Seizure Detection with Artificial Neural Networks

A Senior Project presented to the faculty of the

Electrical Engineering Department

California Polytechnic State University, San Luis Obispo

In partial fulfillment of the requirements for the Degree of Bachelors in Science

2014 – 2015

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Abstract

The aim of this project is to enhance the daily lives of those who are prone to seizures by identifying seizure onsets through external devices. The approach consists of a non-invasive monitoring system, such as an electroencephalogram (EEG) device that measures brain activity, and an Artificial Neural Networks (ANN) that detects seizures in epileptic patients. For this senior project, EEG signals are obtained from an MIT database. The EEG signal is filtered by a low-pass filter to reduce random noise, and a notch filter to remove power line interferences. The discrete wavelet transform is then used to find the energy distribution of different frequency bands. The ANN, trained by the back propagation algorithm, detects seizure based on the above features extracted by the wavelet transform. Computer simulation results show the proposed approach is successful with a seizure detection rate of 94.21%.

Chapter 1: Introduction

OVERVIEW

Our bodies are complex control systems; we constantly receive input and derive an output to be executed. The system has a control center to which all information is seen and processed, the brain. Our brains use networks derived of several components: dendrites, sending weighted signals to activate synapses, to which neurons determine if a signal is to be emitted through axons, to possible activated more synapses (a model is shown in Figure 1 below). These networks are emergent, and can be described through a set of nodes and connections between these nodes. This network activity uses signals that are realizable through charge distribution and flow. Stationary and moving charges thus produce electromagnetic waves that can be non-invasively measured using and EEG. Given the complexity of the human body, an ideal representation of these networks may present a plausible way to classify signals into executed motions.

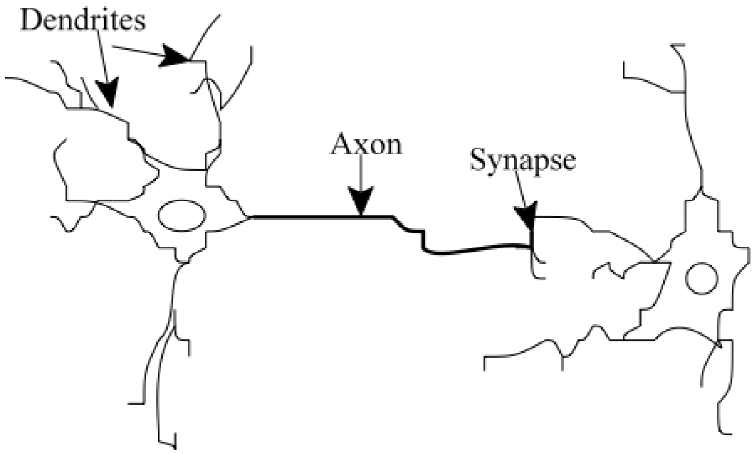

Figure 1: Neural Network [1]

Brain Computer Interfaces (BCI) is communication systems where humans interact with external devices using merely their brain activity. Thus it has been a recent motivation to increase the functionalities of BCI devices. Noninvasive brain activity monitoring systems are desired for implementation, the following table compares some of the options.

Table 1: Brain activity monitoring systems

Device	Advantages	Disadvantages	Price
EEG	• Can be used in many places (not bulky) • High temporal resolution • Relatively tolerant of subject movement • Silent • Can detect covert processing • **Can be used in subjects who are incapable of making a motor response**	• Low spatial resolution on scalp • Poorly determines neural activity that occurs below the upper layers of the brain • Long time to connect subject • Poor signal-to-noise ratio	Low relative cost
MEG	• Promises improved spatial resolution coupled with extremely high temporal resolution • Independence of head geometry • Non-invasiveness	• Requires equipment consisting of liquid helium • Sometimes aggravate • bulky	Expensive
fMRI	• High spatial resolution on scalp (better than EEG and MEG)	• Bulky-use of 1-ton magnet • Aggravate • Involves exposure to high-intensity magnetic fields	Expensive
PET	• Can identify specific location in the brain at which various neurotransmitters can be found • Noninvasive	• Bulky • Exposure to radio ligands	Expensive $1,000-$1,200 per scan!

For the purpose of this project the EEG method of Electroencephalograph is the primary source to our data. The low cost measurement set up and low demanding technical requirements have led to extensive research for EEG based BCI's thus, more data bases have been built. Modern technological advancements have resulted in the development of consumer grade EEG devices such as Emotive EPOC, Neuroski Mindwave and Myndplay BrainBand. Proposal of consumer-grade EEG-BCI devices now seems plausible; however major improvements in the extraction and classification stages must be made. The current market for these algorithms is discussed below.

