Enhancement of Hearing-Aid

A report submitted for the course named Project V (CS-410)

By

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Abstract

As there is no coordination between Central Nervous System and Impairments devices. So the aim is build such a module which will provide the signal to hearing aid by taking the feedback from brain. The feedback from the brain will be EEG(Electroencephalogram) signal. Dataset for module was collected at IIIT Delhi in the previous summer. Main aim of the project is to design a software that will predict the amount of variations in ear of disable person. By finding the amount of disability in the ear, module will automatically tune itself and person with disability will be able to hear properly. For this Idea I am going to present the paper in the upcoming Conference. I have already written the portion of paper in this winter. Output of the project will be the amount of tuning required for module to tune itself.

Declaration

I declare that this submission represents my idea in my own words and where others' idea or words have been included, I have adequately cited and referenced the original source. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/sources in my submission. I understand that any violation of the above will be a cause for disciplinary action by the institute and can also evoke penal action from the sources which have thus not been properly cited or from proper permission has not been taken when needed.

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To Whom It May Concern

This is to certify that the report entitled **"Categorizing Users Based on their Behaviour for Hindi"** submitted to by "Dhananjay Singh", has been carried out under my supervision and that this work has not been submitted elsewhere for a degree,diploma or a course.

Signature of Supervisor

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Signature of HoD

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Signature of Examiner 4: ______________________

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- Dhananjay Singh

Contents

List of Figures

Chapter 1

Introduction

Outline: This chapter presents the following:

1. Introduction of project.
2. EEG (Electroencephalogram)
3. Hearing-Aid

1.1 Introduction

Electroencephalography (EEG) is most commonly used in the Cutting edge research in the field of Engineering, Neuromedical, and Biomedical Engineering. The EEG signal can be used for Brain Computer Interface [1], Sleep Analysis [2], and seizure detection [3]. EEG consist of 2-Dimension data with time on one axis and channel on other axis. The value at particular time and from the paerticular channel is the potential variation on the scalp due to firing in the Neuron. The basic pipline used for EEG processing is Artifact removal, feature extraction and classification. Artifacts are the sudden changes or the disturbance in the Normal EEG signal due to heart, eye blinking, eyes movement, and muscles in general. We can remove these artifacts using Independent Component Analysis (ICA) [4], ICA is method for Blind Source Separation (BSS). ICA separate EEG signal containing Artifacts into the independent components depending upon the characteristics[5].

Principal Component Analysis (PCA) has shown best result in many applications. In particular PCA has appiled for extraction of Ocular artifacts from EEG Signal, where as PCA doesn't remove the eye artifacts from the EEG Signal, especially when they have equivalent magnitude. we can use Local Fisher's Discriminant Analysis (LFDA) to particularly reduce the dimension of the features[5]. The classification of the EEG signal we can use the traditional approach or the Machine Learning approach. Correlation and cosine simailarity is most commonly used to identify steady-state visual evoked potentials (SSVEPs). Supervised Machine Learning methods like Linear discriminant analysis (LDA), Support Vector Machine (SVM), and Decision tree for classifying the EEG Signal [6][7]. Due to high computation require for training a Neural Network [8], it was not popular but in current era we have Graphical Processing unit (GPU) and avaialbity of large dataset. Todays, Neural Network application for EEG processing is used because Neural Network automatically work on paramter optimization.

Deep Learning has been applied on EEG in studies like Emotion Recognition (16%), Motor Imagery (22%), Mental Workload (16%), seizure detection (14%), sleep stage scoring (9%), event related potential detection (10%), and other studies(13%) [9]-[19]. World more than 466 million people suffer from Hearing Impairment(World Health Orgainisation 2019). Whose hearing threshold is greater than 25 db, is said be Hearing Impaired.

There are many causes of the Hearing Loss like:-

Congenital Causes:- It may be acquired immediately after the birth of the child. This may happen becuase of Hereditary or non-Hereditary or certain complications during the pregrency.

Acquired Causes:- This may happen at any age. It occur due to infection, otitis media, use of certain medicine, injury to head or ear, and ageing [46][47].

A hearing aid is the medical device designed with fine engineering technology which improve the hearing. These hearing aid do certain kind of amplification and signal pre-processing before delivering it to the ear. It is therfore fitted in accordance to the inablity of the person. traditionally hearing aids are fitted with the help of pure tone audiometry (PTA)[48] and speech discrimination testing [49], these test provide the information realted to the degree and nature of hearing loss. Hearing loss increase with increase in the age, it may also fluctuate. There is need where hearing aid automatically find the hearing loss and adjust its parameter according to it.

1.2 EEG Signal Processing

The research and development of BCI produces much enthusiasm among scientists, engineers, clinicians, and the general public. This is due to the development of these systems promises the restoration of lost functions in people with disabilities. It also offers new opportunities and challenges among researchers to improve the quality of life of these people. That is why those who research and develop BCI systems put all their efforts into the discovery of innovative techniques of processing and classification of characteristics to achieve this goal. In recent years the diversity of BCI systems has increased. This is probably due to the fact that with swift technological advances, new EEG signal processing methods have emerged as well as methods for extracting, selecting, and classifying features. In the research, the offline analysis of data has begun to be used more frequently, and in this modality the acquisition, extraction, and classification of data are simulated. This has allowed researchers to vastly improve the techniques and systems before being tested in a real system. The objective of the feature extraction stage for BCI applications is to discover what kind of data will be accurate, reliable, and mainly reflect the intention of the BCI system user. Once chosen, parameters will be extracted from the EEG signal, the designer will have as a new objective to find the most appropriate technique for this process. Then, with the obtained data the classifier that can best discriminate that data should be chosen. To select it correctly there are two different points of view. The first one identifies the best classifier(s) for a certain type of BCI, while the second one identifies the best classifier(s) for a certain type of features. The EEG signal feature extraction technique most used in BCI systems currently is spectral analysis. Specifically, about one-third of BCI designs have used power-spectral features. This method is accurate, simple, and fast. These characteristics are very important at the time of transforming the parameters into a decision to a quick.

