e-0
4	3.7061e-06	7.4477e-06	2.4754e-06	6.2585e-06	5.7655e-06	3.7272e-06	2.8815e-06	5.6275e-06	1.8336e-06	2.6029e-06	3.1711e-0
5	8.8979e-06	8.4728e-05	1.4973e-04	9.0409e-05	7.5348e-05	9.9258e-05	3.3361e-05	1.0320e-04	1.1190e-04	5.8722e-05	5.9637e-0
6	4.7536e-06	1.3065e-05	3.4356e-05	1.1551e-05	1.4213e-05	3.3955e-05	1.2066e-05	2.0260e-05	3.6531e-05	2.9794e-05	3.8042e-0
7	1.0739e-05	9.3465e-06	2.0616e-05	9.9493e-06	1.4786e-05	1.9889e-05	1.6468e-05	2.8106e-05	5.4243e-05	7.1958e-05	3.9499e-0
8	2.2490e-05	5.9507e-06	5.8647e-06	6.7730e-06	8.9325e-06	1.4286e-05	1.3393e-05	1.8061e-05	7.2373e-06	1.2930e-05	1.0846e-0
9	8.4285e-05	1.1399e-04	1.8960e-04	9.3277e-05	1.1706e-04	1.1812e-04	1.2963e-04	1.7312e-04	1.7530e-04	9.8718e-05	9.0241e-0
10	2.4573e-05	4.8919e-05	3.2485e-05	1.2736e-05	1.3161e-05	3.0552e-05	3.0203e-05	1.4092e-05	2.7378e-05	2.4900e-05	3.9374e-0
11	4.2060e-05	1.8048e-05	1.3874e-05	7.2466e-06	8.9763e-06	2.1271e-05	2.3192e-05	9.8513e-06	3.6039e-05	4.1323e-05	3.3446e-0
12	8.5307e-06	9.4534e-06	3.8864e-06	6.1739e-06	7.9237e-06	9.5496e-06	6.7269e-06	5.2874e-06	4.8334e-06	1.2869e-05	7.1614e-0
13	3.1268e-05	1.1072e-04	1.3389e-04	9.4267e-05	9.6130e-05	3.9701e-05	7.6287e-05	1.0012e-04	6.6824e-05	5.1206e-05	5.2946e-0
14	1.7064e-05	2.8754e-05	3.8615e-05	1.1396e-05	2.0670e-05	2.1827e-05	2.8618e-05	2.3997e-05	2.7750e-05	2.5854e-05	5.6835e-0
15	5.5269e-05	2.3647e-05	3.3238e-05	1.0262e-05	2.1246e-05	2.6198e-05	5.4853e-05	3.9454e-05	9.1135e-05	8.5053e-05	8.7550e-0
16	1.0936e-05	5.9910e-06	7.2487e-06	6.9915e-06	8.7197e-06	1.9417e-05	6.5547e-06	1.6720e-05	7.4202e-06	1.4008e-05	4.1328e-0
17	1.5804e-04	1.6108e-04	2.0769e-04	1.7778e-04	1.5990e-04	1.6455e-04	7.4382e-05	2.1237e-04	2.1932e-04	9.5441e-05	1.4877e-0
18	1.9167e-05	5.1481e-05	2.5236e-05	1.6133e-05	1.5011e-05	3.7301e-05	1.9958e-05	1.0914e-05	1.5274e-05	2.3066e-05	4.5437e-0
19	2.3944e-05	1.4876e-05	1.0462e-05	5.2978e-06	9.1494e-06	1.5102e-05	2.1741e-05	8.2441e-06	1.6689e-05	4.8352e-05	2.9685e-0
