INTELLIGENT CLASSIFIER FOR A DIRECT NEURAL INTERFACE

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ABSTRACT

Brain Computer Interfacing (BCI) is one of the new emerging technologies that signify a great potential for the physically disabled. It concentrates on developing new augmentative communication and control technologies for those with severe neuromuscular disorders. It can be used to provide a means of communication for patients suffering from neurological diseases hindering normal communication due to loss of motor function.

B-C interfaces can be used to allow locked-in persons to be able to use their minds to control a computer, which can in turn control any device or system. This area of research was initiated in that devices were controlled by such things that were viewable, like blinking of eyes, jaw clench etc.

Electroencephalogram (EEG) is the foundation of current BCI research. It has been experimentally shown that mental activities (mathematical calculations, motion imagination) give rise to distinct patterns in the EEG signal obtained from certain areas of the scalp.

The project is to design a system that can classify EEG signals related to motion, which can in turn be fed to a mechanical system to produce movement in the desired direction. This involves creating a classifier to identify the class of the EEG signals. Neural Networks is chosen as the classification technique for this project.

DEDICATION

To

Our Parents

Teachers

And the disabled persons, for whom this project was developed.

ACKNOWLEDGMENTS

First of all, We would like to thank Allah Almighty for the successful completion of this project.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Introduction

Persons with sever motor disabilities, particularly of arms and legs are not in a position to carry out their routine activities. But their brain functionalities are normally fully working, and they can generate various thoughts on their own will. These thoughts of a person can be captured from above the human scalp in form of EEG signals of micro volts amplitude. Also, signals of various thoughts differ from one another in respect of the pattern, i.e. absolute values may vary, but the pattern of the pure signal of a particular thought will always be the same. This leads us to the conclusion that if we are able to get clean signals of thought of a person and able to classify those signals into one of the class of thoughts, we can come to know about what that person is thinking about.

We intend to build such a classifier that can take EEG signal of thought of a person and classify it accordingly into one of the classes on which that classifier is trained. Currently, we focus to be able to classify thoughts of 2-dimensional movement of the subject.

Literature review includes the research being done before in the field of Brain Computer Interfacing. This chapter gives the details of research work being done by researchers. Then comes the design of the system. What is the architecture of the system and what are its components. Design includes use cases, Data flow Diagrams, state transition diagrams. After design comes the implementation part. Implementation details include Hardware acquisition, Filters, Classifier and the hardware control part. After design the sign future work is being mentioned. This emphasizes on the future scope in the field of brain computer interfacing (BCI).

PROBLEM STATEMENT

The project is about designing a system that can classify EEG signals related to motion, which can in turn be fed to a mechanical system to produce movement in the desired direction. The scope of the project is limited to identification/classification of signals for 2-D motion.

Literature Review

The idea of direct brain-computer communication was first mentioned in (Vidal 1973), and nowadays, more than 20 research groups all over the world are working on this problem. Numerous articles in newspapers or scientific magazines are presenting different approaches and first promising result from those groups. In this context, even the slightest hint at a working device (though extremely slow and not terribly accurate, with often immense hardware requirements) is applauded as a huge success. [1]

A brain-computer interface is intended to enable its user to communicate – as opposed to the standard input method involving keyboard and mouse (which works well for most people)- becomes more and more popular. On the one hand, using a mind-controlled input device requires almost no effort. It needs no muscle contraction, and the user “only” has to have a clear mind. This makes persons with severe physical disabilities the main target group. Especially persons suffering from the so-called “locked-in” syndrome are the ones that need such a device, since they have almost no motor control (apart from maybe unreliable control of some facial muscles), which means that they can neither talk, nor move feet, legs, arms or hands. [1]

First, this is a well known fact that all the thoughts are generated in brain. Berger showed that electrical signals (electroencephalogram) of these thoughts can be recorded externally from the scalp of human subjects **[2]**

Research at Colorado State University showed that each thought has a particular signal pattern. If several mental states can be reliably distinguished by recognizing patterns in EEG, then paralyzed person could communicate to a device like wheelchair by composing sequences of these mental states. The detection of patterns in EEG produced from normal mental states is a very difficult problem. EEG signals are recorded by surface electrodes and can contain noise as a result of electrical interference and the movements of the electrodes on the scalp. Another problem is that EEG can be corrupted by eye blinks and other muscular activities that produce signals of greater magnitude. Other problems are more cognitive in nature; the concentration of a person can very while the person is supposedly performing a single mental task. [3]

This research focused on comparing four representations of EEG signals and their classification by a two-layer neural network with sigmoid activation functions. The neural network was implemented on a CNAPS server (128 processors, SIMD architecture) by Adaptive Solutions, Inc., gaining a 100-fold decrease in training time over a Sun Sparc 10 for a large number of hidden units. [3]

If a signal can be correctly classified, it possibly opens a new means of communication between the physically-disabled persons and their environments. Various intelligent systems have been applied for EEG classification problem in past to come up with better techniques in an attempt to make the interaction between humans and their environments more efficient. [4]

Anderson made use of feed forward back propagation neural networks for the classification of five mental tasks, and their network was able to achieve classification ratio in the range of 38-71%.[4]

Neural networks were trained to classify half-second segments of six-channels, EEG data into one of five classes corresponding to five cognitive tasks performed by four subjects. Two and three-layer feed forward neural networks were trained 10-fold cross-validation and early stopping to control over-fitting.EEG signals were represented as autoregressive

(AR) models. The percentage of test segments correctly classified ranged from 71% for one subject to 38% for another subject. Cluster analysis of the resulting neural networks hidden-unit weight vectors identifies which EEG channels are most relevant to this discrimination problem. [4]

Charles W. Anderson Erik A Stolze and Sanyogita Shamsunder modeled EEG signals using signal-channel and multi-channel autoregressive (AR) techniques. The co-efficient of these models were used to classify EEG data into one of two classes corresponding to the mental task the subjects are performing. A neural network was trained to perform the classification. When applying a trained network to test data, they found that the multivariate AR representation performs slightly better, resulting in an average classification accuracy of about 91%. [5]

According to Charles W.Anderson and Michael J.Kirby Electroencephalogram (EEG) signals recorded from a persons scalp have been used to control binary cursor movements. Multiple choice paradigms will require more sophisticated protocols involving multiple mental tasks and signal representations that capture discriminatory characteristics of the EEG signals. They recorded six channel EEG from a subject performing two mental tasks. These signals were transformed using maximum noise fraction transformations and classified by quadratic discriminant analysis. In addition, classification accuracy was tested for all subsets of the six EEG channels. Best results were approximately 90% correct when training and testing data are recorded on the same day and 75% correct when training and testing data are recorded on different days. [6]

Another concept of BCI was put forward by Melody M. Moore and Philip R.Kennedy. According to them computer can be controlled directly through brain signals by developing a neurotropic electrode that is implanted in the human motor cortex. Their work was related to the software aspects of the Neural Signals brain-computer interface project and presented a vision and strategy for upcoming research. [7]

A Real-Time Assistive Computer Interface for Users with Motor Disabilities was developed by Barreto, A B, Scargle, S. D and Adjouadi, M. Their study introduced the design of an integrated assistive real time system developed as an alternate input device to computers that can be used by the individuals with severe motor disabilities. An assistive technology device as defined by the Assistive technology act of 1998. The proposed real-time system design utilizes electromyographic (EMG) biosignals from cranial muscles and electroencephalographic (EEG) biosignals from cerebrum occipital lobe, which are transformed into controls for the cursor control functions. This HCL system classifies biosignals into “mouse” functions by applying amplitude thresholds and performing power spectral density (PSD) estimations on discrete windows of data. Spectral power summations are aggregated over several frequency bands between 8 and 500 Hz and then compared to produce the correct classification. The result is an affordable DSP-based system that, when combined with an on-screen keyboard, enables the user to fully operate a computer without using any extremities. [8]

Jack Culpepper performed research work on Discriminating Mental States Using EEG Represented by Power Spectral Density. Artificial neural networks were trained to classify segments of 12 channel EEG data into one of five classes corresponding to five cognitive tasks performed by one subject. Three-layer feed forward neural networks were trained using a validation set to control over-fitting. Independent Component Analysis (ICA) was used to segregate obvious artifactual EEG components from other sources, and a frequency-band representation was used to represent the sources computed by ICA. The most notable result is an 85% accuracy rate on differentiation between two tasks, using a segment of EEG 1/20th of a second long. [9]