1.3 Hearing-Aid

Hearing loss can have a big impact on your life, from your work to your relationships and emotional well-being. Hearing aids can make a big difference, especially if you choose the right people and get help adjusting to them..

1.3.1 How Hearing Aids Help

Hearing aid is a battery operated electronic device designed to improve your hearing. Small enough to be worn inside or behind your ear, they make some sounds louder. It helps you to listen better when it is quiet and noisy. Here's how they work:

1. The microphone picks up the sound around you.
2. The amplifier makes the sound louder.
3. The receiver sends these amplified sounds to your ear.

The receiver sends these amplified sounds to your ear.

Chapter 2

Existing System Study

Outline: This chapter presents the following:

1. Literature Survey
2. Hearing Correction
3. Related Work

2.1 Literature Survey

2.1.1 EEG Processing

EEG is very susceptive to the Noise due to electrode also pick up very small changes in potential. These potential changes may occur because movement of muscle or eye blink. EEG signal is also sensitive to the channel crosstalk [20]. These artifacts can be removed manually(31%), automatically(8%) or left unremoved (27%). Where as other research disn't specify any information about artifacts removal. It was found most of the research had removed these artifacts manually. The artifacts can be removed using ICA, Discrete Wavelets Decompostion (DWT), PCA.

ICA have many advantages like:-

- It avoids the problem of mutual contamination between regressing and regressed channels.
- ICA based algorithm preserve all the recorded trail, Rejection based model when the data is limited, or when blink and muscle movement occur frequently.
- ICA can preserve data at all scalp channels including frontal and particular sites.

ICA have many disadvantage like:-

- ICA can decompose atmost N source from N scalp eletrode. Effective number of independent signal contributing for scalp EEG signal is unkown. so, it become tough to decide N value.
- The assumption made in ICA doesn't satsisfy when training dataset is very small, or when separate topographically distinguishable Phenomena always occur concurrently in data.
- ICA doesn't satsisfy spatially stationary through time for artifacts and neural activity contributing EEG.
- This method need more computation than the Rejection Method.

Most other Research uses the signal in frequency domain so they can remove unwanted bandwidth, These kind of research was used in case where only particular frequency band is the signal of interest. EEG Data is commonly anlysed in Frequency domain because there exists behavioral pattern [4]. Power Spectral Density (PSD), Wavelet Decompostion, and stastical measure of the signal are most frequent input formulations. CNN based Deep learning aproach was found in 52% of the research. The Layer were used alternatively i.e Convulation Layer followed by the Pooling Layer. Activation function selected for the studies were Rectified Linear Unit (ReLU), Exponential Linear Unit (ELU), Leaky Rectified Linear Unit (Leaky ReLU), Hyperbolic tangent (PReLU)[21]-[45].

2.1.2 Hearing Correction

Pure tone audiometric (PTA):- It is used to determine the degree, type, and configuration of the hearing loss. It is the subjective and behavioural measurement of the hearing thresold. It is used in the adults and children old enough to cooperate with the test. PTA used both air and bone condution so it can tell the type of hearing loss using air-bone gap. PTA have many disadvantage like it can't identify the dead region of the cochlea and neuropathies like auditory processing disorder [50]-[52].

Auditory Steady State Response (ASSR):- It is electrophysiologic response of rapid stimuli. It create stastical audiograph for those who don't cooperate with tradtional method. ASSR design and functionality depend upon the company providing it. ASSR is kind of simialr to the Auditory Brainstem Response (ABR) i.e ASSR and ABR measure the bioelectric activity recorded using the electrode. ASSR is used to measure the amplitude and phases in frequency domain. It is the peak detection in Frequency domain [53].

Brainstem Evoked Response Audiometry (Bera):- It is objective assesment of hearing. It has advantage because these method can test hearing loss for even infants for whom audiometry is not helpfull. In this electrical activity of cochlea where recorded according to the stimuli given [54].

Scalp EEG can be utilised to identify the hearing Thresold [59], Frequency selectivity [60], loudness perception[61]. which can be used for fitting the Hearing Aid. Integration of

EEG Recording to the Hearing aid will automatically provide the refitting of the Hearing Aid. We can't incoperate traditonal EEG Recording system in Hearing Aid because of several technical issues. The Technical issue include like wired electrode attached to it, typical large biosignal Amplifier, assistance to placing the electrode and impedence checking while placing electrode. Ear-EEG is new method in which EEG is recorded in and arround the Ear [56][57]. This technology is under development still. Most of the Ear-EEG is recorded using the stationary system in controlled environment and Ear-EEG is also recorded by the use of portable system in many research [62]. Improvement in Ear-EEG and development of miniature Mobile EEG Amplifier[64]. Ear-EEG is used to estimate the hearing threshold[63]. In comparison with the Scalp EEG Ear-EEG showed 20% fewer Threshold estimation. The threshold was found to be elivated from 0.8 db to 7.5db [55].

2.1.3 Related Work

- Research Paper published by A.Nancy, Dr. M. Balamurugan and Vijaykumar S **A Brain EEG Classification System For the Mild Cognitive Impairment Analysis**, in this work they have classified the persons whose brain is not working properly with the help of EEG signal of brain and used SVM to classify the persons.

- Research Paper published by Mohammad H. Alomari, Ayman AbuBaker, Aiman Turani, Ali M. Baniyounes and , Adnan Manasreh **A Machine learning Based Brain Computer Interface**, work is to use a wireless Electroencephalography (EEG) headset as a remote control for the mouse cursor of a personal computer. The proposed system was using EEG signals as a communication link between brains and computers. Signal records obtained from the PhysioNet EEG dataset were analyzed using the Coif lets wavelets and many features were extracted using different amplitude estimators for the wavelet coefficients. The extracted features were inputted into machine learning algorithms to generate the decision rules required for our application. The suggested real time implementation of the system was tested and very good performance was achieved. This system could be helpful for disabled people as they can control computer applications via the imagination of fists and feet movements in addition to closing eyes for a short period of time.