20	6.8973e-06	7.4215e-06	2.7553e-06	5.4910e-06	7.0738e-06	7.3618e-06	1.2826e-05	4.4056e-06	2.1791e-06	1.3590e-05	5.2530e-0
21	8.9554e-05	1.1105e-04	1.8670e-04	9.9192e-05	1.2176e-04	1.2018e-04	6.5730e-05	1.6413e-04	1.8347e-04	7.8172e-05	8.2853e-0
22	2.8840e-05	6.2114e-05	3.3933e-05	1.2656e-05	1.7391e-05	3.4142e-05	2.4756e-05	1.6900e-05	2.4247e-05	2.6860e-05	5.2351e-0
23	4.4119e-05	1.8732e-05	1.5019e-05	6.0234e-06	1.1652e-05	1.4904e-05	2.7777e-05	1.4747e-05	3.7414e-05	5.3899e-05	3.5702e-0
24	8.0317e-06	8.3038e-06	4.7850e-06	8.4961e-06	1.0330e-05	1.0852e-05	1.1444e-05	8.9085e-06	4.2977e-06	1.6540e-05	8.7572e-0
25	6.0658e-05	1.3336e-04	1.4994e-04	9.2958e-05	8.9761e-05	1.1706e-04	8.3189e-05	1.1290e-04	1.1523e-04	6.3315e-05	4.4229e-0
26	2.9726e-05	4.2028e-05	5.2529e-05	1.5479e-05	2.2014e-05	4.5729e-05	3.9435e-05	2.6853e-05	3.1708e-05	3.6060e-05	5.0160e-0
27	5.1189e-05	1.9703e-05	2.5932e-05	1.0366e-05	1.5815e-05	2.1548e-05	5.9319e-05	3.6904e-05	6.6618e-05	6.5185e-05	4.5726e-0
28	9.2428e-06	8.6843e-06	6.4278e-06	8.6879e-06	1.3066e-05	1.5528e-05	5.7140e-06	1.5436e-05	6.9364e-06	1.6493e-05	1.0530e-0
29	5.1478e-05	1.2890e-04	1.4264e-04	1.2638e-04	1.0232e-04	1.1109e-04	7.3188e-05	1.0232e-04	8.5585e-05	5.1569e-05	3.1133e-0
30	2.3034e-05	4.3685e-05	4.3762e-05	1.9692e-05	2.3598e-05	3.7252e-05	3.3634e-05	2.6047e-05	2.7712e-05	2.7845e-05	4.9928e-0
31	6.4523e-05	3.2505e-05	3.7295e-05	1.4409e-05	2.2562e-05	2.7404e-05	8.7111e-05	4.2037e-05	8.8616e-05	9.0303e-05	1.2558e-0
32	9.1756e-06	9.4792e-06	6.4111e-06	7.8478e-06	1.0047e-05	1.4509e-05	4.6310e-06	1.7383e-05	7.2073e-06	1.4791e-05	4.2754e-0
33	4.0153e-05	1.1935e-04	1.1660e-04	1.3621e-04	1.0180e-04	1.1402e-04	6.4457e-05	9.3884e-05	6.1386e-05	4.7217e-05	2.2141e-0
34	1.7545e-05	3.7213e-05	3.6059e-05	1.9153e-05	2.4757e-05	3.6277e-05	2.8013e-05	2.2206e-05	1.9660e-05	2.8136e-05	4.3000e-0