Chapter 2: Background

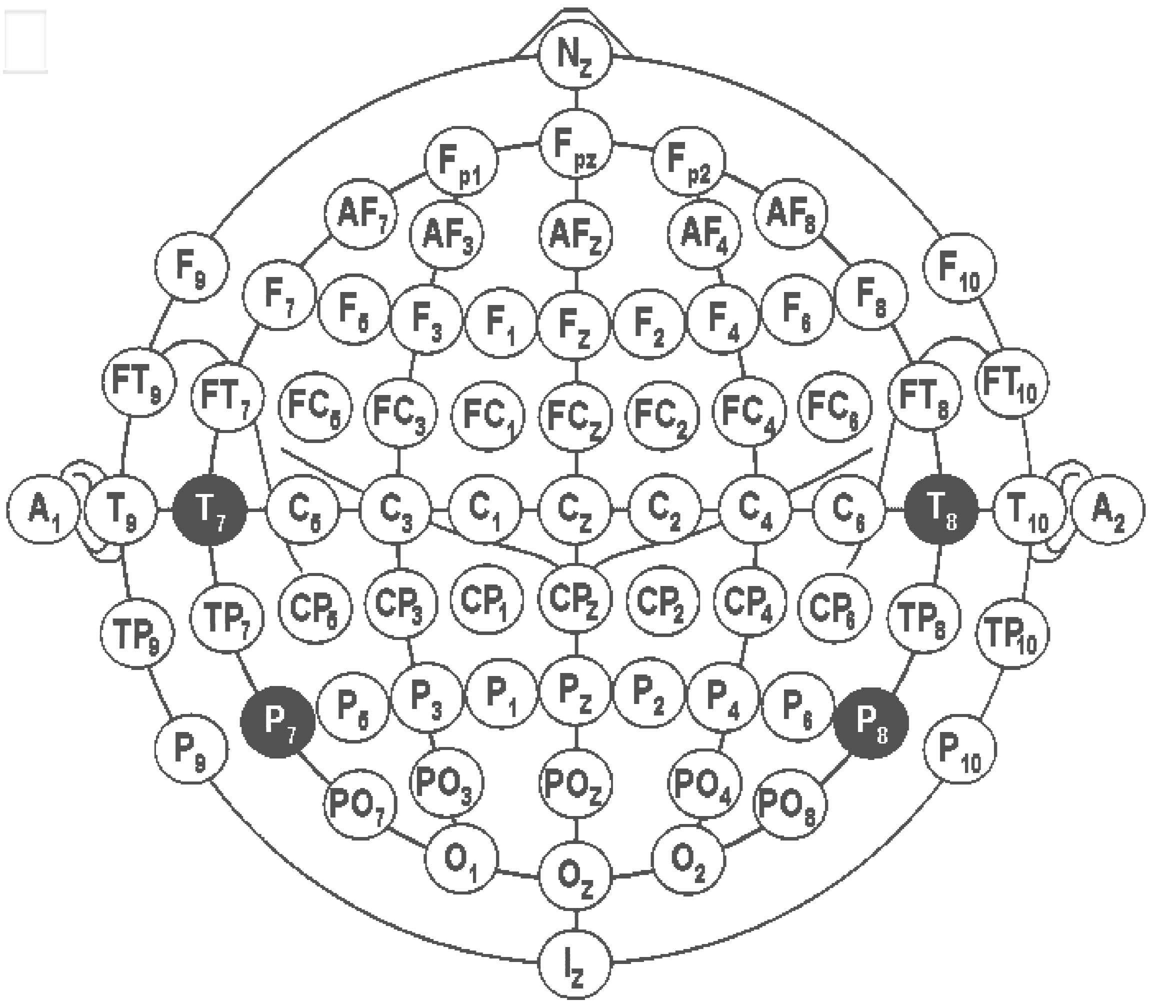

Figure 2: International 10-20 Systems for Electroencephalography [12]

ARTIFICIAL NEURAL NETWORKS

In order to plausibly classify signals, an Artificial Neural Network (ANN) has been created to mimic brain activity. Any network can be classified as a set of nodes, that receive and process inputs to obtain outputs; and connections that determine the information flow between these nodes. ANN is a type of network that sees nodes as “Artificial Neurons”, and then uses the connection activity between these nodes to process information. Artificial neurons are computational models attempting to mimic natural neurons. The Artificial neurons implement an activation function to determine the output such that if the signal strength of the synapse reaches a relative threshold the neuron will fire an electric spike through

the axon a model is shown in Figure 3 below. ANN's require 2 phases the learning phase and the retrieving phase. In the retrieving phase the final neuron values represent the desired output to be retrieved [4].
In the learning phase a back propagation algorithm is used to adjust weights to obtain the desired output from the network.

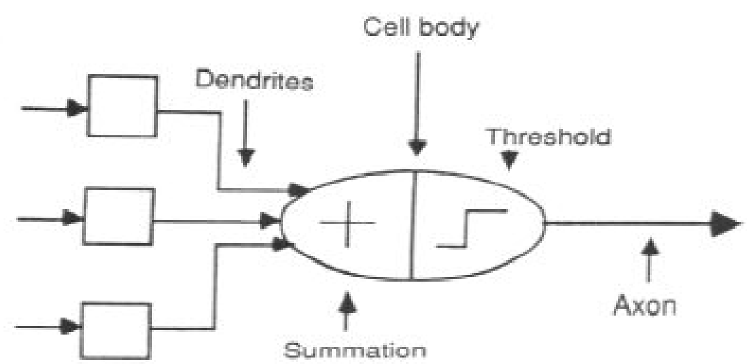

Figure 3: Artificial Neuron [4]

THE BACKPROPAGATION ALGORITHM

In order for an artificial neuron to function as a natural neuron it must have the ability to learn. A natural neuron will activate upon a received a signal from the dendrites; the neuron will then send out spikes of electric activity to axons terminated by synapses. The synapses will inhibit or excite the received spike into electrical effects that propagate through the axon to other neurons. If the excitatory input received is sufficiently large relative to the inhibitory input it will send electric activity down its axon. Thus, learning occurs by changing the effectiveness of the synapses so that the influence of one neuron or another changes [4]. To best mimic this behavior Rumelhart and McClelland created the Back Propagation Algorithm. The network has 3 layers; inputs, a hidden layer and outputs. The Back Propagation Algorithm is used in feed forward ANN's such that the signal is forward and the errors are propagated backwards. The artificial neuron will receive an input to which the output depends only on the activation function. The network is given examples of inputs and outputs, the obtained outputs are then computed and the error is measured. A gradient descendent is then used for adjusting weights; this metric is inversely proportional to the rate of change of the error signal. Thus as if a large weight contributes a lot to the error, the adjustment will be greater than if it contributes a smaller amount [3]. This process is repeated until minimal error exists.

DISCRETE WAVELET TRANSFORMATION

The wavelet transform is particularly useful in this case because it allows for temporal resolution. The wavelet transform works by allowing a mother wavelet to preform multiresolution decomposition as shown in Figure 4 below, and a scaling function to preform multiresolution analysis. The mother wavelet is stretched and scaled then correlated to the signal of interest. In essence the DWT is able to capture both the frequency and time location of the signal in question.

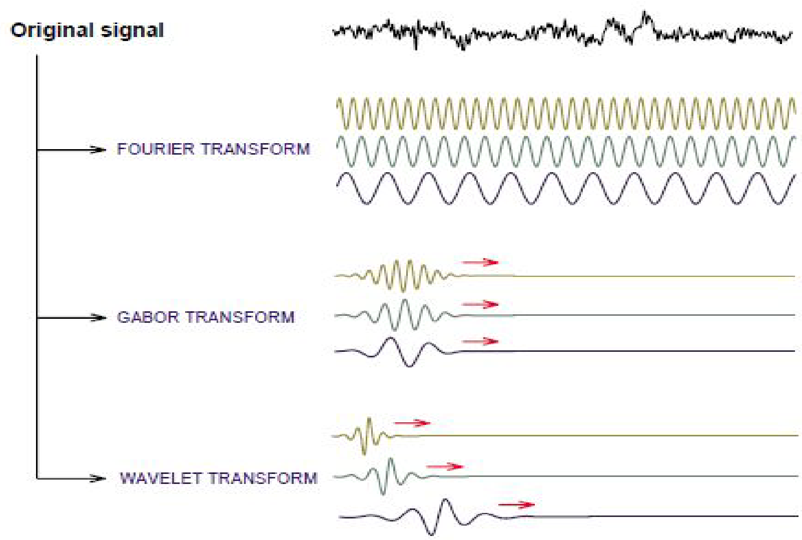

Figure 4: Frequency and Time-Frequency Methods [1]

Once a signal is received from the MIT database a method of feature extraction must exist.

Chapter 3: Literature Review

EEG signal classification requires two phases: feature extraction and feature classification. In this report feature extraction is implemented using the Discrete Wavelet Transform, and feature classification is implemented using the back propagation algorithm to derive appropriate weights for an ANN. However, there are several proposed methods in the research market. A brief overview of these methods is presented below through the summarization of applicable articles.

