EEG based Mental Workload Classification Using Hilbert Huang Transform

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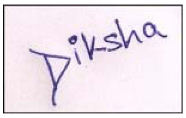
I Diksha Kalra Roll No. 2K18/SPD/03 student of M.Tech (Signal Processing and Digital Design), hereby declare that the project Dissertation titled **"EEG based Mental Workload Classification Using Hilbert Huang Transform"** which is being submitted by me to the department of Electronics and Communication of Delhi Technological University, Delhi in partial fulfillment of requirements for the award of degree of Master Of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship, or other similar title or recognition.



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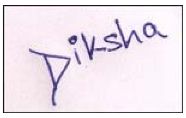

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ABSTRACT

This work aims to classify human stress levels for rest v/s mental arithmetic task. In this work, a publicly available EEG During Mental Arithmetic Tasks dataset is used, comprising of EEG data of 36 participants. A 23-channel EEG device was used for collecting the data while the participants were solving arithmetic problems. This induces a short-time stress which is captured by the EEG device. For efficient classification of stress levels pre-processing is done by applying filters and Independent Component Analysis.

This study employs the Hilbert Huang Transform for determining the Time-Frequency aspect of feature extraction which was not considered in prior studies utilising this dataset. Features namely variance, mean frequency, maximum frequency and sample entropy are computed on the dataset. We also apply the feature selection in order to determine a subset of features which contributes most to the classification accuracy of this proposed method. SVM and K-NN are used as classifiers. This work achieves a maximum accuracy of 91.6% using SVM classifier trained on the complete set of features and 100% accuracy when trained on subset of features. It is observed that accuracy of the model is significantly improved by using the feature selection method. This work highlights the efficiency of time-frequency domain features for mental workload classification.

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Chapter 1

INTRODUCTION

1.1 STRESS

Now a days, people live at a frantic pace and in a nearly constant state of competition. Whether it is office, school, colleges or any situation people, constantly try to prove themselves better than others. At this fever pitch, stress is a natural response to the information being received by the body as potentially harmful or problematic.
Over the evolution of humans, stress is a response when a person deals with difficult situations. Whenever a stressful condition arises, neurons present in our head activate the pitutary gland, which in-turn produces hormones that release corticotropin, which is circulated in the entire body via the sympathetic nervous system. This triggers the adrenal gland which releases adrenaline and cortisol. Adrenaline raises the respiratory rate, and pulse and prepare our muscles to react to perceived danger. Whereas cortisol increases the release of dopamine and blood glucose, which allow us to face challenges.
When stress is in limit, it may prove to be a motivator to help people survive in hostile surroundings and face challenges. As it is said, "Excess of anything is bad", in similar way, when stress increases and becomes a part of our daily routine it is extremely harmful for the body. Stress has degenerative effect over time. A sustained state of emergency affects the neurons associated with memory, as well as inhibiting the release of certain hormones, eventually leading to depression. Some of the secondary affects of stress include insomnia, irritability, anxiety, and high blood pressure. It also leads to premature

aging. It affects digestive system, skin etc. Hence, detecting stress at early stages can be beneficial. Practicing mind fullness, taking help of psychiatrist can reduce stress amounts but, sometimes people are unaware that they are living in a continuous stress state.

In order to identify stress, questionnaires such as Perceived Stress Scale (PSS) [1], NASA Task Load Index (NASA-TLX) [2] were used in some studies [3]. It was seen that these questionnaires are not a reliable measure to be used for stress level predictions, as people don't have complete knowledge about their mental health and it may lead to inaccurate predictions. Another method to identify stress levels without human intervention is by using wearable devices which are portable and measure accurate readings which are then processed to predict stress levels. Some of these wearable devices include Electroencephalogram (EEG), Electrocardiogram (ECG), Electromyogram (EMG), and Electrodermal Activity (EDA). Apart from these eye blink, respiration rate, pulse, pupil size can also be used for stress prediction.

In real time, stress can be induced by mental arithmetic tasks like complex mathematical problems [4], Stroop color test [5], Montreal Imaging Stress Test [6], conducting interviews, impromptu speeches, etc.; thereby creating a situation where a person will definitely experience stress. During these activities the participant wears the device so that it can capture the readings while the subject is under stress. Then the captured data is processed in order to make some meaningful conclusions.

This study focuses on using EEG Signals as a way to measure stress. The following sections of this chapter discuss about the human brain, different areas of brain, EEG, different EEG bands, and application of EEG in other domains.