Ruey-Song Huang, Tzyy-Ping Jung and Scott Makeig performed research on Analyzing Event-Related Brain Dynamics in Continuous Compensatory Tracking Tasks. The dynamics of electroencephalographic (EEG) activity in continuous compensatory tracking tasks were analyzed by independent component analysis (ICA) and time-frequency techniques. In one-hour sessions, 72-channel EEG was recorded while a healthy volunteer attempted to use a trackball to keep a drifting disc in a bulls-eye in the center of screen. Disc trajectory was converted into a moving measure of disc error. Local minima (perigees) indicated moments when the disc started to drift away from the center. Subject performance was indexed by root mean square disc error in a 20s epoch centered on each perigee, high error generally indicating drowsiness. Maximally independent EEG processes and their equivalent dipole source locations were obtained using the EEGLAB toolbox. Component activations were epoched in 5s time intervals time locked to perigees. Following disk perigees during (drowsy) periods of high disk error, significant spectral changes were observed. One of the 70 independent components was located in or near primary visual cortex. During periods of poor (drowsy) performance, it had increased mean tonic alpha/theta activity, with a further phasic alpha/theta increase following perigees [1, 2]. At the same time, low alpha activity of a second component located in or near cingulate gyrus increased, and 10-30 Hz EEG activity of a third component in the left somatomotor cortex increased briefly. The alpha activity of the somatomotor component persisted through the following distance maximum. These spatiotemporal phenomena were consistently observed across three sessions within subjects. Thus, event-related EEG brain dynamics can be detected and modeled in a continuous behavioral task without impulsive event onsets. [10]

Torsten Flezer and Bernd Freisleben constructed HaWCoS: The “Hands-free” Wheelchair Control System .A system allowing to control an electrically powered wheelchair without using the hands was introduced. HaWCoS - the "Hands-free" Wheelchair Control System - relies upon muscle contractions as input signals. The working principle was as follows. The constant stream of EMG signals associated with any arbitrary muscle of the wheelchair driver was monitored and reduced to a stream of contraction events. The reduced stream affects an internal program state which is translated into appropriate commands understood by the wheelchair electronics. The feasibility of the proposed approach was illustrated by a prototypical implementation for a state-of-the-art wheelchair. Operating a HaWCoS wheelchair requires extremely little effort, which makes the system suitable even for people suffering from *very* severe physical disabilities. [11]

Design

Design Summary

The system was designed keeping in view the four objectives mentioned earlier (Including one optional objective). The System was basically divided into two parts: A Hardware part and a Software part. The hardware part would deal with the input from brain and the output to the interfaced hardware (if implemented). The software part was further subdivided into software core and front end.

As per literature review [12], a Neural Network based classifier was found to be suitable for classification of movement related tasks. Also, the AR model method was used for feature extraction from EEG signals, as it is proved to be the most effective feature extraction method by Anderson [3].

Also, a number of noise sources were identified in the EEG signals. The main categories of noise sources are:

- Line Noise
- Artifacts

Line Noise is relatively easy to remove, using a simple band stop or notch filter. EEG artifacts consist of noise mainly from the body itself and are much harder to remove using simple signal filters without corrupting the EEG signals. An ICA filter will be used to cater for these artifacts as specified by [17]. These filters will be combined in a filter module.

Therefore the software core will consist of the NN based classifier and a feature extraction module plus a filter module to eliminate or suppress unwanted noises from the signals.

Using this architecture for the software core, design for the rest of the system was laid down. The documents prepared during the design process include:

- Use Cases (system view from a user perspective)
- System Data Flow Diagrams
- System State Transition Diagram
- Software State Transition Diagram
- Data Dictionary (to accompany the DFDs)

Also a set of test cases would be designed when the system is implemented. All the documents are included following this text. Figure