3.1. High accuracy classification of EEG signals [5]

Table 2: Progression of techniques to achieve 90% accuracy in finger tapping [5]

Contributor /implementation	Feature Extraction Methods	Result/improvement	Problems
Pfurtscheller	LVQ algorithm applied to C3 and C4 EEG Channels	80% accuracy for 3 subjects	-Features were in pre-defined frequency bands - ERD is subject related so different subjects have different spatial localizations
Muller-Gerking	CSP	Can use more channels of signals	Vector features are large (same as input: N by K)
N/A	PCA + CSP	Output Vector features are: p by K	Vector features still have K columns
Forward stepwise feature selection method	OLS	Can be used to generate new features based on training set	For one subject
Chung et. Al.	PCA+CSP+OLS_2	Preset values of initial network become less critical	For one subject
SVM classifier	PCA+CSP RBF and OLS	90% accuracy on a self-paced finger taping dataset	For one subject

This article addresses methodology that achieved the high accuracy detection of the left and right finger movement by combining the Common Spatial Patterns (CSP) and Principal Component Analysis (PCA) to improve signal classification. To further improve the accuracy the Orthogonal Least Square algorithm (OLS) provides efficient implementation of the forward stepwise feature selection method to provide a well-chosen selection of features from input vector features.

As an alternative to the back propagation algorithm a brief summarization of the CSP+PCA method is shown below (for in-depth algorithms review reference [5]).

CSP+PCA method intuitive overview [5]:

Given: N-channels spatial-temporal EEG signal (X)

X: N by K matrix and K denotes the number of samples in each channel.

Process (CSP): Derive the covariance as a function of X which is an N-dimensional vector at time k, this will allow for the estimation of the covariance matrices for left (S_L) and right (S_R) hand data respectively. Once normalized the CSP is extracted

based on simultaneous diagonalization of the left and right hand covariance matrices to maximize the differentiation between the two groups. Taking the sum of these covariance matrices gives the eigenvectors and eigenvalues of R (the covariance of the total sample set). CSP features are then calculated using the transformation in equation 1.

$$W = \lambda^{1/2}U^T \tag{1}$$

Process (CSP + PCA): This approach makes use of a transformation matrix (W_s) by only using the *p* principal eigenvectors from U, these are the most significant eigenvectors hence the ones with the biggest eigenvalues. Then, in order to reduce the size of the covariance matrices for the left and the right hands by making use of only the principal eigenvectors, $S_{L,}$ S_R are derived by taking the product of: W_s, the normalized diagnalized covariance of the left, and the transposed matrix (W_s^T); the same is done using the normalized diagnalized covariance of the right for the right movements. Now making use of equation 2 below it can be found that S_L and S_R share a common eigenvector matrix. Thus for each trial a data matrix (X_{nxk}) is transformed to a smaller matrix(Y_{pxk}) to increase the accuracy of the final features to be classified.

$$S_L + S_R = W_sRW_s^T \tag{2}$$

This method of Support Vector Machine (SVM) classification reaches 90% (best results for given data set using the data set from the BCI Competition 2003. This data set includes 316 training trials and 100 test trials. 20-fold cross validation is used throughout the training process for parameter optimization.

3.2. Signal decomposition by multi-scale PCA and its applications to long-term EEG Signal classification [6]

The methodology proposed in this paper was for epileptic seizure detection. The task of long-term observational study is then addressed for epilepsy diagnoses. These methods were applied to a publicly available EEG database similar to the proposed data source of this senior project.

Table 3: Methodology Solutions to Signal Classification Difficulties

Practice	Problem	Method	Aim
Data obtained from minimal number of participants/ patents	Fewer signals	Signal Segmentation techniques applied to long-term signals to convert original signal into a set of smaller signal segments (CPS+PCA)	Stationary signal segments and zero cross-correlation
deal with complexities of biomedical signals in pattern classification	Signals extremely long thus, to capture each stage of signals a high dimensional feature vector is required	Multi-variate feature extraction or signal decomposition (DWT)	Coefficients at each scale of wavelet decomposition is approximately stationary and less auto-correlated this forms a good basis for statistical methods such as PCA
Discrete Wavelet transform used for feature extraction	Does not extract the spatial feature information of signals (primarily a temporal decomposition)	Multi-scale PCA, this applies PCA, at each scale decomposition, to the wavelet coefficients	De-noising and decomposing complex biomedical signals in both spatial and temporal domains
New Classification	Extracted features have same temporal dimension N as the original signals	Empirical Classification (EC)	Classification decision based on the minimum variances of ratios