Fig. 10. Right Hemispheric Power: Right hemisphere channel powers in delta, theta, alpha and beta bands. Four rows contains one channel of information. The last two bands of the last channel, rows 35 and 36 are not shown. The first 11 patients can be seen. Power spectral densities of channels X1, T3, F7, T5, F3, C3, P3, and O1 are shown.

the measuring phase of the general EEG data. Plotting the features clearly shows relationships between channels and can be seen in Figure 5.

Interestingly, the features of each patient seem to follow a similar but not exact pattern. Power spikes are generally seen in the same regions for all patients. Small differences in the magnitudes and phase of these spikes can be noticed and an the support vector machine will classify based on these types of differences. As part of the framework, code was created to concatenate these feature matrices and to be input into a support vector machine. The SVM used for this project was SVMlight which requires a particular input format. The conversion from a feature matrix to an SVMlight input matrix code can be seen in the appendices. Separation was performed based on gender, and the SVMlight was able to distinguish gender with low accuracy. More details on this separation was excluded because it is not in the vein of the report concerning depression. Seperation by gender is a topic of a different nature. Gender seperation was done only to show the system working and the conversions had been done correctly. After this seperation was

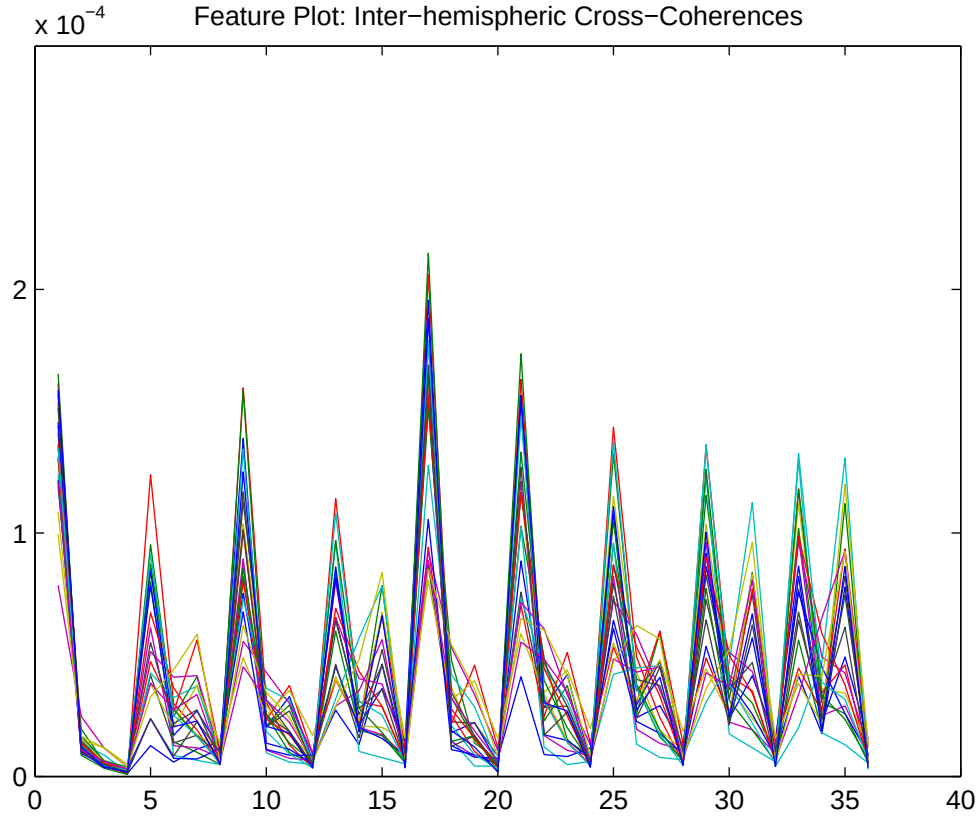

Fig. 11. Cross Coherence: Cross coherence across hemispheres. Cross Power spectral densities of channels X, T, F, T, F, C, P, and O are shown.

completed and the SVM was shown to be working, the system was ready for inputing massive feature matrices from depressed patients.

6. CONCLUSIONS

In conclusion, the software framework appears to be working adequately. The system can easily implement features discussed in the papers with only slight modifications to the code. The storage of coherences across all possible channel combinations drastically speeds up the process of analyzing the data at the cost of roughly 10 gigabytes of space. The shear volume of the data requires usage of a computational grid and cannot possibly be completed on a home desktop computer in a reasonable time frame. The initial coherences calculated on individual trials show large amounts of high frequency content and are not suitable for direct usage. Averaging functions across the six trials were made to deal with this issue and all average coherences were calculated and saved with the usage of the McMaster ECE grid. The averages were shown to work similar to lowpass filters, reducing the magnitudes of the signals but increasing the signal to noise ratio. All functions were tested through creation of the final feature matrices to be input into the SVM. These included frequency, power, and power ratio feature matrices. A variety of of functions were assembled to create these feature matrices. These functions easily implemented inter-hemispheric related features such as brain asymmetries which were even observed in normal patients on several channels. Finally, conversion functions were created to transfer the feature matrices into SVMlight. The system is essentially ready for implementation on depressed patients. The wide variation of readings in normal patients shows depression seperation would be a difficult task. With further research, data and optimization of machines the seperation of depressed individuals seems promising.