Use Cases

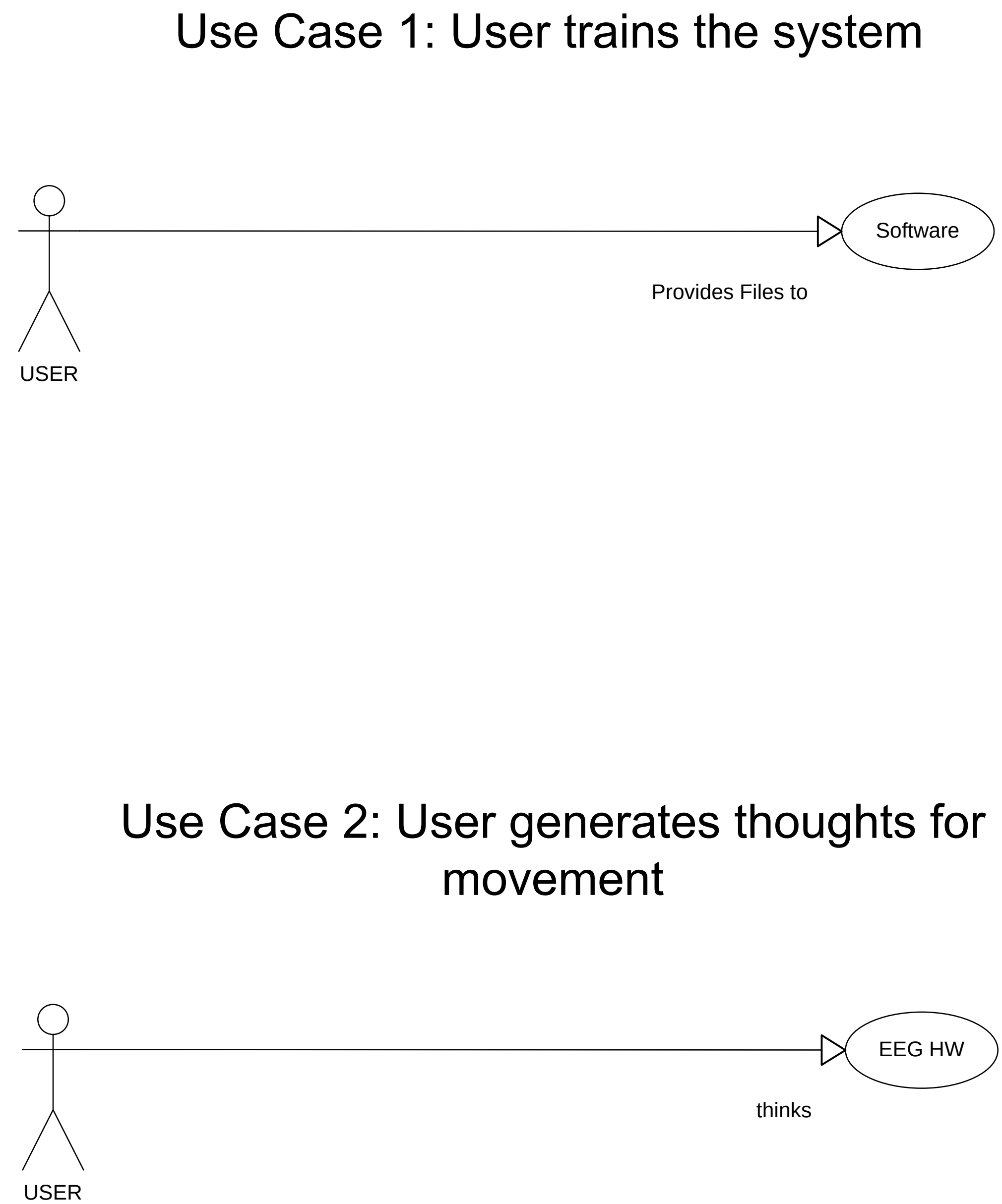

Figure 1: System Use Cases

Data Flow Diagrams

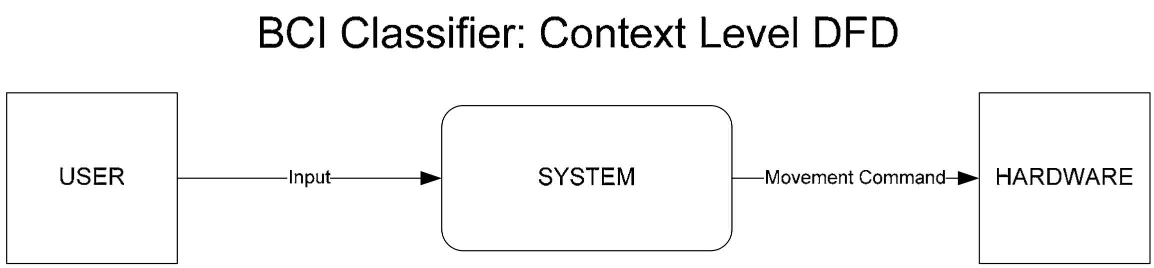

Figure 2: System DFD - Context Level

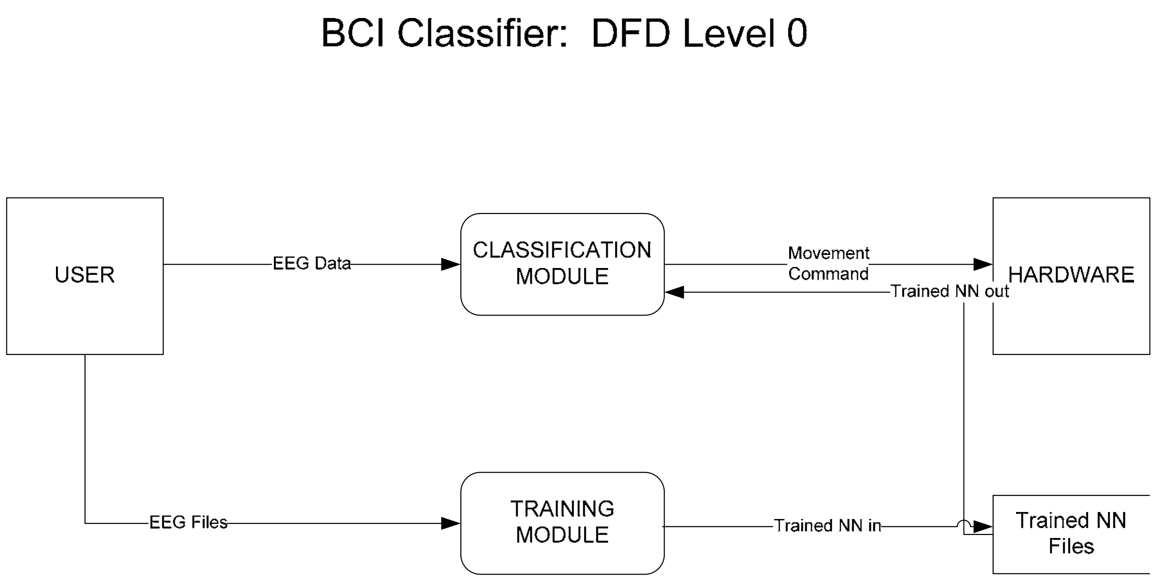

Figure 3: System DFD – Level 0

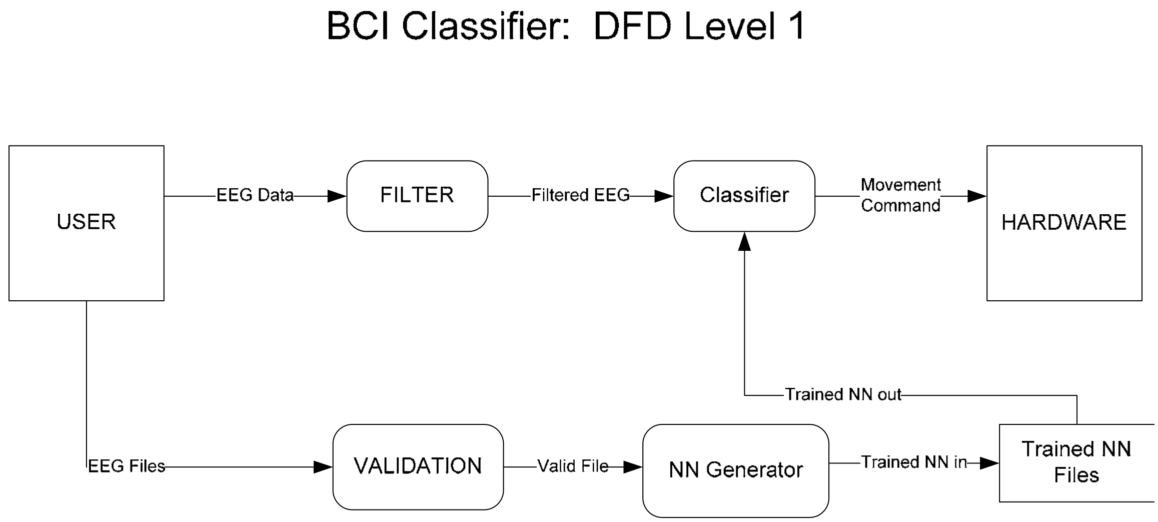

Figure 4: System DFD –Level 1

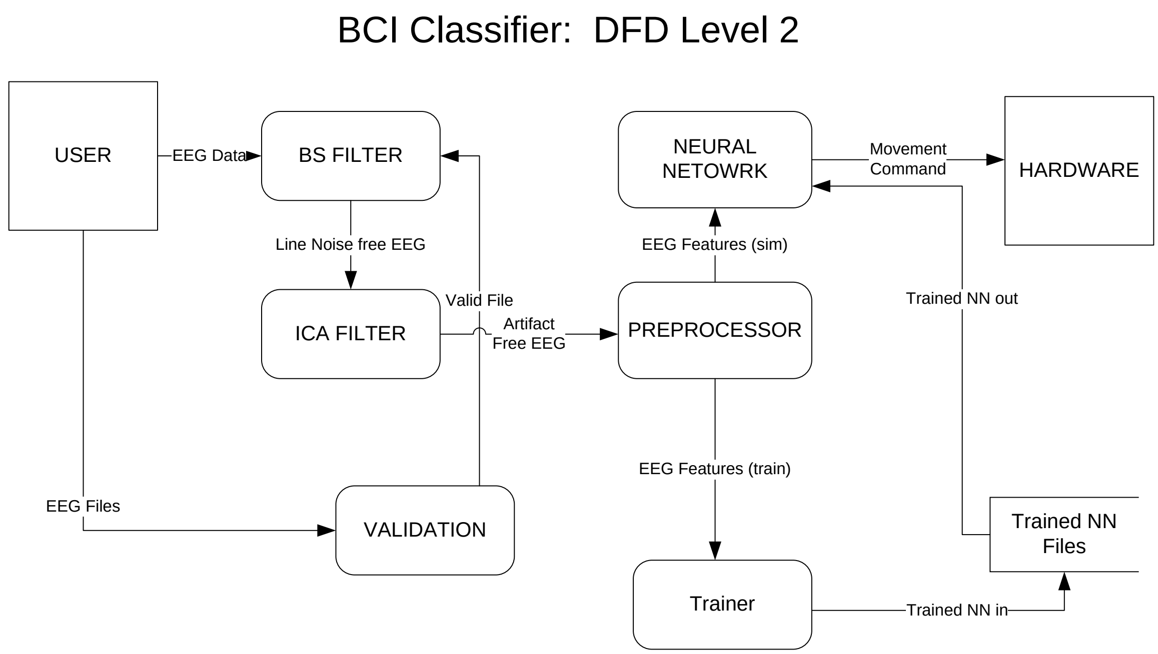

Figure 5: System DFD – Level 2

State Transition Diagrams

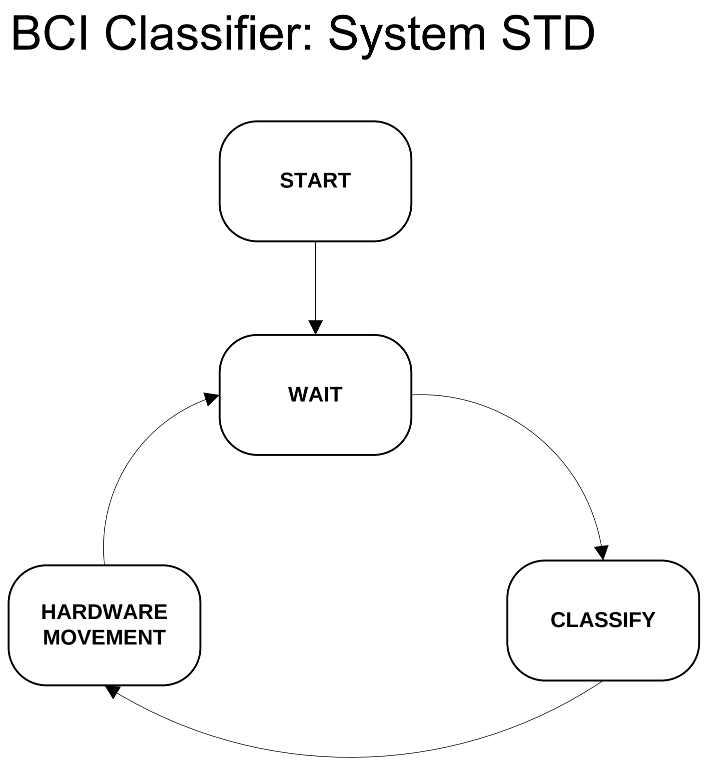

Figure 6: System STD

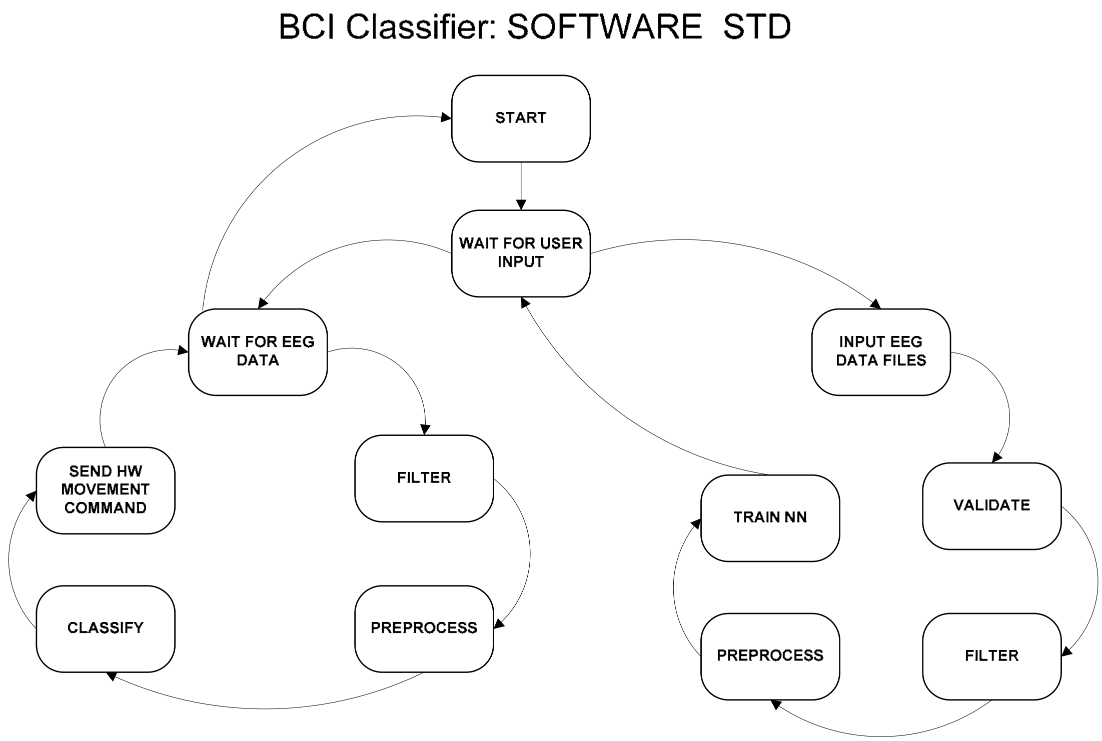

Figure 7: Software STD

Data Dictionary

This Data dictionary contains the following information about the system

- Data Flows
- Data Stores
- External Entities
- Processes

Data Flows

Table 1: System Data Flows

Name	Source	Destination
EEG Data	User	BS Filter
Line Noise Free EEG	BS Filter	ICA Filter
Artifact free EEG	ICA Filter	Preprocessor
EEG Features(sim)	Preprocessor	Neural Network
Movement Command	Neural Network	Hardware
Valid File	Validation	BS Filter
EEG Features(train)	Preprocessor	Trainer
Trained NN in	Trainer	Trained NN Files
Trained NN out	Trained NN Files	Neural Network
EEG Files	User	Validation

Data Stores

Table 2: System Data Stores

Name	ID #	Description	Data flow in	Data flow out	Contents	Access Method	Physical implementation
Trained NN Files	0	Stores trained neural networks for use in the system	Trained Network In	Trained Network Out	NN Data Structure	File Stream	MAT File

External Entities

Table 3: System External Entities

Name	Description	Associated Data Flows
User	The primary user and administrator of the project.	EEG Data EEG Files
Hardware	The Hardware to be moved in response to user input	Movement Command

Processes

Table 4: System Processes

Name	Description
BS Filter	Applies Band Stop Filtering to remove line noise
ICA Filter	Removes artifact present in EEG
Validation	Check the user provided EEG Files
Neural Network	Classifies the EEG Data based on features

Preprocessor	Creates feature set from EEG Data
Trainer	Creates a Neural network from an EEG feature set

Implementation

Four major parts of the system are as given below.

1. Hardware Acquisition
2. Filter
3. Classifier
4. Hardware Control

We will now discuss about all of them in detail here that how we planned about all of them.

Hardware Acquisition

Since our aim is to be able to navigate in a 2-dimensional environment using thoughts, so we must have some means of capturing thoughts, some means of being able to extract the thoughts from human brain in a form that can be stored and manipulated in a computer system. Only thing that can at first come to human brain is that there must be something that is to be inserted into skull, actually touching the brain directly whose task is to read the thoughts traveling around inside brain. But thanks to Berger [2] who made this job easier for researchers by showing that there is no need to get into skull for reading thoughts. Human thoughts are present in form of electrical signals outside the skull. They are very weak signals (micro volts) and contain various noises too, but, they do contain information about the thought of the person, that can be extracted out of those signals, how, that is the other issue.

So, first part is to acquire some hardware that can read signals from above the scalp. By searching around for such systems, we come to know that there are various varieties of such systems that do the job by making use of small electrodes. A few systems are show below.

Figure 8: Examples of EEG Acquisition Systems

There are various parameters of such systems, like

- What is reference voltage for each electrode?
    - Is it ground?
    - Or the neighbor electrode?
    - Or some other common reference voltage?
- What's the sampling rate of the system?
    - Sampling rate is the number of data samples per second. Greater the sampling rate, greater the information available to us about the thought.
- How many are the electrodes in number?

  System can have various numbers of electrodes ranging from a few to many hundreds.
- What is the placement of electrodes?

That is, how are the electrodes arranged on the skull?