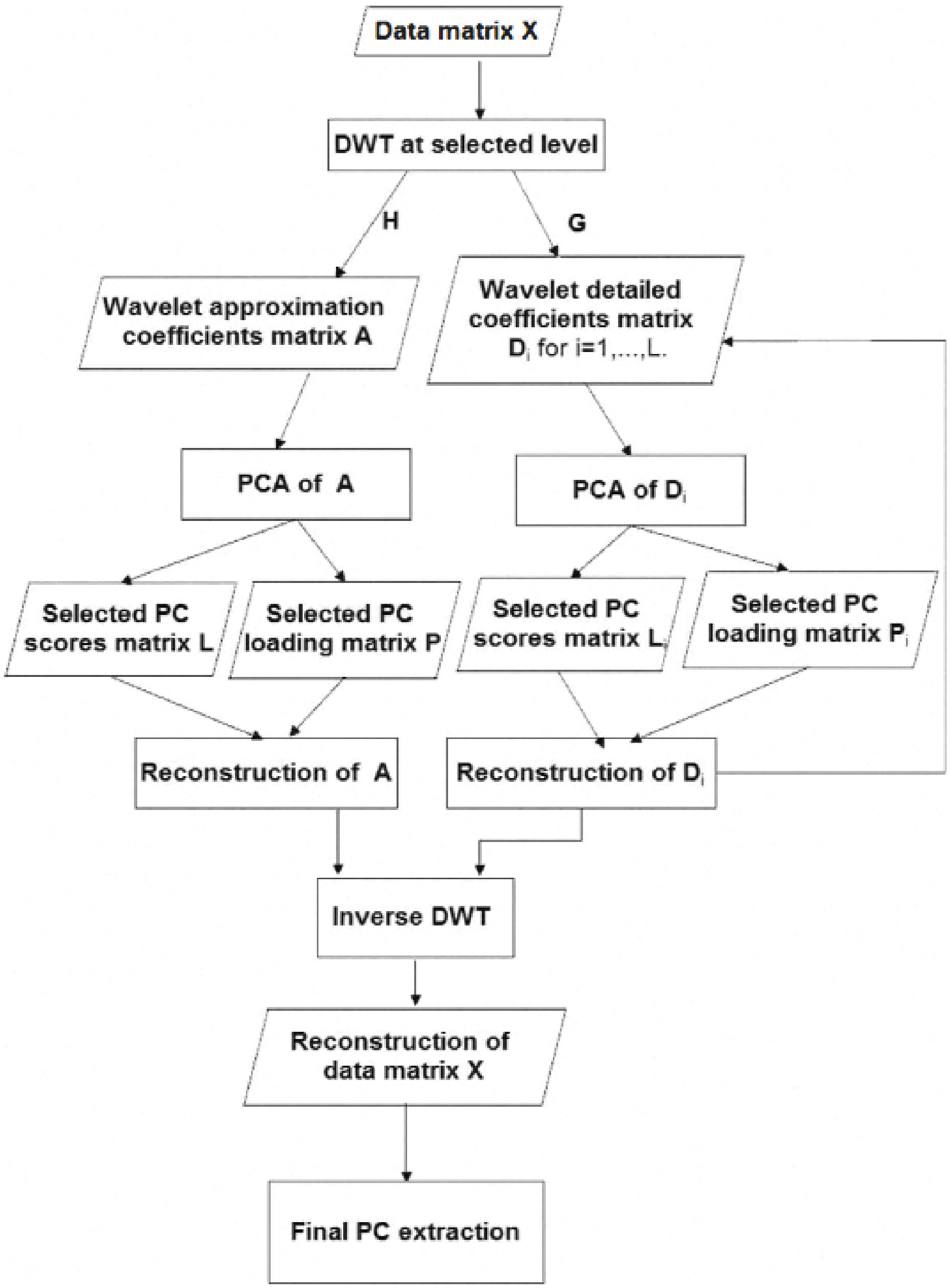

Figure 5: Flow Chart of the Multi-scale PCA Method [6]

3.3. Performance Comparison using five ANN methods for classification of EEG signals of two mental states [7]

This article simply preformed test for five different ANN methods for classification. For the signal extraction phase the feature vectors were composed

using the Event Related Desynchronization (ERD), and then the most significant frequency bands were extracted using the Wavelet Packet Transform (WPT). A comparison of training techniques other methods is presented below.

Table 4: Comparisons of different ANN training methods [7]

Tasks / Techniques	Baseline and movement
Gradient Descent BP method	90%
Resilient Back Propagation	95%
Conjugated Gradient BP	92.5%
GD BP with Momentum	90%
Levenberg-Marquardt	92.5%

Some overall improvements to aid to these articles include temporal filtering to reduce noise and classification performance could be improved by applying proper band-pass filter.

Chapter 4: Computer Simulation Results on Seizure Detection

4.1. System description

Background

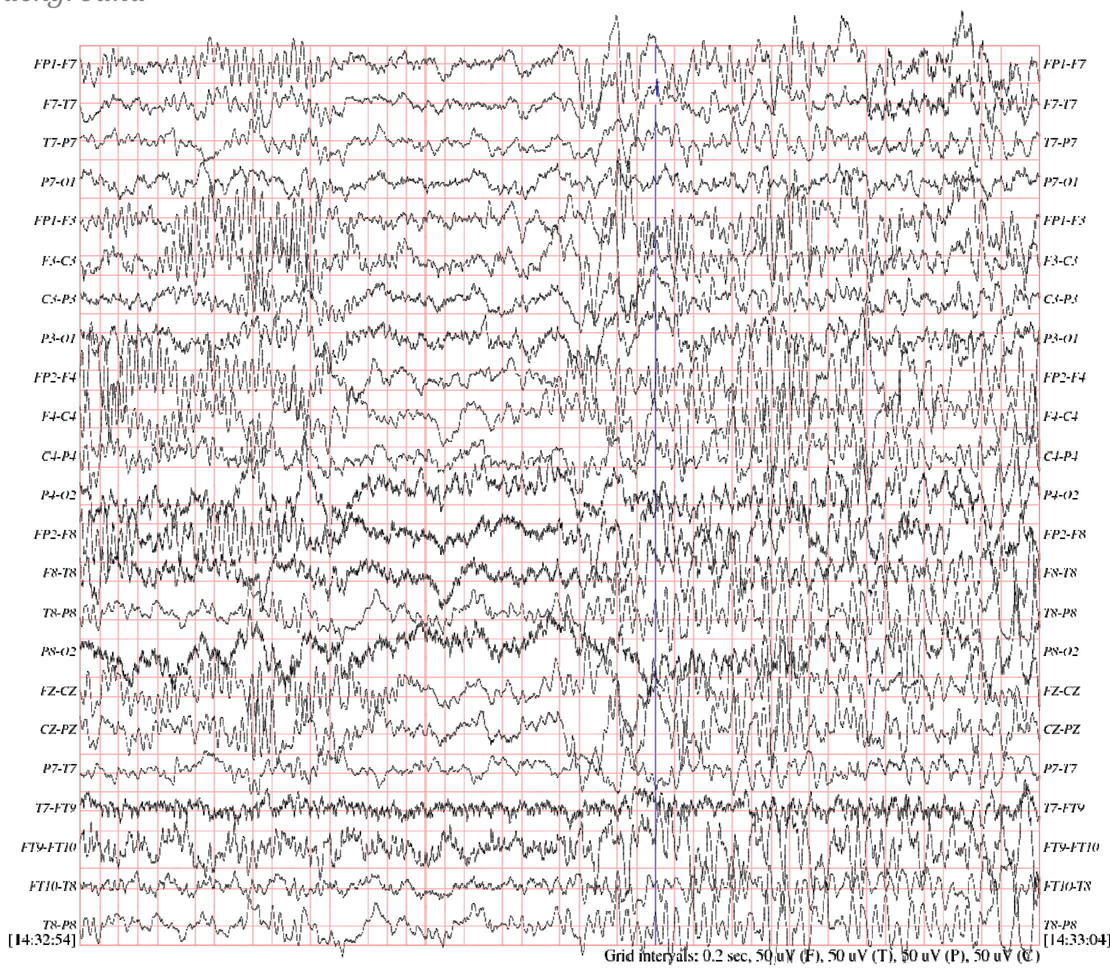

Figure 6: EEG signals taken from subjects under seizure tests [12]

Figure 6 above shows an example of a signal to be processed into energy/ power distributions to help aid onset seizure detection. The signal is composed of many different frequencies thus analyzing it in the time domain shows minimal benefit. Analyzing the signal in the frequency domain will allow for relative energy distributions in certain frequency band to be extracted. The wavelet transform is particularly useful in that it greatly reduces the size of the data.