A. Recommendations

Recommendations for further work would be in the area of creating a custom feature selection and support vector machine specifically for the purposed of depression. The parameters of the SVM can also be tweaked along with the number of features input to increase accuracy. The framework potentially could include a method by which it automatically increases or decreases parameters until maximum separation in the feature space occurs. Computational requirements would be quite high for such an algorithm and methods such as the Monte Carlo algorithm would need to be used to find the most suitable parameters. In addition to this, more papers could be researched and their features tested to increase the accuracy of the system.

7. APPENDICES

A. Coherence Function

```
function [Xcoh,freq] = getCoherence(x1,x2)
X= xcorr(x1,x2,'coeff'); //normalized cross-correlation
Ts = 0.0049;
Fs = 1/Ts; //pre-definded, 205 Hz
L = size(X);
L = L(1);
NFFT = 2nextpow2(L); // Next power of 2 from length of y
Xcoh = abs(fft(X,NFFT)/L);
freq = Fs/2*linspace(0,1,NFFT/2+1); // f size is around 32769
//Xcoh = Xcoh(1:30000);
freq = freq(1:30000);//only considering to 30000 point (46.7 Hz)
end
```

B. Average Coherence Function

```
function [AVGcoh freq] = getAveragedCoherence(patient,e1,e2)
//channels only from 1 to 24
root = '/home/oreillj/dropbox/HamNorms0/';
load('patients.mat');

   //open raw data files
data1 = dlmread(strcat(root,patients(patient).name,'/ECV01R01.txt'),'',2,3);
data2 = dlmread(strcat(root,patients(patient).name,'/ECV01R02.txt'),'',2,3);
data3 = dlmread(strcat(root,patients(patient).name,'/ECV01R03.txt'),'',2,3);
data4 = dlmread(strcat(root,patients(patient).name,'/ECV01R04.txt'),'',2,3);
data5 = dlmread(strcat(root,patients(patient).name,'/ECV01R05.txt'),'',2,3);
data6 = dlmread(strcat(root,patients(patient).name,'/ECV01R06.txt'),'',2,3);

   //take desired columns
x1 = data1.data(:,e1);
```

```
x11 = data1.data(:,e2);
x2 = data2.data(:,e1);
x22 = data2.data(:,e2);
x3 = data3.data(:,e1);
x33 = data3.data(:,e2);
x4 = data4.data(:,e1);
x44 = data4.data(:,e2);
x5 = data5.data(:,e1);
x55 = data5.data(:,e2);
x6 = data6.data(:,e1);
x66 = data6.data(:,e2);

   //obtain coherences
[X1 freq] = getCoherence(x1,x11);
[X2 freq] = getCoherence(x2,x22);
[X3 freq] = getCoherence(x3,x33);
[X4 freq] = getCoherence(x4,x44);
[X5 freq] = getCoherence(x5,x55);
[X6 freq] = getCoherence(x6,x66);

   //averaging
AVGcoh = (X1+X2+X3+X4+X5+X6)/6;
f = freq;
end
```

C. Stored Coherence Function

```
   function AvgCoh = getSavedAvgCoh(patient,e1,e2)
cd('/home/surf/Documents/School/4BI6/HamNorms0/');
filename = [ 'AvgCoh ' num2str(patient) ' ' num2str(e1) ' ' num2str(e2) '.mat' ];
AvgCoh = load(filename);
```

```
AvgCoh = AvgCoh.m;
end
```

D. Stored Power Function

```
   function AvgPow = getSavedAvgPower(patient,e1,e2,freq0,freq1)
m = getSavedAvgCoh(patient,e1,e2);
onef = 642.2826; //one step in Hz
n0 = round(freq0*onef);
n1 = round(freq1*onef);
N = n1-n0;
Power = 0;cohfunctionAp
for k=n0:n1
Power = Power + m(k);
end
AvgPow = Power;
end
```