1.2 BRAIN

Human brain is a three-pound organ which controls the human body. It interprets signals coming from the outside world, thoughts and gives instruction to the other body parts. It controls human emotions, decision making ability, intelligence, creativity and memory. Brain is divided into two hemisphere left and right each governing separate functions. Left brain controls speech, arithmetic ability, writing, etc. whereas right brain controls spatial ability, creativity and so many other functions. There are different lobes in human brain each with distinct ability to control different functions. The different brain regions are described below and is shown in Figure 1.1:

- Occipital Cortex: Responsible for processing of visual information (color,light).
- Parietal Cortex: Interprets signal from vision, hearing, and motor. Interprets language and words.
- Temporal Cortex: Responsible for language processing.
- Frontal Cortex: Responsible for control and monitoring our behavior, emotions, judgement, problem solving skills, and concentration.

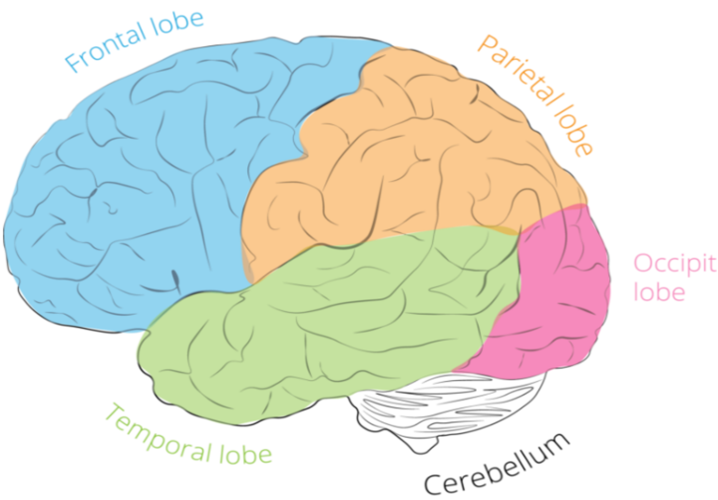

Figure 1.1: Human brain lobes

1.3 ELECTROENCEPHALOGRAM (EEG)

EEG represent the electrical activity of the brain. Whenever, a person is subjected to a stimulus, in response to that the neurons present in the brain fire in sync and this activity is recorded by the EEG device in terms of voltage or current. EEG devices like Emotiv Epoc, Neurosky Mindwave, EEG cap and many more, tracks and record the brain waves. The entire process is non-invasive and safe. In order to capture these waves, electrodes are placed on the human skull in accordance with the 10-20 International system [7]. These electrodes capture the variation of brain waves. Electrodes can be categorized as dry or wet electrodes depending on the presence of gel solution. Number of electrodes ranges from 1 to even 256 electrodes placed on human skull.

The placement of electrodes on skull is depicted in Figure 1.2 where the electrodes on the right side of brain are numbered even and the electrodes on the left side of human skull are represented using odd numbers. Also, different letters stands for different lobes of human brain such as 'F' stands for frontal region, 'O' for occipital, 'P' for parietal, 'T' for temporal, 'C' for central region of the brain. The data captured using the EEG devices is then processed to detect brain abnormalities which may be a sign of brain disorders like epilepsy, Alzheimer's. These waves are able to determine the sleep stages, attention and stress levels of individuals.

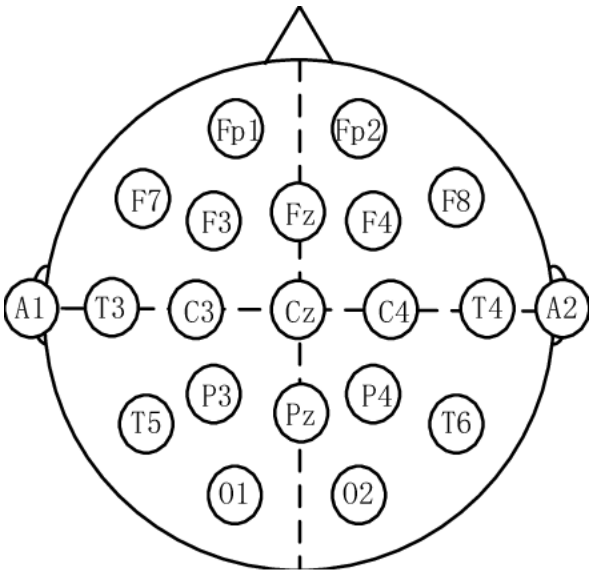

Figure 1.2: Electrode placement according to 10-20 International System

The amplitude of EEG signal is very small in the range of $-100\mu V$ to $+100\mu V$. EEG signals are divided into various sub-signals depending on the frequency range. The different bands and activities associated with them are as follows:

- Delta band (0-4 Hz) : Associated with Deepest level of relaxation, self healing and Deep Sleep
- Theta band (4-7 Hz) : Associated with feeling Deep and Raw Emotions, light sleep or Rapid Eye Movement (REM) sleep.
- Alpha band (8-15 Hz) : Associated with calmness and meditation when eyes are closed, creativity and learning.
- Beta band (16-31 Hz): Associated with conscious state of mind, when a person is in deep thought, alertness, focus, concentration.
- Gamma band (32-50 Hz): Associated with higher processing thoughts and when a person tries to combine two different senses together.

EEG has several advantages over other conventional techniques such as:

- Non-invasive
- High temporal resolution
- EEG devices are portable, less bulky and are more frequently used as compared to Functional Magnetic Resonance Imaging (fMRI), Positron Emission Tomography (PET), Magneto-encephalography (MEG), etc.
- EEG does not aggravate claustrophobia, unlike fMRI, PET, MRS.
- Hardware cost is significantly low.
- EEG is relatively tolerant to subject movement.

1.4 APPLICATION OF EEG SIGNALS

EEG is used in many research fields like sleep study, emotion recognition, stress detection, epilepsy, Alzheimer's and many more because of its non-invasive nature, availability of portable and wearable devices like Emotiv Epoc, NeuroSky Mindwave , cost effectiveness, and good software support to view, process, store, and analyse the EEG signals. Some of the applications of EEG signals in different research areas are described below:

- Emotion Recognition: Recent studies are focusing on classifying human emotions using brain wave. EEG headsets are used for data acquisition. After data collection pre-processing and feature extraction are performed on the EEG data, and then different classifiers are used for determining the accuracy of valance and arousal.
- Sleep stage classification: There are two sleep stages Non-Rapid Eye Movement sleep which ranges from wake fullness to sleep stage and Rapid Eye Movement (REM) sleep when the person is in dream state. Since, EEG bands like delta, theta , alpha, beta reflects the sleep stages they are used for classification. Feature extraction and classification is done in order to classify sleep stages.
- Gaming using EEG device: Games to enhance focus and attentive power are paving way for future gaming prospects. Wearing EEG device while playing games can help determine the focus and alertness of participants. Also, wearing EEG devices while paying games paves way for moving car, objects through power of thoughts. We just have to create a thought in our mind about moving objects and it actually moves.

1.5 MOTIVATION

It is seen that people are more focused on how to make themselves look better by spending so many hours in gym, shopping malls and other similar activities, but they are very little concerned about their mental health and as a result when body shows sign in individuals experiencing stress, anxiety, it generally goes un-noticed. This lack of information and concern about mental health leads to depression and in worst cases it leads to death. With so many suicides happening because of severe stress, anxiety, and depression it becomes need of the hour that individual's should be aware about their mental health and if not some system should be designed which should be able to predict the stress levels of individuals.

The news that we see on TV, time spent on social networking sites like Instagram, Facebook, the content available on internet and human thoughts specifically negative ones, can lead to stress and even depression. If by any means, one can assess the stress level of a person on daily basis while they are performing tasks, or while watching videos or while reading content posted on social networking sites and other browsers, stress level of individuals can be determined. And hence, the content can be customized or doctor's could be notified in case of emergency situations to help individuals during tough times and situations.

Also, if a person becomes anxious or stressed after watching a particular content, then it can be determined, and related videos or information content can be removed from the person's browser window.

Real-Time stress analysis, can help the psychologist to treat individuals having stress and anxiety issues much more efficiently. Stress analysis can be done either by using speech or facial expression or by using physiological signals like EEG, ECG, etc. The latter method is preferred as there is minimal human intervention, presence of portable and accurate devices to capture and process the data.