Procedure

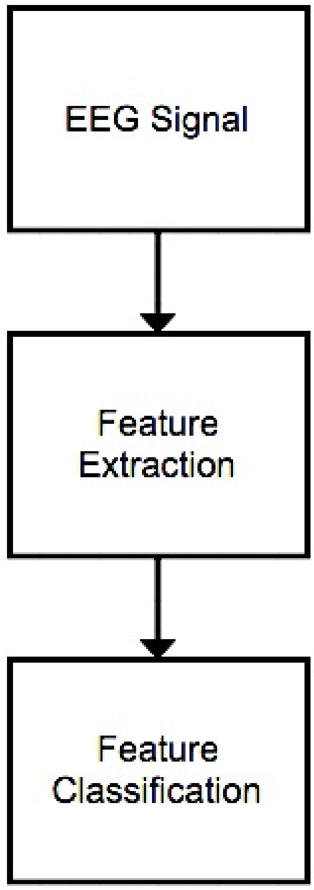

Figure 7: EEG Classification Block Diagram

Table 5: EEG Classification Library-Functional Requirements

EEG Classification with Discrete Wavelet Transforms and Energy Distribution	
Input	User thoughts ➔EEG Signals: from the MIT database
Output	An ANN that will accept multiple energy levels depending on the movement.
Functionality	Feature Extraction ➔ MATLAB function to implement wavelet Transform Feature Classification➔ MATLAB function to preform Back Propagation algorithm

This implementation consists of an EEG signal from the MIT database that will be filtered. During filtering the signal will be ran through a low pass and a band

pass filter. During feature extraction a wavelet transform will be used to establish energy/ power distributions of certain frequency bands. The ANN will then implement the back propagation algorithm to learn appropriate weights. These types of movements can be classified using an EEG.

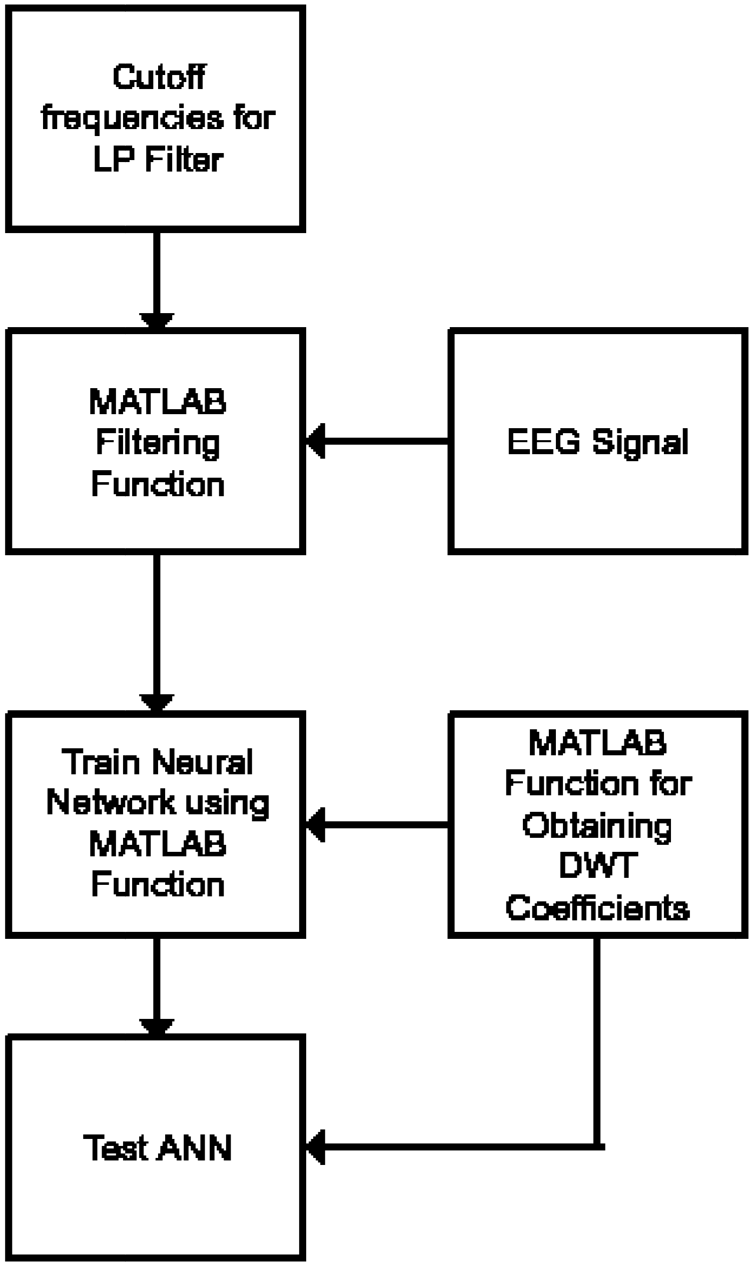

Figure 8: EEG Classification Procedure

Table 6: Summary of Figure 8

	Relative input process	Relative output process
Inputs	Cutoff frequencies- the low pass may be around .5-1Hz; the notch may be 50Hz or 60Hz depending on data extraction methods; if used the band pass cutoff frequencies will be derived later EEG signals will be inputted to a C program that will filter signals appropriately	The frequency specifications can be inputted to a matlab function (hamming, Butterworth ect.) that will derive the filter The coefficients will then be hard coded into a C program that will convolute with an inputted signal (EEG)
Process	DWT will be performed on filtered coefficients then the BPA will serve as a training Algorithm	Once the training algorithm sees minimal error classification of an ANN will be achieved
Outputs	The ANN achieved will then be able to recognize when the classified movement is performed	

4.2. Computer Simulation

Figure 2. This was an 11 year old female who was monitored several days following withdrawal of anti-seizure medication in order characterize the seizures necessity of surgical intervention. These signals were sampled at 256 samples/second with 16-bit resolution. This subject experienced 7 seizures during this experiment.

Feature Extraction

The seizure data was first downloaded from the MIT database than ran through and "edfread" function found on the MATLAB website. The 200 seconds before and after each of the 7 seizures was used as the non-seizure data and all data during seizures was used for seizure data. A level 5 Debauchees Wavelet Decomposition was implemented using the "wavedec" function found in the MATLAB wavelet toolbox. The wavelet used a one second window. The first 6 seizures were used for training the ANN and the last seizure was used for testing.