- Research Paper published in 2017 by Corinna Bernarding, Daniel J. Strauss, Ronny Hannemann3, Harald Seidler4, Farah I. Corona-Strauss1,5 **Neurodynamic evaluation of hearing aid features using EEG correlates of listening effort** In this study, they propose a novel estimate of listening effort using electroencephalographic data. This method is a translation of their past findings, gained from the evoked electroencephalographic activity, to the oscillatory EEG activity. To test this technique, electroencephalographic data from experienced hearing aid users with moderate hearing loss were recorded, wearing hearing aids. The investigated hearing aid settings were: a directional microphone combined with a noise reduction algorithm in a medium and a strong setting, the noise reduction setting turned off, and a setting using omnidirectional microphones without any noise reduction. The results suggest that the electroencephalographic estimate of listening effort seems to be a useful tool to map the exerted effort of the participants. In addition, the results indicate that a directional processing mode can reduce the listening effort in multitalker listening situations.

Chapter 3

System Design & Implementation

Outline: This chapter presents the following:

1. Pre-processing
2. Feature Extraction
3. Feature Selection: Dimensionality Reduction
4. Classifiers
5. Performance Evaluation
6. My Work

3.1 Preprocessing

The first step of the project is to collect information through electrodes located on the skull. The process of receiving the EEG signal is usually accompanied by noise, which comes from various sources. These karate actuators originate from the use of eye-blinking (EOG), electrocardiogram (ECG), motion kinetic (EMG), and any external sources associated with the equipment involved in the system. Crater actuators may have similar amplitude to the EEG signal and are therefore difficult to detect. Signal preprocessing is the process of eliminating noise or obtaining a free-artifact signal to extract reliable features. EEG acquisition systems can be set up to filter the majority of craft materials using the hardware. These filters are designed to prevent any change or distortion in the signals. High-pass filters, usually with a cut-off frequency of less than 0.5 Hz, are used to eliminate very-low-frequency components, such as respiratory disturbances. On the other hand, high-frequency frequency noise with low-pass filters can be reduced by a cut-off frequency of 50-70 Hz. 50 Hertz hollow frequency notch filters are often required to ensure complete rejection of a strong 50 Hertz power supply.

Some models not involved in artifact processing directly affect the feature vector. Features can be obtained from a contaminated signal, perhaps because they do not reflect the user's intentions. Therefore, it is recommended to preprocessing the brain signal before uncovering the symptoms, thereby increasing the signal-to-noise ratio. In some cases, other biological signals such as ECG, EMG and EOG are also present in the records. These codes share the same bandwidth with EEG, so it is important to find a technology that prevents EMG and EOG from losing EEG information. Examples of these methods are Principal Component Analysis (PCA) or Free Component (ICA), Adaptive Noise Concentrations or Adaptive Filters (AF). The PCA decomposes multichannel eigenvalues into components such as neural activity and noise, and then the calculated noise can be extracted from the original EEGs. In general, PCA is also used for denoising and feature extraction steps, so they are described in the following section. The use of AF requires a reference signal. For example, to eliminate the eye-glaring cortex, the EOG must be recorded from the FP1 and FP2EEG electrodes. In finding ERP signals, for example, the reference signal is obtained using the average of several ERP components. ECG cancellation from EEGs is a common example. It is also common to divide the signal into smaller parts. This partition is recommended to give signal partitioning features and to generate online and real-time commands. Common Average Reference (CAR) is another process used in BCI systems to amplify the signal. CAR is determined by subtracting the average of all EEG channels from each individual channel. This reduces the effect of distant sources but may introduce some unwanted spatial smearing. For example, artifacts from one channel can be spread to other channels.

3.2 Feature Extraction

Project's mission is to turn brain function into a command-to-control system; The user creates scalable signals that serve his purpose. The processing of this data is done using a specific algorithm, which allows us to extract useful information from the EEG. Therefore, it is important to have a good signal-to-noise ratio for the data at this stage.

Some features extracted from the EEG, for example, amplitude values, band power (BP), power spectral density (PSD) values, autoregressive (AR) and adaptive autoregressive parameters, time-frequency (Tf) features, and inverse model-based features . Each of these parameters means different processing methods. The attributes in the properties depend on the technology used and this affects the classification choice. Various EEG facility extraction techniques Are further described.

3.2.1 Time-Domain Analysis

EEG signals are a function of time so directly estimated features are referred to as time-domain analysis. Some time-domain parameters are, for example:

- ***Amplitude:*** refers to the signal instantaneous energy. The maximum and minimum values are also used as well as the standard deviation and the mean value.
- ***Regularity:*** obtained using an autocorrelation function, which measures the similarity of a signal with itself.
- ***Synchronicity:*** gives an idea of how similar signals are to each other or what events occur at the same time.

3.2.2 Spectral Analysis

In spectral analysis, the signal is decomposed into several parts of the spectral domain. Therefore, in order to extract the frequency characteristics, the Fourier transform (FT) must be described in terms of its frequency components, which are completed using the signal. The best tool for this job is Fast Full Time (FLFT). Frequency properties can be used by the brain to isolate different emission. Generally, the relevant properties are collected according to the PSD.

There are five major brain waves distinguished by their different frequency ranges. These frequency bands are: alpha (: 8 to 13 Hz), theta (: 4 to 7 Hz), beta (: 13 to 30 Hz), delta (: 0.5 to 4 Hz), and gamma (: higher than 35 Hz) waves. Beta wave is associated with active thinking, attention, or solving concrete problems. The gamma wave band is a good indication of event-related synchronization (ERS) of the brain.

Through the advancements in BCI research the features from frequency analysis have demonstrated to be one of the best approaches to recognize the mental tasks based on EEG signals.Some spectral features estimated from the FFT of the EEG channels are: maximum power, frequency of maximum power, mean and peak frequencies, cumulative power, relative power, standard deviation of the power, and so on.