But choosing which hardware system to use depends upon the type of project for which that hardware is being acquired. So, that doesn't matter at all that what is the reference voltage for each electrode, but what really matters is that those electrodes are that much in number and are placed such that the required information is able to be obtained out of those. In addition to that, sampling rate must also be of some reasonable value, as it is easier to determine the pattern of a signal from, say, 500 samples as compared to 50 samples.

For our case, where we want to navigate in a 2-dimensional environment, we need a system that has that much sufficient electrodes and placed in such a way that can obtain sufficient "movement related" signals from the brain. Now, as we know from the brain study, the position in brain, where movement related signals are generated, we decided to make use of 10-20 system shown in figure 9.

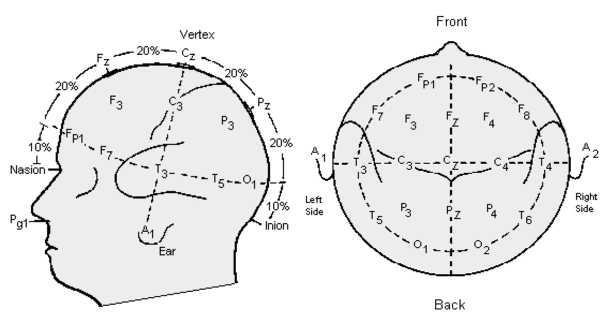

Figure 9: 10-20 System for EEG acquisition

For an online implementation, we do need some form of portable EEG system that can be attached to some motorized wheelchair but for the development of the Neural Network Classifier, a fixed EEG system was traced around, and was one found at Military Hospital, Rawalpindi. This system was used for the recording of movement related signals, and the testing of the software system being built.

Filter

Signals obtained from EEG are in the form of a series of voltage values coming to the computer system from electrodes obtained from the human skull. So, 6 electrodes means "6 trains of numbers" continuously coming. These values are not the pure thought's signals. But contain noises from various sources. Given below is a brief description of various noises.

Noise Types

Line Noise

In this modern era, almost every thing operates on electricity, so does an EEG acquisition system too. Human thoughts get transferred in form of voltage values from the skull to the electrodes placed on the skull and travel to the computer system port in a wire. All of this activity is electrical and involves the movement of electrons, and this movement of electrons inserts some noise in the actual values of the voltage signals read from the skull. This type of noise is referred to as line noise here.

Line noise, in the language of signals is a range of frequency components added to the EEG signal. This frequency range may vary from place to place. This frequency in Pakistan is 50Hz.

Artifacts

Three known artifacts present in the EEG signals are

- Eye
- Pulse

- Muscle Movement

Since values read from the skull are in micro volts, a very minute amount, so, any kind of muscular movement of the body parts near head generated a lot of variation in the EEG signal values moving towards toward the electrodes. Similar is the case when some eye movement is made, and also, the pulse makes some variations in the EEG signals. These noises need to be taken care of too.

Noise removal

So, various noise removal techniques were incorporated for removal of these noises, discussed below.

Band Stop Filter

This technique was used to cater for the line noise. As, a signal contains various frequency components, and also, line noise consists of some particular frequency component, or a continuous range of frequency components, so, those frequency components can be subtracted from the EEG signal to obtain line noise free signals.

EEGFILT method from EEGLAB Toolbox [13] was used to achieve this. In Pakistan, line noise is of the frequency 50Hz. Therefore, frequency components in the range of 48 – 52Hz were removed from the EEG signal.

This gives us a line noise free EEG signal. These signals were used to train and test the designed system, to get the classification accuracy of the system. Results are given in the Results and analysis section in Table 6 and Table 7

Immediate previous results to these one contain the classification accuracies obtained from the line noise contained signals, and that seems strange to see that line noise contained signals gives higher classification accuracy. This was assumed to be because of the reason that sufficient EEG activity lies in the line noise frequency range (48 – 52Hz). So, removing the line noise also removes that valuable information from the signal that differentiates between two classes of signals. So, line noise removal was finally dropped from the software system.