1.6 PROBLEM STATEMENT

In this fast paced life each and every individual at some point of time experiences stress. Experiencing too much stress can lead to health issues and it even leads to depression. Keeping this issue in mind, a methodology to predict stress levels of individuals is presented in this work.
The main objective of this research work is to classify human stress efficiently for rest v/s mental arithmetic tasks. Mental arithmetic task is used to induce acute stress in participants and the brain signals are captured using an EEG device. For efficient classification of stress, various factors play an important role like, pre-processing techniques employed for noise and artefacts removal, features extracted from the data set and lastly, the classifiers used for the classification. This work employs the EEG During mental arithmetic tasks dataset [8]. Feature Selection techniques are also applied in order to select a subset of features which play a significant role in stress level classification.

The rest of the report comprises of eight major chapters. Chapter 2 introduces the recent and relevant literature that has motivated this study. Chapter 3 focuses on the various pre-processing and signal processing techniques that are commonly applied for EEG signal processing. Chapter 4 describes the different feature domains and features that can be computed in each domain. This is followed by the feature selection techniques discussed in chapter 5, that can be applied in order to determine the prominent set of features which play a major role in determining the classification accuracy. Chapter 6 briefly describes the machine learning algorithms, followed by chapter 7 which elaborates the methodology adopted in this study. We report the results obtained by our proposed method in chapter 8, comparing our work with other authors. Finally we conclude our findings and share insights for future work in chapter 9.

Chapter 2

RELATED WORK

In literature, different techniques are available for stress measurement namely subjective analysis and objective analysis. In subjective analysis questionnaire or interviews conducted by experts are used to predict the stress levels of participants. Perceived Stress Scale (PSS) [1], NASA-TLX [2], Stress response inventory (SRI) [9] are few sample questionnaires that are available for stress prediction. Objectively stress can be measured using physical as well physiological signals. Physical changes can occur in human beings while the are experiencing stress in terms of facial expression may change, respiration rate, speech, pupil size, eye blink rate etc. Physiological signals like Electroencephalography (EEG), Electrocardiography (ECG), Electrodermal Activity (EDA), Electromyography (EMG) can also be used for stress prediction. In [10] author used both questionnaire and EEG data for stress level classification.

Based upon the duration of exposure to stimuli, stress can be Perceived (long-term) and Acute (short-term). Perceived stress occurs when a person is under prolonged stress conditions like a demoting career, or a failed marriage, poverty, and Post Traumatic Stress Disorder (PTSD). In [11] author classified the perceived mental stress using the 4-channel EEG device. They considered two scenarios, pre-activity phase and post-activity phase. The subjects have to give presentation in front of other people and their EEG signals were captured before presentation, during and after the presentation. Accuracy of 92.85% and 64.28% was achieved using SVM, Naive Bayes and MLP. On the hand, acute stress is the intense, overwhelming and unpleasant response when a person experiences momentary stress like a lapse at work, or failing an exam etc. Since Acute stress envelopes activities like mental arithmetic tasks, mock interviews, public speaking, etc., it can be measured easily. Several studies measuring acute stress are described below. Fan et al. [12] proposed a study to detect acute stress by conducting cold presser challenge and lukewarm hand immersion challenge on 32 participants using EEG device. EEG signals were recorded for pre, press and post states. Recurrence Quantification Analysis (RQA) measures were computed as features and classification was done using SVM, and Least Absolute Shrinkage and Selection Operator (LASSO).

Efficient classification of stress using EEG signals depends on various factors such as artefact removal technique employed to remove noise present in the data, features extracted from clean data and machine learning models employed for classification of stress into different states.

Artefacts like power line noise, eye movements, muscular movements, faulty electrodes and many more contaminate the EEG signals when recording the data during a task. It is of high importance that the data should be clean for accurate prediction of stress states. Thus, researchers implement various techniques like filtering, thresholding, Discrete Wavelet Transform (DWT), Independent Component Analysis (ICA) for artefact removal. Once the EEG data is clean, we can investigate different features and classifiers for effective stress prediction. We describe some of the prominent researches in the field of stress prediction using EEG signals in this section.

Hafeez et al. [13] used a 50 Hz notch filter for removal of power line noise, and applied ICA, and filtering techniques for removal of ocular and muscular movement noise. Utilising clean EEG data; they evaluate the Power Spectral Density of Alpha, Beta, and Theta bands for 14 subjects. The study concludes with a remark of 85% of students experiencing stress before the examination.