Lioa et have developed an EEG-based BCI device for an archery game control. To control the game, the power of alpha rhythm is computed from the EEG of the user's forehead when a user concentrates on a target. Rebsamen et proposed a control strategy to drive a wheelchair in a building environment by thoughts. The user selects the destination in a list of predefined locations of interest using a slow but safe P300 EEG interface. The robotic wheelchair navigates autonomously toward the destination following virtual guiding paths. The interface was tested in only two subjects

3.2.3 Time-Frequency Analysis: Wavelet Transform

The timing features provide only the temporal information of the signal, as well as the frequency characteristics, the optimal spectral resolution. The most desirable features are the timing and frequency information of the signal simultaneously. Time-frequency representation (TFR) does the same. Time and frequency. The TFR represents the time signal in the representation function of the frequency. This is a simple way to express the concept, but there are actually theoretical aspects to classifying TFRs, which is not the purpose of this chapter. Several TFRs, such as the Short-Term Fourier Transform (STFT), the Wigner - Ville distribution, and the Choi Williams distribution. But this is by far the most popular wavelet transform (WT) and its features. To be sure, WT is a time-scale representation of the signal and decomposes into final amplification and approximation signals; All of these are associated with the sampling frequency of the original signal.

Most models of BCIs using TFR methods use WT-based feature extraction algorithms. The choice of a particular wavelet is an important factor in obtaining useful information from wavelet analysis. Previous knowledge of EEG signals can be very useful in determining the appropriate wavelet. The discernment process is done by a bank of filters that allow the parameters to be captured and applied over time as well as with frequency.

3.3 Feature Selection: Dimensionality Reduction

The previous section described different feature extraction methods for BCI, but not all extracted features can be used to control the system. A big difficulty in designing a BCI is to choose the right features from as many features as possible. Multiple features can be extracted in multiple intervals from multiple channels by providing high level feature vectors. The amount of data required to correctly describe different classes can increase significantly with the size of feature vectors. In any classification problem, this problem is called the "curse of measurements". So, after extracting the properties, select the most feasible ones and create the same vector with as few features as possible. Selecting the best features for classification is critical to classification performance. For example, if two or more attributes are interrelated, they represent unnecessary information that confuses classification. Fortunately, effective optimization algorithms can be applied to reduce the number of features and increase the classification performance.

Feature selection and / or dimensionality reduction techniques vary from basic statistics to more sophisticated algorithms, such as mean power, median and standard deviation analysis of variance analysis (ANOVA), Mann-Whitney test, genetic algorithm, PCA, and differential sensitivity to statistically significant differences between paths. test. To analyze differences between group means, ANOVA uses a collection of statistical models in which the variation observed in a particular variable is divided into factors that cause different variance sources. The Mann-Whitney test is a parametric test comparing the mean values of two different data populations. This test is usually combined with Lambda of Wilks (LW) standards. LW measures the ratio between the variable in the group and the total variable, which is a direct measure of the importance of the variables. Therefore, the method selects the most relevant variables to determine, for example, the benefits of the user. As mentioned earlier, PCA is a technique that is often used because of its versatility. PCA is used in the preprocessing phase, feature extraction and feature reduction.

The Mann-Whitney test is a nonparametric test that compares the mean values of two different data populations. This test is usually combined with the Lambda of Wilks (LW) criterion. LW measures the ratio between within-group variability and total variability, and is a direct measure of the importance of the variables. So in this way the method selects the most relevant variables to identify, for example, the BCI user's intentions. PCA is an often-used technique in BCI due to its versatility, as was mentioned earlier. PCA is used in the preprocessing stage, in feature extraction, and in features reduction.

3.3.1 Genetic Algorithm

Genetic algorithm (GA) is an optimization process to determine whether a particular attribute is most efficient. In GA, the population of candidate solutions to the optimization problem (called individuals or phenotypes) develops into better solutions. Evolution usually starts from a population of randomly generated individuals, a recurring process. At each iteration, a generation of the specified population is calculated and the characteristics of the individuals are estimated. Evaluation is the ability of individuals to perceive an activity as an objective, which solves the problem. Depending on their physical appearance, some representatives of the population may be left to make room for newly created people. The next iteration of the algorithm uses a new generation of candidate solutions. Typically, the algorithm ends when the maximum generation is produced or the population reaches a satisfactory fitness level. GA has been implemented for automatic feature extraction in P300 detection; They argue that the extracted features of the algorithm can be understood in terms of the signal properties that contribute to the classification success, which provides new insights into brain function research. BCI has a number of contributions by GA to reduce the level of interest to the reader.

3.3.2 Distinctive Sensitive Learning Vector Quantization

Differential Sensitive Learning Vector Quantization (DSLVQ) is the first classification method; However, it can be used for feature selection in BCI studies. It has been refined into a learning vector quantization (LVQ), a competitive study based on the neural network algorithm. The DSLVQ method finds many unique features to arrive at the correct classification. This applies to frequency domain properties; A weight for each attribute is determined as a measure of significance level, and the appropriate weight for each measurement is calculated through a repetitive learning process. DSLVQ finds very discriminating features for a given class and subject, searching for a linear approximation appropriate to the problem. The size of the weight indicates how detailed the symptoms are.

There are many works in BCI that use this feature selection method. For example, Jamalou and Micheli (2015) used the DSLVQ method to select properties of generalized spatial models that apply to maximize the effects of event-related desynchronization and ERS on multichannel electroencephalogram-based BCI systems. In Kara and Balbinot (2012), the DSLVQ and lateralization index are used to extract the most relevant features and to select the subject-specific parameters. Volunteers were asked to perform ot affective hand movement toward the arrow (stimulus) indicated in BCI systems based on brain signals from the somatosensory cortex.

3.4 Classifiers

The purpose of classification is to describe the boundary between classes and label them based on their measured characteristics. Specifically, in the system, the task is to determine the user's intentions based on the feature vector, which is the hallmark of the brain function that provides the feature stage. This step is the global process, which involves a strategy of deciding which features to choose and how to combine them. To optimize system performance. More sophisticated, such as classifiers or machine learning algorithms as a set of features. In a multi-dimensional feature space, this boundary is converted into a separating hyperplane. The purpose is to find the hyperplane with maximum distance from all classes (control commands).