Independent Component analysis

Independent component analysis (ICA) is the technique used for removal of artifacts from such signals [17] .

Basic idea of ICA is to decompose the signal into as much different components as possible. Take the word "component" in its crude sense, like parts, summing up which gives the original signal. Important points to be noted about this technique are

- These independent components are not like that if there are four artifacts, then there will be five independent components, four for the artifacts and one for the EEG activity. No, it is not like that. There can be more than one component for one artifact, and also one component may be containing more than one artifact. In short, ICA has no information about the signal and the artifacts present in the signal. It just decomposes the signal into maximally possible independent components, using mathematical operations. It just separate out various parts of the signal that are not found to be mathematically related to each other.
- That cannot be made sure that ICA will always decompose a signal in such a way that EEG activity signals get separated from the other artifacts. There might be the case that some EEG activity signals get into some other component that we might

later remove from the signal considering that component an artifact, so loosing our valuable information too about the EEG activity.

In order to apply Independent component analysis to our EEG signals, EEGLab [13] was used. ICA was applied by opening the EEG data in EEGLab Toolbox and then applying ICA to it after specifying the channel locations of the EEG data. Channel location file depends upon the EEG Acquisition system used. Sample file for 10-20 system was provided with the EEGLab Toolbox, which was used. ICA was applied to the 19 electrodes data, which produced 19 independent components. Figure 10 is one of the 19 components outputs obtained after ICA application.

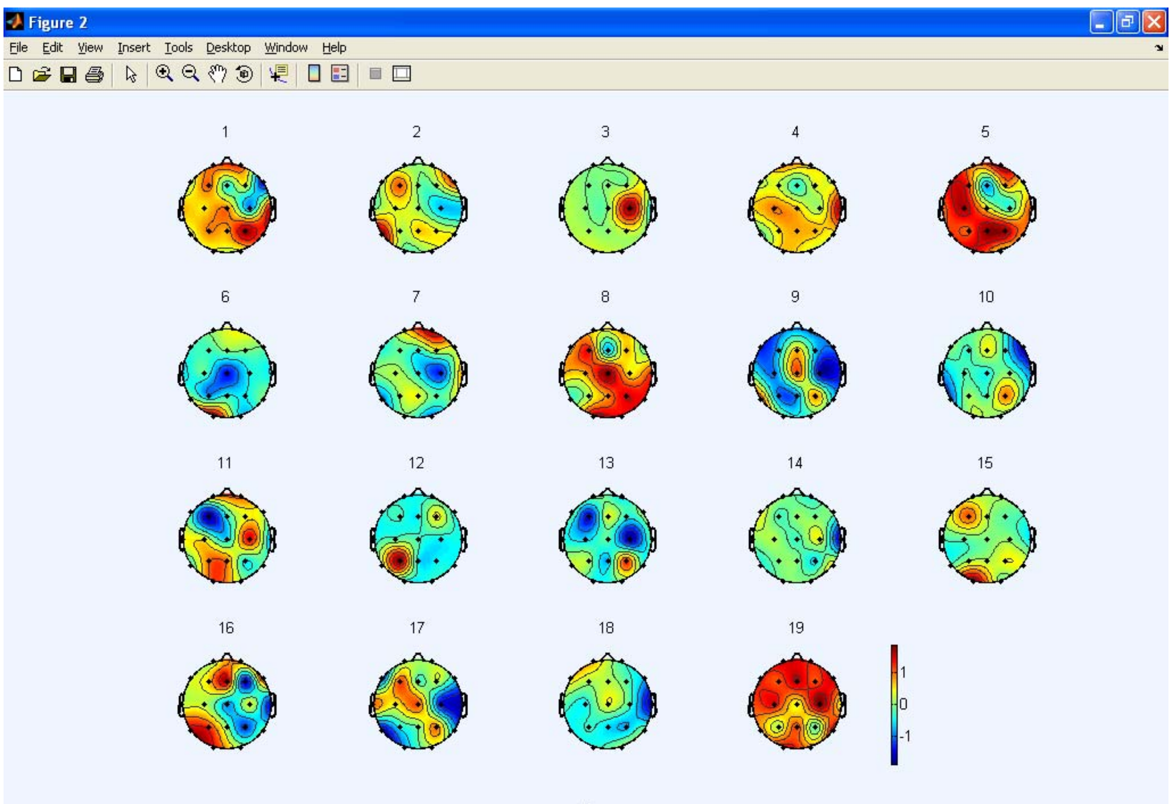

Figure 10: EEG components separated by ICA

In this figure, small points represent the electrode placement, and various colors represent the intensity level of the signal activity in that electrode region. So, for example, component no.2 is redder in the front part, and we may take this component as eye moment and reject it. Similarly, take another example of the component no. 4. This is redder in left middle part as compared to right, so we may take it as left hand movement activity and keep it.

While experimenting with independent component analysis to remove artifacts, we observed that it always takes more than 20 seconds to apply ICA to EEG data of almost 1 second. So, in our case, where we want to implement it online on a motorized wheel chair, it becomes impossible to make use of ICA, as user will generate a thought and his thought will be converted to actual movement after almost 25 seconds. This time was calculated on a Pentium 4 2.6 GHz computer with 512 MB RAM, running Microsoft Windows XP and Matlab 7.0

So, even if we improve the computer system, this is not going to increase the speed of ICA too much. Let’s suppose that it outputs the artifact removed signal after 10 seconds instead of 20 seconds. Even in that case, user thought will be converted to actual movement after 11 or 12 seconds, and even this response time of the system is too slow, that makes the system useless. So, finally it was decided to drop this technique too from the finally implementation of the software system.

Conclusion

Two filter techniques were tested for the removal of two kinds of noises and both were dropped from the final implementation of the system because of the reasons mentioned above

Classifier

Various kinds of systems are used to solve various problems, like some problems need embedded systems to be solved efficiently, some require a straight forward computer based program.

For, our problem of 2-dimensional movement, we need to be able to classify between various signals. These signals are not some fixed values that can be fed into computer, and then compared later on while online implementation using if else statements. Rather, signal values can vary each time for one particular thought. However, there is one pattern in one kind of signals between same thoughts. For example, let’s suppose we have five samples for the right hand movement of a person. All those samples will never be same exactly at any time, however, a pattern will exist in each of the sample, and that pattern will always be the same.

Based on this discussion about our problem, we conclude that we need such a system that can be made to learn a pattern and then can be used to identify from the pattern in which class this thought lies. Intelligent system have been proved to be best for the systems where some learning is required and some operation is to be performed based on that training. So, we are using intelligent systems for our purpose.

Why Neural Network

There are various kinds of intelligent systems available these days, like Bayesian Classifiers, Genetic Algorithms, and Neural Networks. Each kind of system is used in some particular scenario. From literature review, we came to know about the preference of neural networks to other intelligent systems. Also, neural network has the quality of being immune to noise [18]. So, we have decided to practice with neural networks too for this project.

Selection of NN

Now, in neural networks, there are various types of neural networks available. They differ from each other minutely on the basis of their design parameters like learning rate, learning rule etc.

In order to find out the best type of Neural Network for EEG signals classification, experiments were performed with pre-recorded data set of five mental states, called Purdue Data Set. The Purdue dataset was acquired by Aunon and Keirn [14] in the University of Purdue and has been taken from seven subjects during performance of five different mental tasks. An elastic electrode cap was used to record from positions C3, C4, P3, P4, O1 and O2 on the scalp. The data were recorded at a sampling rate of 250 Hz with a 12 bit A/D converter.

EOG signal was also provided to detect EOG based artifacts. The electrode placement for the Purdue EEG dataset is shown in Fig.2 [7]:

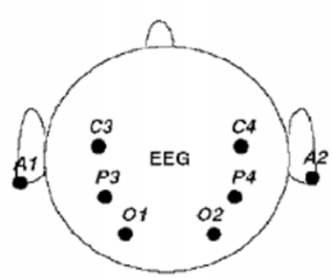

Figure 11: Electrode placement for the Purdue dataset. [16]

The mental tasks are as follows.

(1) ***Baseline task***. The subjects were asked to relax as much as possible.

(2) ***Letter task***. The subjects were instructed to mentally compose a letter to a friend or relative without vocalizing.

(3) ***Math task.*** The subjects were given nontrivial multiplication problems, such as 31 times 42.

(4) ***Visual counting task***. The subjects were asked to imagine a blackboard and to visualize numbers being written on the board sequentially with the previously written number erased before a new number is written.

(5) ***Geometric figure rotation.*** The subjects were asked to visualize a particular three-dimensional block figure being rotated about an axis.