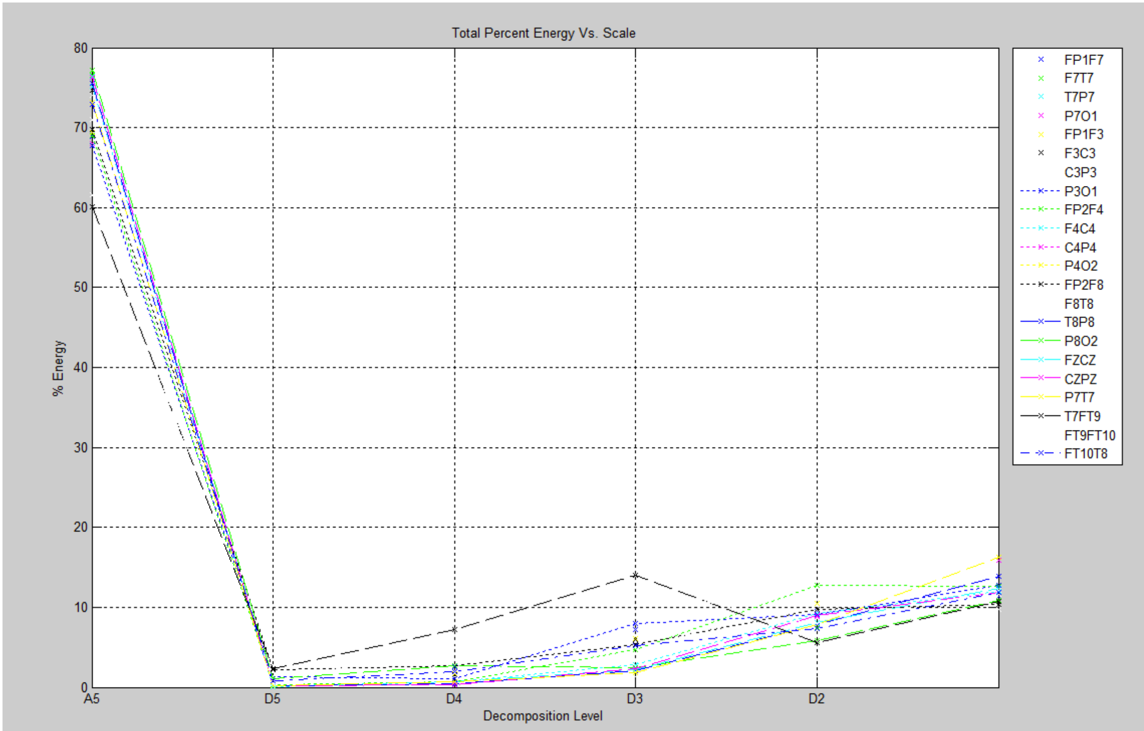

Figure 9: Total Percent Energy Distribution (Seizure)

Figure 9 compares the total percent energy per channel range during a seizure. The plot represents the total percent energy (y-axis) each electrode contributed during each decomposition level (x-axis).

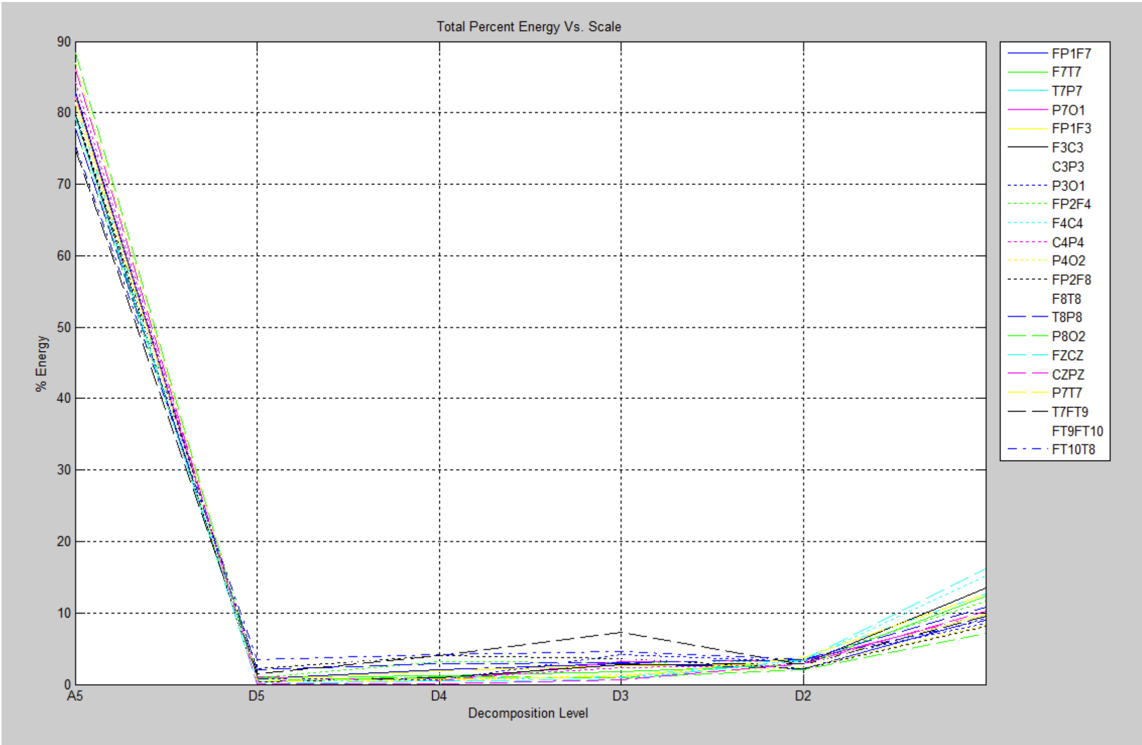

Figure 10: Total Percent Energy Distribution (non-seizure)

Figure 10 compares the total percent energy per channel range during a normal state (no seizure) plot represents the total percent energy (y-axis) each electrode contributed during each decomposition level (x-axis).