Over the past 50 years, many clustering and classification techniques have been developed. Among them, association rules, artificial neural networks, linear discriminant analysis, hidden Markov modeling, K-means clustering, fuzzy logic and support vector machines have been applied to BCI systems. The mathematical basis of these methods has been developed and they are well described in the specific literature.

3.4.1 Support Vector Machines

Support vector machines (SVMs) are the most popular classification of BCI applications; It can be used to find a set of hyperplanes or hyperplanes for multidimensional data. This hyperplane belongs to the feature space, which divides the feature vectors into two or more classes. SVM provides a unique solution to reduce the risk of a classification of missing examples. SVM selects hyperplanes that increase the distance between adjacent training models Hyperplanes. SVM can be considered a linear classification because it uses one or more hyperplanes and nonlinear with kernel function (Gaussian or radial basis in BCI applications). In the nonlinear SVM data space, a more sophisticated decision boundary leads to greater classification accuracy.

Due to the popularity of SVM classifiers in BCI, its general classification is good in performance and strong against measurement scales. These advantages are at the expense of implementation speed. However, real-time BCIs require SVM speeds. Another advantage of SVM is that it deals with their values correctly. As mentioned, SVM is often used in BCI due to binary-to-multiclass problems; Gauss Zion SVM has been applied to BCIs to characterize the possibilities posed by the P300.

3.4.2 Linear Discrimination Analysis

Linear discriminant analysis (LDA) is based on a linear combination of non-discriminating variables (selected characteristics), which allows to increase the differences between groups and minimize group differences. Those linear combinations are called classification functions. There are many functions such as classes to classify. LDA provides acceptable accuracy without excessive computational requirements and is compatible with fast response BCI systems.

LDA is used in systems such as the P300 speller, multiclass, hybrid or synchronous BCI. Furtia et al. (2009) investigated whether P300-based BCI users could spell using an auditory-based ERP spelling system in contrast to visual equivalence. There were fifteen healthy participants. Parameter analysis was performed using Stepwise LDA. Fasley et al. (2011) examined how the classification of infrared spectroscopy (NRS) data complements the current real-time EEG classification. They proposed a hybrid NIRS-EEG BCI to improve the classification performance of the sensory-motor rhythm. The properties obtained were used as features of the LDA. Another comparative study between ERD BCI, SSVEP BCI and ERD-SSVEP BCI was proposed by Allison et al. (2010). They used LDA to classify the parameters. Other reports using LDA include Edlinger et al. (2011) and Brunner et al. (2011), Yong et al. (2011).

3.4.3 Neural Networks

Classification of neural networks (ANNs) used in a variety of disciplines, including computer science, biomedical engineering, physics, and neuroscience. ANNs are a mathematical analog of low-level activity of biological neurons; Its purpose is to simulate brain activity in solving problems. ANNs are widely used in pattern recognition because they are capable of learning from training data. The algorithm distributes the knowledge of the problem to each neuron (functional unit) and its connections are tied to different weights. ANNs can map the "problem" after training with the described features. During the training phase, feature vectors are used as inputs and the network adjusts its weights and biases to establish the relationship between input patterns and P outputs. Once trained, ANNs can identify patterns associated with a training data set. This is why ANNs are associated with different applications because they perform pattern recognition to establish user intentions. Another important aspect is the design or construction of ANNs; In short, these include the amount of neurons and membranes. The number of inputs and P outputs to solve is related to the problem. Finally, the learning algorithm specifies different network structures.

The most common is the ANN Multi-Layer Perceptron (MLP). In addition, the following ANNs have been used in the design of BCI systems: Learning Vector Quantization (LVQ); Radial Basis Function (RBF); Bayesian Logistic Regression Neural Network (BLRNN); Probabilistic neural networks (PNN); And fuzzy, limited impulse response neural networks (FIRNN).

3.5 Performance Evaluation

To date, EEG signal processing techniques, feature extraction and reduction techniques, and classifiers for project have been described. All of these steps follow the end goal: project implements user goals. The most desirable situation is 100 percent success, but how can it be measured? Okay, that's why the performance appraisal is necessary to raise this level to perfection.

Since the entire chapter is focused on the EEG signal rather than the system, we will discuss the performance evaluation of the classification output rather than the performance of the entire system. Several measures of performance such as classification accuracy, kappa coefficient, correlation information, sensitivity, specificity and confusion matrix have been proposed in BCI.

The most common and simplest way to measure the classification performance of a binary system is to determine the true identity number or true positive (TP). This leads to false positives (FP) and other related indicators such as misclassification or detection; False negative (FN), falsely rejected; Right negative (TN), rightly rejected. These values are obtained from the confusion matrix. With these parameters, indicators of more popular sensitivity and specificity can be estimated.

3.6 My Work

This project is trying to enhance the hearing-aid device by providing the amount of turning required for any person suffering from hearing loss. These days the problem of hearing loss is solved using the hearing aid device. This technique works well but this is a static approach, it can be made dynamic by taking the EEG signal from the brain and after the complete calculation, an amount of hearing loss can be estimated.This estimation alone can solve the problem by a static method. The estimated value will be provided to hearing-Aid device and hearing-aid will adjust itself to work similarly as in static method. Here is the sequence of task done by me.

- Data of 200 peoples(Some were having hearing loss and rest did not have) collected in AIIMS(2019). EEG data was calculated with the help of a software named Emotive. EEG data is collected using the EEG electrod costisting positive, negative and ground terminals. The voltage measured is in micro-volts so it need to be amplified. For amplifying the signal a circuit is used which consist of five stages. The Instrumentation Amplifier, 60 Hz Notch Filter, 31Hz Low Pass Filter, Gain Stage, and Clamper Circuit. Each of these stages contribute in their own way to amplify and also filter the noise from the EEG signal. The gain of the entire circuit is about 5140 V/V. The data is sampled at a sampling rate of 838 Hz. Any remaining noise from the signal can be removed by passing it through a digital low-pass filter, if required.
- Data was stored in the form of Signal containing a lot of noises so Data was pre-

processed using some well-known techniques of Brain-Computer Interface. For this work, a fixed amount EEG frequency range was taken and rest are discarded.