Data were recorded for 10 s during each task, and each task was repeated five times per session. The dataset was downloaded from the internet [15] as a Matlab MAT file. The dataset consisted of a Cell array with 325 elements. 10 trials were completed for each task with Subject 1, Subject 3, Subject 4 and Subject 6. 5 trials were recorded for subject 2 and subject 7. 15 trials were recorded for subject 5. No more than 5 trials were carried out on a single day. One trial for Subject 4 letter task was corrupted, that reduced the effective data available. First 5 trials from each task were selected for experimentation.

Signal Representation

An important term regarding signal representation is window size.

Window Size

Window Size is the size of that data set at which we are looking at one time.

Consider there are 9 electrodes connected. So, instantaneously, we will be getting 9 values from the EEG hardware. Bu these 9 values can't be used for any inference, as, they are the values at any particular instant and you can well imagine that single thought is not present at some time approaching 0. It has some time span over which this thought is present. So, electrical signals of one particular instance mean nothing, but electrical signals of some particular time span represent a thought and we have to use them for our experimentation.

Selecting a window size

Next point arises about how much this window size should be, i.e. how much time span of thoughts will be enough for a good inference? Based on the study regarding this, we came to know about the window size of 5 seconds as a suitable one [3]. We experimented ourselves too in order to verify that by experimenting with the Purdue Data Set, taking various window sizes. For that data set, results were verified according to that given in the paper. These results are given in the results and analysis section next in Table 6 and Table 7.

To confirm these results and window sizes, experimentation of various window sizes was made with personally recoded data set as well. Description of that recording and the results will be described later.

Feature Selection

After a suitable window size is selected, certain preprocessing is done to extract features from the EEG signals. The feature vector is a signature of the EEG signal which specifies the content of the signal completely. Research has shown that AR models are the best feature extraction method for EEG signals [3].

Our Dataset

In order to develop a system based in the scope of the project, which was to be able to navigate in a 2-dimensional environment using thoughts, recording of the brain signals while actually performing the movements of the arm was done at Military Hospital, Rawalpindi. Though, aim was to navigate using thoughts, but for initial experiments, human brain signals, while actually moving the arm, were recorded. This recording was done at 500Hz with Neurofax EEG 1100 system. The subject was 21 years old, right handed male with no known medical conditions. Recording was done with closed eyes for baseline task and left and right hand movements in two directions, left and right. This data is also made available for other researchers all over the world [16].

Hardware Control

Hardware control was an optional part of the project objectives. After the classifier was up and running, we built a model of a motorized electrical wheelchair. The wheels were connected to a motor through a chain.

The chair was interfaced to the computer using parallel port. The motors of the wheelchair required a 12 volt power supply. Only 3.3 volts are available when a parallel port outputs logic 1.

To remedy this, the chair was connected to an external 12V supply through a voltage controlled switch. The switch was operated by the voltage from the computer parallel port. The complete interface circuit with the wheelchair is given in figure 12.

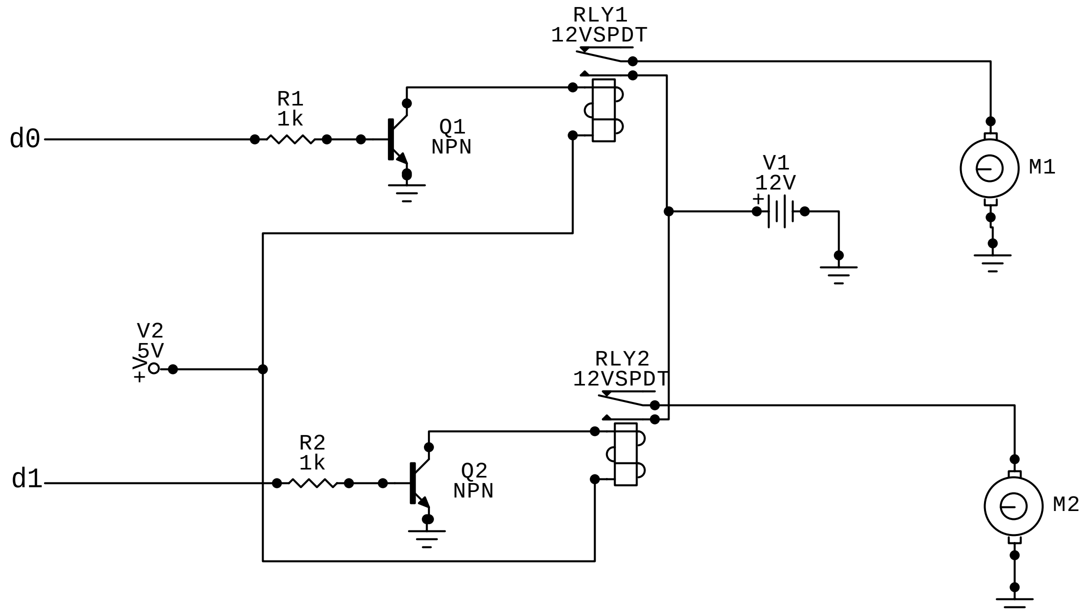

Figure 12: Hardware interface circuit diagram

The Motor M1 was connected to the right wheel of the chair and M2 was connected to the left wheel. The ground, d0 and d1 inputs were used from a standard ECP parallel port, with the pin out as shown in figure 13. The inputs correspond to pin 2, 3 and 25 respectively.

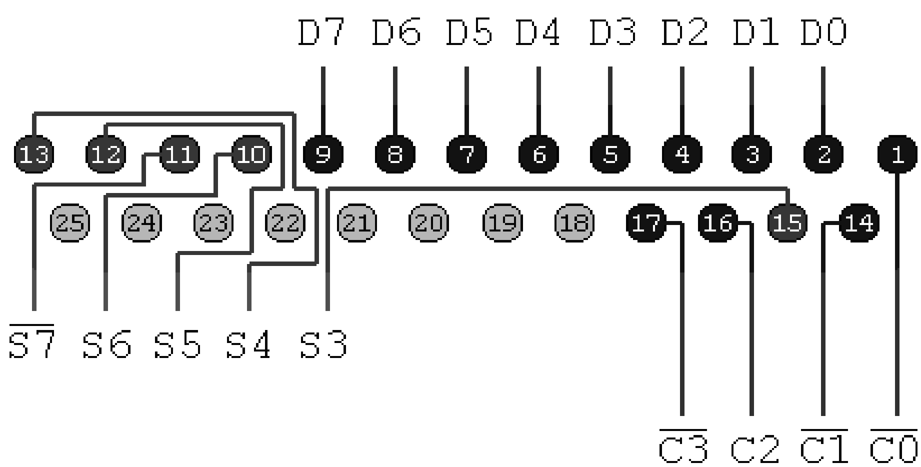

Figure 13: ECP parallel port

The two outputs from the classifier were used to run the wheelchair in either of the 2 configurations. Forward Movement or clockwise turn. The values in table 5 were used to initiate the movement

Table 5: Hardware Movement commands

Decision	Byte	D0	D1	Movement
Left	3	1	1	Forward
Right	2	0	1	Clockwise

Results and Analysis

The preliminary experiments in this project used a number of window sized and orders of the AR model to determine the best possible window size and the AR model order. The results found are discussed below.

For the purdue dataset, data from two persons, “Subject 1” and “Subject 3” is used. The accuracy for subject 1 is given in table 6 and plotted in figure 14 and figure 15. The accuracy for subject 3 is given in table 7 and plotted in figure 16 and 17.

Table 6: Classification Accuracy - Subject 1

Window Size (left)/AR model Order (down)	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0
3	0.55	0.71	0.87	0.89	0.90	0.92	0.90	0.90
4	0.50	0.63	0.77	0.83	0.82	0.87	0.90	0.93
5	0.50	0.67	0.83	0.86	0.87	0.90	0.92	0.92
6	0.45	0.72	0.80	0.81	0.84	0.89	0.90	0.90
7	0.46	0.58	0.71	0.79	0.85	0.84	0.83	0.86

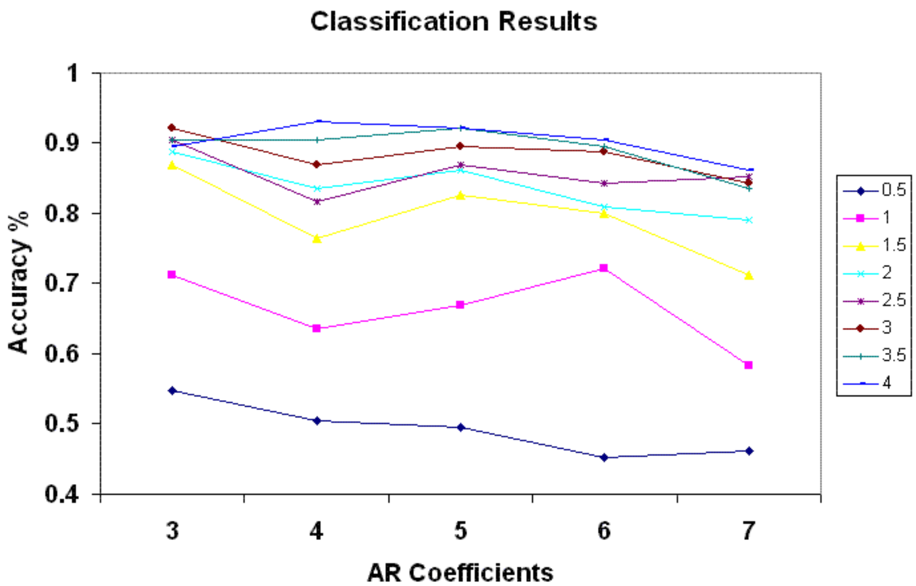

Figure 14 : Classification Accuracy - Subject 1 (by AR coefficients)