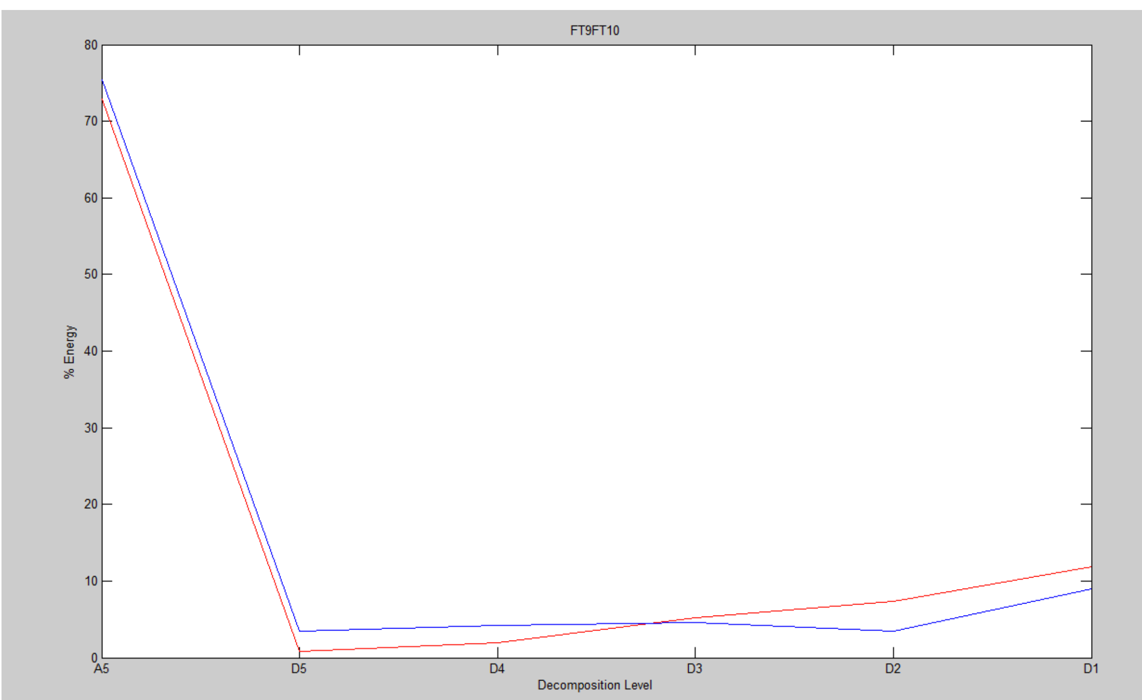

Figure 11: Seizure Vs. Non-Seizure Energy Distributions

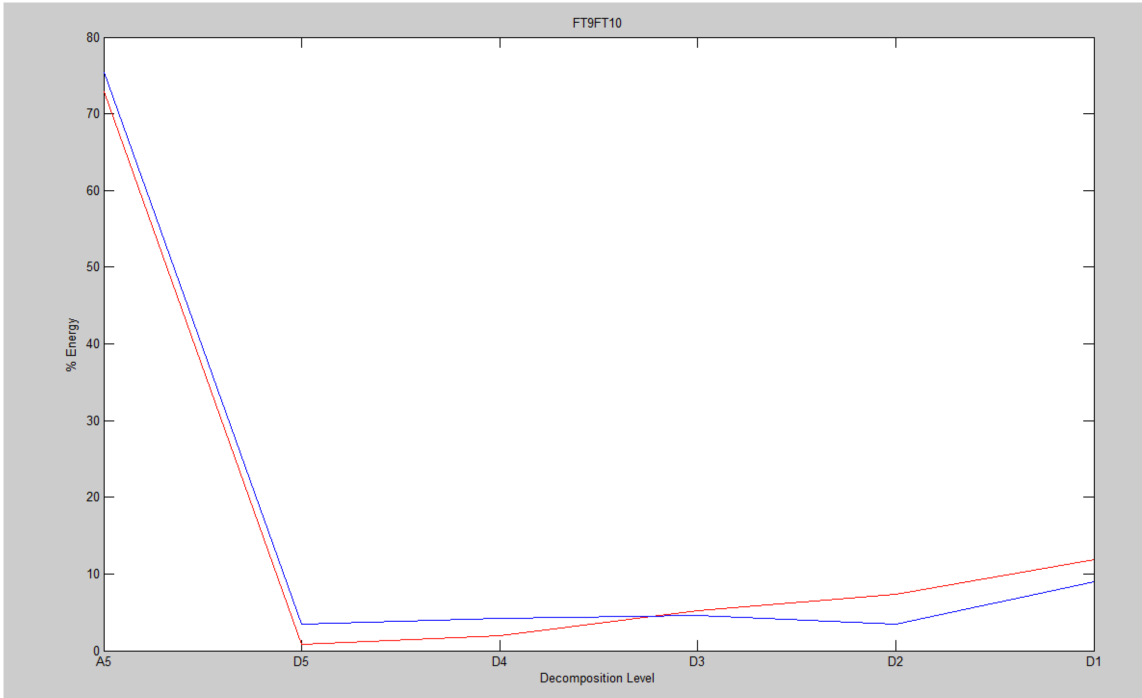

Figure 11 shows the percent energy the FT9FT10 channel contributed during each level. The red represents the energy distribution during a seizure, where the blue represents a normal state. Each scale represents a frequency range. Using the wavelet transform one can view these frequency distributions over chosen time intervals. The D3, D2 and D1 levels increase in energy during a seizure. This means that seizures have more energy in higher harmonics.

Feature Classification

For the first part of testing a level 5 Debauchees Wavelet Decomposition was ran on the input data. Once the energy distributions were extracted the data was ran through a multilayer feed forward neural network. The 'trainbfg' function was used in the MATLAB toolbox to train the network. This function is the BFGS Quasi-Newton Back-Propagation. There are 132 inputs, one hidden layer with 5 hidden neurons, and an output layer. The Hidden layer and the Output layer used the 'tansig' transfer function. All weights were initialized using the rand function.

4.3. Results

The testing data was ran through the ANN, then the output was ran through a 'hardlim' function such that if the ANN predicted a 0.5 a seizure occurred, and if the ANN predicted below a 0.5 there was no seizure. The results are shown below in Table 7, where Correct and incorrect detection represents the ANN accuracy of the overall data set. A correct non-seizure detection means there was no seizure and the

ANN correctly identified it. Correct seizure detection means there was a seizure and the ANN correctly identified it. A false negative means there was a seizure and the ANN did not detect it. A false positive means the ANN detected a seizure when there was no seizure. The ANN was 94.21% accurate overall, however there were 12 cases where the ANN failed to recognize a seizure.

Table 7: Seizure Detection Results

Output	Correct Detection	Incorrect Detection	Correct non-Seizure Detection	Correct Seizure Detection	False Negative	False Positive
Total Predicted	472	29	383	89	12	17
Percentage (%)	94.21	5.79	96.96	83.96	3.04	16.04

Chapter 5: Conclusion and Future Work

Further testing will consist of pre-filtering, different decomposition levels, different layers and different training functions. We will also extend the data set and run the ANN for multiple subjects. I will also attempt to classify features by just using the most prominent channels.

For further improvements tempera filtering used to reduce noise can be optimized and classification performance could be improved by applying proper band-pass filter (IIR).

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Appendix A: MATLAB code

MATLAB function for extracting file data

```
%function for data extraction
function [input_test, desired_test, input, desired] =
extract_file_data(num_test, num_train, num_of_seizures,channel, subject,
level)

for p = 1:num_of_seizures
    FILENAME = strcat(subject, '_', channel, '_', num2str(p));
    fid = fopen(FILENAME,'r');
    nLines(p) = 0;
    while (fgets(fid) ~= -1);
        nLines(p) = nLines(p) + 1;
    end
    fclose(fid);
end
fprintf('Extracting file data...\n')
input = [];
desired = [];
inputTemp = [];
desiredTemp = [];
for p = 1:num_train
    for i= 1:nLines(p)
        [feature_vect] = read_files(level, subject, channel, p, i);
        inputTemp(1:level+1,i) = feature_vect(1:level+1);
        desiredTemp(1,i) = feature_vect(level+2);
    end
    input = [input inputTemp];
    desired = [desired desiredTemp];
end

input_test = [];
desired_test = [];
inputTemp = [];
desiredTemp = [];

for p = num_train+1:num_train+num_test
    for i= 1:nLines(p)
        [feature_vect] = read_files(level, subject, channel, p, i);
        inputTemp(1:level+1,i) = feature_vect(1:level+1);
        desiredTemp(1,i) = feature_vect(level+2);
    end
    input_test = [input_test inputTemp];
    desired_test = [desired_test desiredTemp];
end
end
```