- After removing noise, project brakes the signal in different bands(alpha, beta, delta, etc..)
- The project uses Logistic Regression for classifying data into two groups, one with hearing loss another having no hearing loss.
- Accuracy of the project is around 74 percent which can be further improved using different Machine Learning algorithms.
- Another approach for categorizing the persons I used(as our Institute expects) is from scratch. In this method, I have calculated a cutoff frequency of EEG signals of the healthy person and then simply written a program to get the difference between frequencies.
- Then the project calculates the gradient using the Linear Discrimination Analysis technique. It provides an appropriate relative voltage which can be used as a cutoff signal for a person who does not have hearing loss.
- For estimating the result, the input EEG signal is compared with the cutoff estimated above, if this difference is a high person who has hearing aid and hearing-aid device need to train itself appropriately.

3.6.1 Output

Output of the project is accuracy of the project using Logistic Regression, Testing for 100 user having hearing loss or not with the help of their EEG signals along with the amount of tuning required in each signal. It was very difficult to get exact tuning because it is only possible with the help of Doctor to express so I have displayed everything as output. Amount of tuning is defect in different(64) channels.

Chapter 4

Conclusion

This project proposed a new classification system for checking the hearing capacity of person using the EEG signals from brain. Data had been stored with the help of Emotive Software and different techniques of Brain-Computer Interface was used to pre-process data. After pre-processing the data feature detection and extraction was done. Here all the 64 features were useful so there was no need of feature selection then EEG data was broken into different bands (alpha, beta, delta,..) and only useful band was used for calculation. For checking the hearing loss in human Logistic Regression has been used and for calculating the amount of tuning required a simple approach has been used. For calculating the amount of tuning required average of all 64 channels was calculated which gives the the gradient line for the comparison between the testing data. Project is helpful to enhance the hearing-aid device by providing the appropriate feedback using EEG signal of the person. Module will take the EEG signal from brain and will send a feedback to hearing-aid. By this way people do not need to visit the clinic for re-adjustment of hearing-aid.

4.1 Future direction

- EEG data can be used for different experiments and all the tests done in hospital(for checking different diseases) can be done using study of EEG signals up-to some extends but the problem is that it is very tough to get the exact EEG signal and there is no device till date to give exact result. If exact results can be calculated it is very easy to do all the tests in hospital within seconds.
- Using the EEG signal and Machine learning Algorithm information stored in Human brain can be evaluated.
- Using EEG signal and Machine learning algorithm every thing that is done physically can be implemented by just a simple instruction from brain.

Appendix A

User manual

A.1 Step to Install the System

Here are the list of libraries that need to be already installed before execution of project.

1. Numpy
2. Pandas
3. sklearn
4. python3

If all the libraries are installed then go inside the folder and run command python dhananjay.py.

Bibliography

[1] Y. He, D. Eguren, J. M. Azorín, R. G. Grossman, T. P. Luu, and J. L. Contreras-Vidal, “Brain–machine interfaces for controlling lower-limb powered robotic systems,” J. Neural Eng., vol. 15, no. 2, p. 021004, Apr. 2018.

[2] S. Motamedi-Fakhr, M. Moshrefi-Torbati, M. Hill, C. M. Hill, and P. R. White, “Signal processing techniques applied to human sleep EEG signals—A review,” Biomed. Signal Process. Control, vol. 10, pp. 21–33, Mar. 2014.

[3] G. Chen, “Automatic EEG seizure detection using dual-tree complex wavelet-Fourier features,” Expert Syst. Appl., vol. 41, no. 5, pp. 2391–2394, Apr. 2014.

[4] P. D. Velu and V. R. de Sa, “Single-trial classification of gait and point movement preparation from human EEG.,” Front. Neurosci., vol. 7, no. June, p. 84, Jan. 2013.

[5] A. Srinivasulu and M. Sreenath Reddy, ”Artifacts Removing From EEG Signals by Ica Algorithms.”,ISSN: 2278-1676 Volume 2, Issue 4 (Sep-Oct. 2012), PP 11-16

[6] A. subasi, M. I. Gursoy, and M. Ismail Gursoy, “EEG signal classification using PCA, ICA, LDA and support vector machines,” Expert Syst. Appl., vol. 37, no. 12, pp. 8659–8666, Dec. 2010.

[7] K. Lee, D. Liu, L. Perroud, R. Chavarriaga, and J. del R. Millán, “A brain-controlled exoskeleton with cascaded event-related desynchronization classifiers,” Rob. Auton. Syst., vol. 90, pp. 15–23, Apr. 2017.

[8] Y. Lecun, Y. Bengio, and G. Hinton, “Deep learning,” Nature, vol. 521, no. 7553, pp. 436–444, 2015.

[9] F. C. Morabito et al., “Deep convolutional neural networks for classification of mild cognitive impaired and Alzheimer’s disease patients from scalp EEG recordings,” 2016 IEEE 2nd Int. Forum Res. Technol. Soc. Ind. Leveraging a better tomorrow, pp. 1–6, 2016.

[10] D. Kim, S. Member, K. Kim, and S. Member, “Detection of Early Stage Alzheimer ’ s Disease using EEG Relative Power with Deep Neural Network,” pp. 352–355, 2018.

[11] Y. Zhao, “Deep Learning in the EEG Diagnosis of Alzheimer’s Disease,” 2014 Asian Conf.Comput. Vis., pp. 1–15, 2014.

[12] V. Baltatzis, K.-M. Bintsi, G. K. Apostolidis, and L. J. Hadjileontiadis, "Bullying incidences identification within an immersive environment using HD EEG-based analysis: A Swarm Decomposition and Deep Learning approach," Sci. Rep., vol. 7, no. 1, p. 17292, 2017.

[13] U. R. Acharya, S. Lih, Y. Hagiwara, J. Hong, H. Adeli, and D. P. Subha, "Automated EEG-based screening of depression using deep convolutional neural network," Comput. Methods Programs Biomed., vol. 161, pp. 103–113, 2018.