E. Power Ratio Function

```
   function PowRatio = getPowRatio(patient,e1,e2,bands)
// average pow e1 over e2
freq0 = bands(1,1);
freq1 = bands(2,1);
freq2 = bands(1,2);
freq3 = bands(2,2);

   pow0 = getSavedAvgPower(patient,e1,e1,freq0,freq1);
pow1 = getSavedAvgPower(patient,e2,e2,freq2,freq3);

   PowRatio = pow0/pow1;
end
```

F. Save Coherences Function

```
for k = 1:22 //pateints
for h = 1:24 //all cross-channel relations
for t = 1:24
if(k == 13)
continue;
end
if(t==h)
continue;
end
m = getAveragedCoherence(k,h,t);
cd('/home/oreillj/Coherence');
if(t¿h)
filename = [ 'AvgCoh ' num2str(k) ' ' num2str(h) ' ' num2str(t) '.mat' ];
end
if(t¡h)
filename = [ 'AvgCoh ' num2str(k) ' ' num2str(t) ' ' num2str(h) '.mat' ];
end
save(filename, 'm');
end
end
end
```

G. Frequency Feature Matrix

```
function m = freqFeatMat(e1,e2,freqs)
nChannels = length(e1);
nPatients = 22;
nFreqs = length(freqs);
```

```
   nRows = nFreqs*nChannels;
nCol = nPatients;
m = zeros(nRows,nPatients);// 13 col will need removal

   for k = 1:nPatients
if(k == 13) // 13 is useless for now
continue;
end
for s = 1:nChannels
for q = 1:nFreqs
e11 = e1(s);
e22 = e2(s);
freq = freqs(q);
cRow = s*q; //current channel times freq of interest
cCol = k; // current column is current patient
val = getSavedAvgCohatF(k,e11,e22,freq);
m(cRow,cCol) = val;
end
end
end
end
```

H. Power Feature Matrix

```
   function m = powFeatMat(e1,e2)
bands = [.5 4 8 14; 4 8 14 30]; // the delta theta alpha beta bands
nBands = 4;// for now the bands are locked as these
nChannels = length(e1);
nPatients = 22;
nRows = nBands*nChannels;
nCol = nPatients;
```

```
m = zeros(nRows,nPatients);// 13 col will need removal


   for k = 1:nPatients
cRow = 1;
cCol = k; // current column is current patient
for s = 1:nChannels
for q = 1:nBands
e11 = e1(s);
e22 = e2(s);
lowFreq = bands(1,q);
highFreq = bands(2,q);
val = getSavedAvgPower(k,e11,e22,lowFreq,highFreq);
m(cRow,cCol) = val;
cRow = cRow +1;
end
end
end
end
```

I. Power Ratio Feature Matrix

```
   function m = powRatioFeatMat(e1,e2, bands)
nChannels = length(e1);
nPatients = 22;
nCol = nPatients;
nRows = nChannels;
m = zeros(nRows,nPatients);// 13 col will need removal
for k = 1:nPatients
if(k == 13) // 13 is useless for now
continue;
end
```

```
for s = 1:nChannels
e11 = e1(s);
e22 = e2(s);
cCol = k;
cRow = s;
val = getPowRatio(k,e11,e22,bands);
m(cRow,cCol) = val;
end
end
end
```

J. SVMlight Conversion M File

```
   nm = size(m); //create feature matrix m prior to running this code
nClasses = nm(2);
nFeatures = nm(1);
classifier = ones(1,nClasses); // this matrix will be input
for r=1:10
classifier(r) = -1;
end

   file1 = fopen('test.dat','w');

   for k=1:nClasses
class = num2str(classifier(k));
if(classifier(k)¿0)
fprintf(file1,'+');
end
fprintf(file1,class);
fprintf(file1,' '); v for q=1:nFeatures
feature = num2str(q);
```

```
value = num2str(m(q,k),'10.18f');
fprintf(file1,' ');
fprintf(file1,strcat(feature,':',value));
end
if(k =nClasses)
fprintf(file1,");
end
end
fclose(file1);
```

8. REFERENCES

REFERENCES

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9. VITA

NAME: Jason O’Reilly

PLACE OF BIRTH: Oakville, Ontario

YEAR OF BIRTH: 1987

SECONDARY EDUCATION: Notre Dame Secondary School (2000-2005)