MATLAB code for feature extraction

```
%The end product of this program should give feature vectors
%here are the channel names
channels = {'FP1F7'...
    'F7T7'...
    'T7P7'...
    'P7O1'...
    'FP1F3'...
    'F3C3'...
    'C3P3'...
    'P3O1'...
    'FP2F4'...
    'F4C4'...
    'C4P4'...
    'P4O2'...
    'FP2F8'...
    'F8T8'...
    'T8P8'...
    'P8O2'...
```

```
    'FZCZ'...
    'CZPZ'...
    'P7T7'...
    'T7FT9'...
    'FT9FT10'...
    'FT10T8'};
%obtain seizure data
pre_samp =  256*200;        %how many samples before seizure
post_samp = pre_samp;
subject = 'chb01';

[seizure_data, header, data, seizures] = seizure_times(subject, pre_samp,
post_samp);

%extract features from seizure data
window = 256;        %one second wavelet window
wav_lev = 5;
mother_wavlet = 'db4';
place_hold = 1;
feature().in = [];     %input to ANN
feature().out = [];    %1=seizure happened 0=seizure didnt happen

for q = 1:(7)
for i = 1:22
    feature(i).channel = channels(i);
    for j = 1:window:length(seizures(q).data)
        [C, L] = wavedec(seizures(q).data(i,j:j+window-1),wav_lev, mother_wavlet);
        [Ea,Ed] = wenergy(C, L);
        for p = 1:length(seizure_data)
            if (pre_samp< j)&&(j <(pre_samp+1+(str2num(seizure_data(p).end_time)-
str2num(seizure_data(p).start))*256))
                feature(i).out = 1;
                p = length(seizure_data)+1;
            elseif (p == length(seizure_data))
                feature(i).out = 0;
            end
        end
        feature(i).in = [Ea,Ed];
            feature_vect = [feature(i).in feature(i).out];
            Filename = strcat(subject, '_', channels(i), '_', num2str(q));
            save(char(Filename), '-ascii', 'feature_vect', '-append')
    end
end
end
```

MATLAB code for ANN

```
%ANN number 2
level = 5;
subject = 'chb01';
channel =  {'FP1F7';...
    'F7T7';...
    'T7P7';...
    'P7O1';...
    'FP1F3';...
    'F3C3';...
    'C3P3';...
    'P3O1';...
    'FP2F4';...
    'F4C4';...
    'C4P4';...
    'P4O2';...
    'FP2F8';...
    'F8T8';...
    'T8P8';...
    'P8O2';...
    'FZCZ';...
    'CZPZ';...
    'P7T7';...
    'T7FT9';...
    'FT9FT10';...
    'FT10T8'};
num_of_seizures = 7;
num_test = 1;
num_train = 6;
```

```
[inputTrain desiredTest inputTest desiredTrain] = seperate_data(num_of_seizures,
num_test, num_train, channel(21), subject, level);
inputTrain = inputTrain./100;
inputTest = inputTest./100;

H_neron = 5;
net =  feedforwardnet([H_neron])% H_neron H_neron H_neron])
net.trainFcn = 'trainlm';
net.layers{1}.transferFcn = 'tansig';
net.layers{2}.transferFcn = 'tansig';


net = configure(net, inputTrain, desiredTrain);

%Initialize weights with rands func
%net.initFcn = 'initlay';
net.layers{1}.initFcn = 'initnw';
net.inputWeights{1,1}.initFcn = 'rands';
net.biases{1,1}.initFcn = 'rands';

net.layers{1}.transferFcn = 'tansig';
net.layers{2}.transferFcn = 'tansig';
net.trainParam.epochs = 1000;
net.trainParam.goal = 1e-7;
net.trainParam.min_grad = 1e-20;
net.trainParam.max_fail = 1000;

net = train(net, inputTrain,desiredTrain);%, 'reduction', 9);

ytrain = net(inputTrain);

figure(5)
plotconfusion(desiredTrain,ytrain)
figure(1)
plot(1:(length(desiredTrain)),ytrain)
hold on
plot(1:(length(desiredTrain)),desiredTrain, '--red');
xlabel('Vector Space');
ylabel('Output');
title('Training Data');
legend('NN output', 'Desired Output');

y = hardlim(net(inputTest)-0.5);

figure(6)
plotconfusion(desiredTest(1,1:length(desiredTest)),y)
figure(2)
plot(1:(length(desiredTest)),y)
hold on
plot(1:(length(desiredTest)),desiredTest, '--red');
xlabel('Vector Space');
ylabel('Output');
title('Testing Data');
legend('NN output', 'Desired Output');

%calculate error
incorrect_0 =0;
incorrect_1=0;
correct_0=0;
correct_1=0;
correct = 0;
incorrect = 0;
for i = 1:length(y)
    if y(i) == desiredTest(i)
        correct = correct+1;
        if y(i) == 0
            correct_0 = correct_0 + 1;
        else
            correct_1 = correct_1+1;
        end
    else
        incorrect = incorrect + 1;
        if y(i) == 0
            incorrect_0 = incorrect_0 + 1;
        else
            incorrect_1 = incorrect_1+1;
```

```
        end
    end
end

accuracy = correct/(correct+incorrect)
incorrect_0
incorrect_1
correct_0
correct_1

figure(3)
plotroc(desiredTest, y)
```

Appendix B: Analysis of Senior Project

COST

The estimated cost is free. This is a research based project that can be done using a database and software. MATLAB and C are the software programs to be used and are both available for unlimited access. However, an EEG machine may prove useful in gathering new data sets, and to determine energy thresholds. The EE department should get one, but if not consumer grade machines can be purchased at low costs ranging from 50$ to 300$. To improve filtering speed and performance in the act of real time implementation a DSP may be of use. The DSK boards in the annex should be sufficient.

Summary of Functional Requirements

Primary Goal:

The primary goal for this project is to develop accurate ANN's using methods of feature extraction and feature classification when given an EEG signal. These ANN's will then be compiled into a library for future use. The classification of signals should distinguish movements in all major axes to a combination of movements in any of the axes.

Secondary Goal:

Ideally the methodologies used will offer possible development of highly accurate EEG-BCI machines. These machines may be used in a variety of domains including: highly interactive gaming interface; paraplegic ability to regain motor function; military use.

Primary Constraints:

Many different methods have been developed and proven mildly accurate. Problems arise with the lack of participants thus; minimal data will be easily obtained. Also the EEG signals contain lots of noise and are very long thus; techniques for decomposition must be optimized. All these challenges will need to be addressed in order to develop more accurate ANNs then in the current market. If DSP filtering must be preformed real time, a microcontroller/DSP unit must be integrated into the system design, or a method to allow C and Matlab to interact must be explored.

Economic:

EEG-BCI machines are minimal in the economic market. However, with increasing research and huge technological advancements the potential of an economic outbreak in the demand for thought driven devices may become a reality. To make this true commercial friendly EEG gear must be readily available (consumer grade products already on market); but most of the improvement must be made in developing efficient algorithms for feature extraction/classification. Thus once adequate ANN's are established for most motor functions, a huge economic market may be introduced implementing thought driven technologies of all kinds (appliances, smart phones, handicap, gaming, etc..).

A Breif overview of required skills for this project

- Matlab
- C
- Filter Design
- DSP
- Advanced Mathmatics
    - Vector analysis
    - Temporal and special domain analysis
    - Discrete Wavelet Transform
    - FFT
- System integration