[14] E. Gait-pattern, S. K. Goh, H. A. Abbass, S. Member, and K. C. Tan, "Spatio – Spectral Representation Learning for classification," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 26, no. 9, pp. 1858–1867, 2018.

[15] Y. Guo, K. Friston, A. Faisal, S. Hill, and H. Peng, "Brain informatics and health: 8th international conference, BIH 2015 London, UK, august 30 – september 2, 2015 proceedings," Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics), vol. 9250, pp. 306–316, 2015.

[16] G. Vrbancic and V. Podgorelec, "Automatic Classification of Motor Impairment Neural Disorders from EEG Signals Using Deep Convolutional Neural Networks," pp. 4–8, 2018.

[17] K. G. Van Leeuwen, H. Sun, M. Tabaeizadeh, A. F. Struck, M. J. A. M. Van Putten, and M. B. Westover, "Detecting abnormal electroencephalograms using deep convolutional networks," Clin. Neurophysiol., vol. 130, no. 1, pp. 77–84, 2019.

[18] S. Roy, I. Kiral-kornek, S. Harrer, and I. S. Member, "Deep Learning Enabled Automatic Abnormal EEG Identification," pp. 2756–2759.

[19] A. M. A. B, A. A. B, and T. W. Boonstra, "A Multichannel Deep Belief Network for the Classification of EEG Data," Neural Inf. Process., vol. 9492, pp. 38–45, 2015.

[20] M. . Teplan, "FUNDAMENTALS OF EEG MEASUREMENT," Meas. Sci., vol. 2, pp. 1–11, 2002.

[21] V. Baltatzis, K.-M. Bintsi, G. K. Apostolidis, and L. J. Hadjileontiadis, "Bullying incidences identification within an immersive environment using HD EEG-based analysis: A Swarm Decomposition and Deep Learning approach," Sci. Rep., vol. 7, no. 1, p. 17292, 2017.

[22] W. Abbas and N. A. Khan, "DeepMI : Deep Learning for Multiclass Motor Imagery Classification," pp. 219–222, 2018.

[23] Y. R. Tabar and U. Halici, "A novel deep learning approach for classification of EEG motor imagery signals," J. Neural Eng., vol. 14, no. 1, 2017.

[24] A. Pereira et al., "Cross-Subject EEG Event-Related Potential Classification for Brain-Computer Interfaces Using Residual Networks," 2018.

[25] G. Vrbancic and V. Podgorelec, “Automatic Classification of Motor Impairment Neural Disorders from EEG Signals Using Deep Convolutional Neural Networks,” pp. 4–8, 2018.

[26] Z. Tang, C. Li, and S. Sun, “Single-trial EEG classification of motor imagery using deep convolutional neural networks,” Optik (Stuttg)., vol. 130, pp. 11–18, 2017.

[27] H. Dose, J. S. Møller, H. K. Iversen, and S. Puthusserypady, “An end-to-end deep learning approach to MI-EEG signal classification for BCIs,” Expert Syst. Appl., vol. 114, pp. 532–542, 2018.

[28] A. Antoniades, L. Spyrou, C. C. Took, and S. Sanei, “Deep learning for epileptic intracranial EEG data,” 2016 IEEE 26th Int. Work. Mach. Learn. Signal Process., pp. 1–6, 2016.

[29] J. Zhang and Y. Wu, “Complex-valued unsupervised convolutional neural networks for sleep stage classification,” Comput. Methods Programs Biomed., vol. 164, pp. 181–191, 2018.

[30] M. Liu, W. Wu, Z. Gu, Z. Yu, F. Qi, and Y. Li, “Deep learning based on Batch Normalization for P300 signal detection,” Neurocomputing, vol. 275, pp. 288–297, 2018.

[31] S. Sakhavi, S. Member, and C. Guan, “Learning Temporal Information for Brain-Computer Interface Using Convolutional Neural Networks,” IEEE Trans. Neural Networks Learn. Syst., vol. 29, no. 11, pp. 5619–5629, 2018.

[32] S. Moon and J. Lee, “CONVOLUTIONAL NEURAL NETWORK APPROACH FOR EEG-BASED EMOTION RECOGNITION USING BRAIN CONNECTIVITY AND ITS SPATIAL INFORMATION.”

[33] N. R. Waytowich et al., “Compact Convolutional Neural Networks for Classification of Asynchronous Steady-state Visual Evoked Potentials,” pp. 1–23, 2018.

[34] K. K. Ang and C. Guan, “Inter-subject Transfer Learning with End-to-end Deep Convolutional Neural Network for EEG- based BCI,” no. November, 2018.

[35] V. J. Lawhern, A. J. Solon, N. R. Waytowich, S. M. Gordon, and L. G. May, “EEG-Net : A Compact Convolutional Neural Network for EEG-based Brain-Computer Interfaces,” pp. 1–30, 2018.

[36] J. Liu, Y. Cheng, and W. Zhang, “Deep learning EEG response representation for brain computer interface,” Chinese Control Conf. CCC, vol. 2015–Septe, pp. 3518–3523, 2015.

[37] J. Shamwell, H. Lee, H. Kwon, A. R. Marathe, V. Lawhern, and W. Nothwang, “Single-trial EEG RSVP classification using convolutional neural networks,” vol. 983622, no. May 2016, p. 983622, 2016.

[38] S. Sakhavi, C. Guan, and S. Yan, “Parallel convolutional-linear neural network for motor imagery classification,” 2015 23rd Eur. Signal Process. Conf. EUSIPCO 2015, pp. 2736–2740, 2015.

[39] H. Zeng, C. Yang, G. Dai, F. Qin, J. Zhang, and W. Kong, “Classification of driver mental states by deep learning,” Cogn. Neurodyn., vol. 12, no. 6, pp. 597–606, 2018.

[40] K. . Tsiouris, V. C. Pezoulas, M. Zervakis, S. Konitsiotis, D. D. Koutsouris, and D. I. Fotiadis, “A Long Short-Term Memory deep learning network for the prediction of epileptic seizures using EEG signals,” vol. 99, no. March, pp. 24–37, 2018.