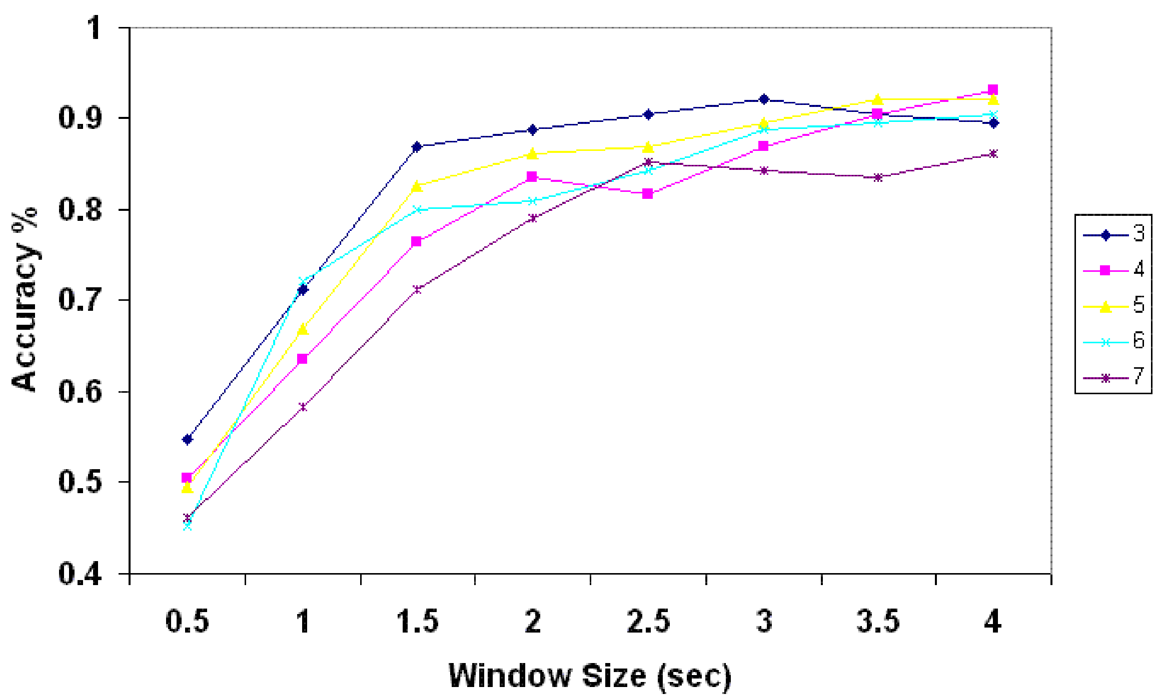

Figure 15 : Classification Accuracy - Subject 1 (by Window Sizes)

Table 7: Classification Accuracy - Subject 3

Window Size (left)/AR	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0

model Order (down)								
3	0.31	0.34	0.41	0.52	0.52	0.53	0.56	0.58
4	0.30	0.35	0.42	0.45	0.50	0.50	0.55	0.55
5	0.31	0.33	0.41	0.41	0.45	0.46	0.51	0.53
6	0.28	0.35	0.42	0.45	0.42	0.40	0.48	0.48
7	0.33	0.27	0.42	0.44	0.45	0.45	0.48	0.53

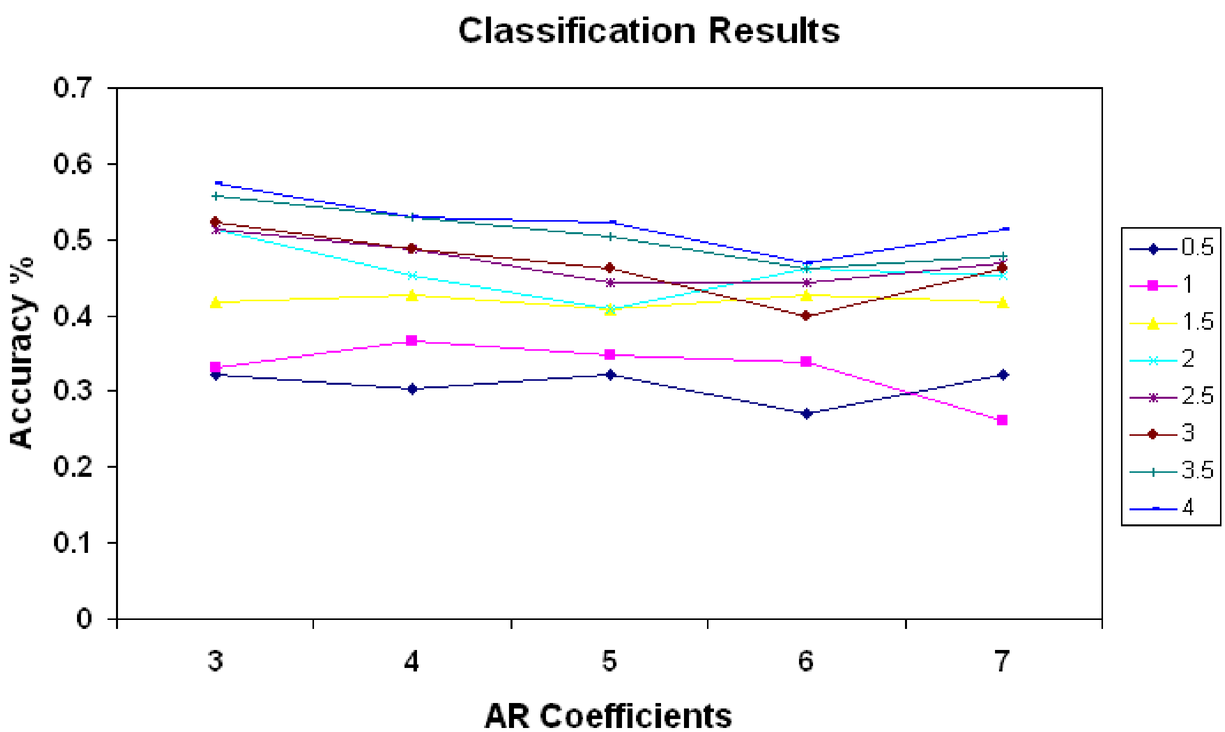

Figure 16 : Classification Accuracy - Subject 3 (by AR coefficients)

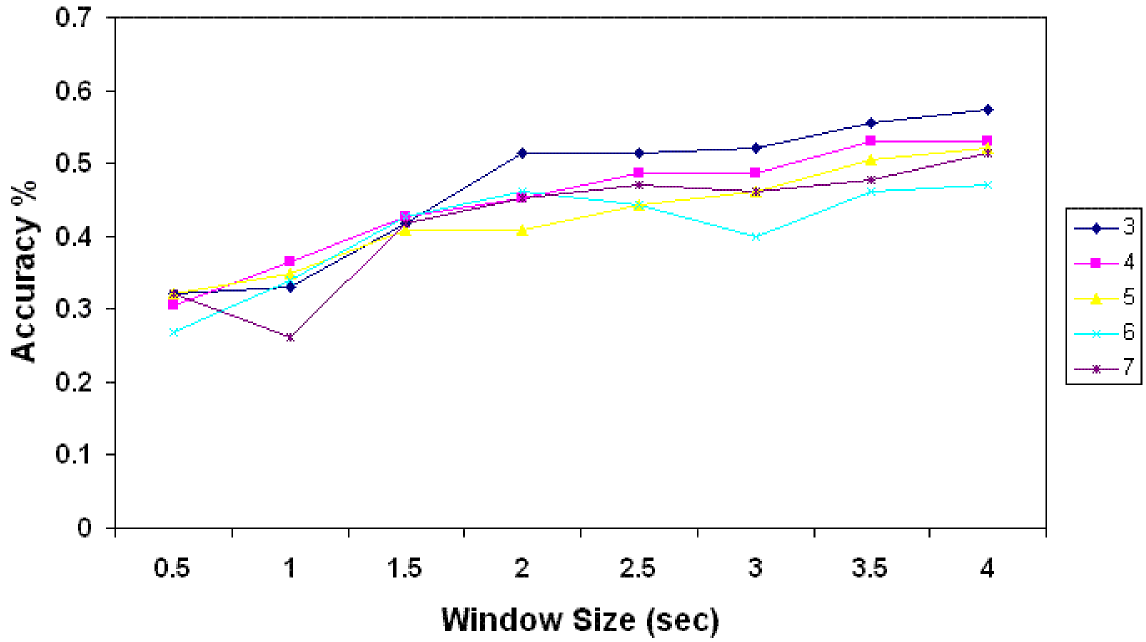

Figure 17 : Classification Accuracy - Subject 3 (by Window Sizes)