[41] I. Ullah, M. Hussain, E. Qazi, and H. Aboalsamh, “An automated system for epilepsy detection using EEG brain signals based on deep learning approach,” Expert Syst. Appl., vol. 107, pp. 61–71, 2018.

[42] J. Teo, C. L. Hou, and J. Mountstephens, “Deep learning for EEG-Based preference classification,” AIP Conf. Proc., vol. 1891, 2017.

[43] X. Ma, S. Qiu, C. Du, J. Xing, and H. He, “Improving EEG-Based Motor Imagery Classification via Spatial and Temporal Recurrent Neural Networks,” no. Mi, pp. 1903–1906, 2018.

[44] D. Ahmedt-aristizabal, C. Fookes, K. Nguyen, and S. Sridharan, “Deep Classification of Epileptic Signals,” pp. 332–335, 2018.

[45] R. G. Hefron, B. J. Borghetti, J. C. Christensen, and C. M. Schubert, “Deep long short-term memory structures model temporal dependencies improving cognitive workload estimation,” Pattern Recognit. Lett., vol. 94, pp. 96–104, 2017.

[46] Lin, F. R., Niparko, J. K., and Ferrucci, L. ”Hearing loss prevalence in the United States”. Archives of Internal Medicine, 171, 1851–1853. doi:10.1001/archinternmed.2011.506, 2011.

[47] Linssen, A. M., van Boxtel, M. P., Joore, M. A., & Anteunis, L. J. ”Predictors of hearing acuity: Cross-sectional and longitudinal analysis.” The Journals of Gerontology Series A: Biological Sciences and Medical Sciences, 69, 759–765, doi:10.1093/gerona/glt172, 2013.

[48] Hughson, W., & Westlake, H. ”Manual for program outline for rehabilitation of aural casualties both military and civilian.” Transactions—American Academy of Ophthalmology and Otolaryngology, 48, 1–15, 1944.

[49] Hagerman, B. ”Sentences for testing speech intelligibility in noise.” Scandinavian Audiology, 11, 79–87, doi:10.3109/01050398209076203, 1982.

[50] Moore, BC, ”Dead regions in the cochlea: conceptual foundations, diagnosis, and clinical applications”. Ear and Hearing. 25 2, 98–116, doi:10.1097/01.aud.0000120359.49711.d7, PMID 15064655, 2004.

[51] Moore BCJ. "Dead Regions in the Cochlea: Diagnosis, Perceptual Consequences, and Implications for the Fitting of hearing aids". Trends Amplif, 5, 1–34, doi:10.1177/108471380100500102, PMC 4168936, PMID 25425895, 2001.

[52] Landegger, LD; Psaltis, D; Stankovic, KM, "Human audiometric thresholds do not predict specific cellular damage in the inner ear". Hearing Research. 335, 83–93, doi:10.1016/j.heares.2016.02.018, PMC 5970796, PMID 26924453, 2016.

[53] John MS, Picton TW. MASTER: a Windows program for recording multiple auditory steady-state responses. Comput Methods Programs Biomed. 2000;61:125-150.

[54] Sohmer, H. and Feinmesser, Cochlear Action Potentials Recorded from the External Ear in Man. Annals of Otology, Rhinology & Laryngology, 76, 427-435, 1967, https://doi.org/10.1177/000348946707600211

[55] Christian Bech Christensen, Renskje K. Hietkamp, James M. Harte, Thomas Lunner, and Preben Kidmose, "Toward EEG-Assisted Hearing Aids: Objective Threshold Estimation Based on Ear-EEG in Subjects With Sensorineural Hearing Loss", Trends in Hearing,vol 22,1-13, DOI:10.1177/2331216518816203.

[56] Martin G. Bleichner and Stefan Debener, "Concealed, Unobtrusive Ear-Centered EEG Acquisition: cEEGrids for Transparent EEG", Front. Hum. Neurosci, Volume 11, Article 163, 2017.

[57] Bleichner, Mirkovic, & Debener, "Identifying auditory attention with ear-EEG: cEEGrid versus high-density cap-EEG comparison." Journal of Neural Engineering, 13, 066004, 2016 doi:10.1088/1741-2560/13/6/066004.

[58] Christensen, Kappel, & Kidmose, "Auditory steady-state responses across chirp repetition rates for ear-EEG and scalp EEG." In 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Honolulu, HI (pp. 1376–1379). Piscataway, NJ: IEEE. doi:10.1109/EMBC.2018.8512527.

[59] Dimitrijevic, John, Van Roon, Purcell, Adamonis, Ostroff, Picton, "Estimating the audiogram using multiple auditory steady- state responses" Journal of the American Academy of Audiology, 13, 205–224, 2002.

[60] Butler, "Effect of changes in stimulus frequency and intensity on habituation of the human vertex potential", The Journal of the Acoustical Society of America, 44, 945–950, doi:10.1121/1.1911233, 1968.

[61] Ménard, Gallégo, Berger-Vachon, Collet, & Thai-Van, "Relationship between loudness growth function and auditory steady-state response in normal-hearing subjects", Hearing Research, 235, 105–113, doi:10.1016/j.heares.2007.10.007, 2008.

[62] Debener, Minow, Emkes, Gandras, & De Vos,"How about taking a low-cost, small, and wireless EEG for a walk?" Psychophysiology, 49, 1617–1621, doi:10.1111/j.1469-8986.2012.01471.x, 2012.

[63] Christensen, Harte, Lunner, & Kidmose, ”Ear-EEG-based objective hearing threshold estimation evaluated on normal hearing subjects.” IEEE Transactions on Biomedical Engineering, 65, 1026–1034. doi:10.1109/TBME.2017.2737700.

[64] Zhou, Li, Kilsgaard, Moradi, Kappel, & Kidmose,”A wearable ear-EEG recording system based on dry-contact active electrodes.” In 2016 IEEE Symposium on VLSI Circuits, Honolulu, HI (pp. 1–2), Piscataway, NJ: IEEE. doi:10.1109/VLSIC.2016.7573559, 2016.