We preprocessed the data by using weighting, which assign more weights to electrodes near the motor cortex and lesser weight to the others. The accuracies obtained before and after weighting are summarized in table 8 and plotted in figure 18

Table 8: Classification Accuracy - Project Specific Data

Window Size	With weighting	without weighting
0.5	89	92
1	92	93
1.5	96	94
2	97	94

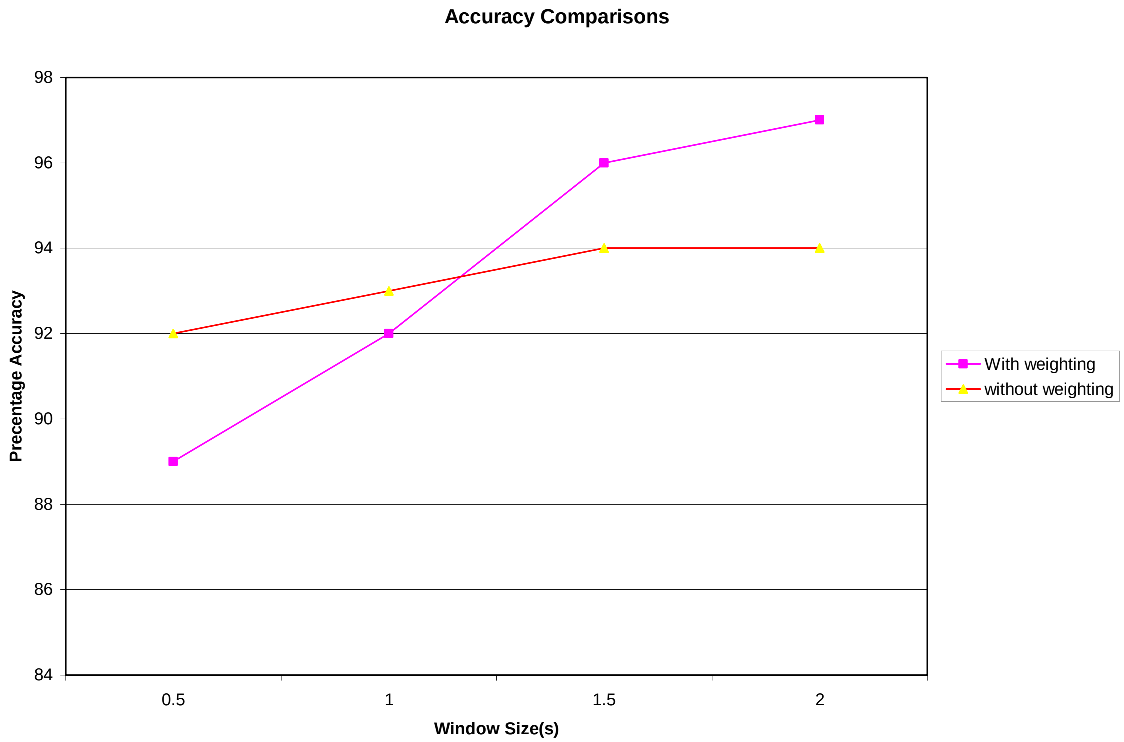

Figure 18 : Classification Accuracy - Project Specific Data

This shows that our preprocessing does increase the accuracy of the classifier

Future Work

Brain Computer Interface (BCI) has a vast scope in near future in the field of Computer Science and Medical. Such human computer interfaces can help physically disabled people. This technology can bring revolution in the field of medical sciences by producing brain controlled devices to help physically handicapped persons.

This work can be enhanced by introducing an online application which includes real time BCI for controlling a wheelchair. Apart from Electroencephalogram (EEG) signals there are some other signals of significance importance which are produced in the human brain like Electrooculogram (EOG) and Electromyogram (EMG) which could also be used for producing such human computer interfaces. Using these signals a BCI can be developed which can classify a large number of human thoughts.

Neural Prosthetics is another emerging technology in the field of Bio Technology. Neural prosthetic devices are artificial extensions to the body that restore or supplement function of the nervous system lost during disease or injury. Neural prosthetics are devices that are used to allow disabled individuals the ability to control their own bodies and lead fuller and more productive lives. Field of neural prosthetics will result in assistive technologies to improve the quality of life by restoring motor and communicative functions for individuals with spinal cord injuries, Amyotrophic Lateral Sclerosis, and stroke.

In future high-performance neural prosthetic systems can be designed, which are also known as brain-computer interfaces (BCIs) and brain-machine interfaces (BMIs). These systems can translate neural activity from the brain into control signals for prosthetic devices, which assist disabled patients by restoring lost function.

A new brain-computer-interface technology could turn our brains into automatic image-identifying machines that operate faster than human consciousness. Researchers at Columbia University are combining the processing power of the human brain with computer vision to develop a novel device that will allow people to search through images ten times faster than they can on their own.

DARPA, or the Defense Advanced Research Projects Agency, is funding research into the system with hopes of making federal agents' jobs easier. The technology would allow hours of footage to be very quickly processed, so security officers could identify terrorists or other criminals caught on surveillance video much more efficiently.

The brain emits a signal as soon as it sees something interesting, and that "aha" signal can be detected by an electroencephalogram, or EEG cap. While users sift through streaming images or video footage, the technology tags the images that elicit a signal, and ranks them in order of the strength of the neural signatures. Afterwards, the user can examine only the information that their brains identified as important, instead of wading through thousands of images.

Brain Computer interface can turn thoughts into words. What a man thinks could be generated in the form of a text document by developing a human computer interface.

References

[1] Torston Felzer, On the Possibility of Developing a Brain Computer Interface (BCI) , Department of Computer Science , Technical University of DarmStadt, Germany.

[2] Berger H, 1929, Ueber das Elektrenkephalogramm des Menschen, *Arch Psychiatr Nervenkr* **87** 527–70

[3] Charles W.Anderson, Saikumar V.Devulapalli, Erik A.Stolz. EEG Signal Classification with Different Signal Representation. *Neural Networks for Signal Processing [1995] V.Proceedings of the 1995 IEEE Workshop*

[4] C.W. Anderson and Z. Sijercic. Classification of EEG signals from four subjects during five mental tasks. Intl. Conf. on Engineering Applications of Neural Networks, 407--414, 1996.

[5] Charles W.Anderson, Erik A Stolze and Sanyogita Shamsunder, Discriminating mental Tasks Using EEG Represented by AR Models.

[6] Charles W.Anderson Michael J. Kirby. EEG Subspace Representations and Feature Selection for Brain-Computer Interfaces. Colorado State University

[7] Melody m. Moore Philip R. Kennedy Human Factors Issues in the Neural Signals Direct Brain-Computer Interface Georgia State University Atlanta, GA 30303-4013

[8] Barreto, A. B.,Scargle, S. D., Adjouadi, M A Real-Time Assistive Computer Inerface for Users with Motor Disabilities Department of Electrical and Computer Engineering Florida International University, Miami, FL., 33174

[9] Jack Culpepper Descriminating mental Tasks Using EEG Represented by Power Spectral Density Department of Computer Science Harvey Mudd College Claremont, CA 91711

[10] Ruey-Song Huang, Tazzy-Ping Jung, Scott Makeig Analyzing Event-Related Brain Dynamics in Continuous Compensatory Tracking Tasks

[11] Torsten Felzer, bernd Freisleben HaWCoS The “Hands-free” wheelchair Control System Department of Electrical engineering and Computer Science University of Siegen Holderinstr. 3, D-57068 Siegen, Germany

[12] Rezaei S, Tavakolian K, Nasrabadi A M and Setarehdan S K Differnet Classification techniques considering Brain Computer Interface Applications 2006 *J. Neural Eng* **3** 139-44

[13] http://www.sccn.ucsd.edu/eeglab

[14] Keirn Z A and Aunon J I A New Mode of communication between man and his surroundings1990 *IEEE Transactions on Biomedical Engineering,* **37(12)** 1209-14

[15]http://www.cs.colostate.edu/eeg/?Summary#Data

[16]http://projectbci.googlepages.com

[17] James N Knight, Signal fraction analysis and artifact removal in EEG, Master of Science Thesis, Department of Computer Science, Colorado State University.

[18] Tom Mitchell, Machine Learning, 1997, McGraw Hill

Index