Sharma and Chopra [14] employed Instantaneous Frequency of various Intrinsic Mode Functions (IMFs) obtained by applying Hilbert Huang Transform (HHT) as a feature. The data was cleaned using wavelet decomposition and a joint combination of 0.75 Hz high-pass filter and 45Hz FIR filter. This work reports a maximum accuracy of 92.86% using the SVM classifier.

Blanco et al. [15] propose a real-time stress prediction system using the Emotiv

Epoc Headset on 18 subjects. The raw EEG data obtained from headset was cleaned by subtracting the least-squares line of best fit, and then the data was passed through a bandpass filter network of Chebyshev type II filters. Band Power and Root Mean Square (RMS) value of signal were extracted as a feature from the artefact free data, and Logistic Regression (LR), QDA and K-NN were used for prediction achieving a maximum accuracy of 78.70%.

Hasan and Kim [16] employed the publically available DEAP dataset comprising of 32 subjects for stress prediction. The data was averaged out to standard reference, and bandpass filter of range 4-45 Hz was employed for data cleaning. Various time-domain features like RMS, Peak-to-Peak value, Kurtosis, Skewness, Hjorth parameters like Mobility and Complexity along with time-frequency domain features like Power Spectral Density (PSD), Energy and Wavelet sum of the entropy of different EEG bands were computed. This work achieves a classification accuracy of 73.38% for KNN classifier.

Nagar and Sethia [10] proposed a real-time stress prediction system, using a single electrode Neurosky Mindwave device and collected data of 63 students. Thresholding technique was employed to remove EEG data having an amplitude above 100 uV, and frequency components above 50Hz were removed using a suitable low-pass filter. The band power ratio of different EEG bands, namely Alpha, Beta, Delta, and Theta, was computed as features. PSS-14 questionnaire response of students along with extracted features was given as input to the KNN classifier, achieving a maximum accuracy of 74.43%.

Diez et al. [17] employed Empirical Mode Decomposition (EMD) method to extract the time-frequency domain features. Data of 7 subjects performing five different mental tasks was collected using a suitable EEG device. Various features were computed namely variance, root mean square value, complexity, shannon entropy, mean and central frequency. These features were given as input to linear discriminant and neural network classifiers achieving a maximum accuracy of 91%.

Vanitha and Krishnan [18] extracted time-frequency domain features using Hilbert Huang Transform (HHT). Data of 6 healthy subjects was collected using the Emotiv Epoch EEG headset while the subjects were solving mathematical questions in limited time. NASA-TLX stress scores were also filled by the subjects and are employed for classification of stress levels. SVM was used for classification achieving a maximum accuracy of 89.07%.

Ahammed and Ahmed [19] used the publically available EEG During Mental Arithmetic Task [8] database for stress prediction during rest and mental task. Multivariate Multiscale Entropy (MMSE) was used as a feature, and the channel selection was applied to determine stressed regions of the brain. The SVM classifier was employed achieving 90% accuracy for rest v/s mental stress and 87.5% accuracy for good v/s bad counting.

Chapter 3

BACKGROUND

Efficient Prediction of Stress depends upon the following factors:

- Pre-Processing Techniques
- Signal Processing Techniques
- Features Extraction
- Classification

In this chapter various Pre-Processing and Signal Processing Techniques used in Stress Prediction are described.

3.1 PRE-PROCESSING TECHNIQUES

EEG signals get easily contaminated with artefacts due to there sensitive nature, especially when the sources are not brain. There could be various technical or person's own behavioural and physical activity which can cause artefact to occur. The former may include power lines noise (50/60 Hz) , or because of broken EEG electrodes or leads. Artifacts can even occur due to placement of excessive gel on electrodes, impedance fluctuation of EEG device or in-terms of electromagnetic noise which can effect EEG equipment.

Various other reasons could be Person's own behavioral and physical activities related to electrical activity generated by heart, blinking and movement of eyes, stretching of muscles or body movement and sweating and so on which could result in artifact generation in EEG Signals. These artifacts can be inspected manually by expert eyes, but automatic artifacts detection is encouraged in automated system designs, otherwise artifacts can corrupt the results. A wide range of artifact removal methods exists and are described as follows:

3.1.1 Band-Pass Filter:

One of the most common and highly applied technique to remove EEG artifacts is to pass the signal through a filter and only keeping the signal of frequency range desired. Generally, a band-pass filter in range 0.5Hz-45 Hz is used and the rest of the frequency range data is ignored.

3.1.2 Notch Filter:

Power lines noises can be eliminated by applying a 50/60 Hz notch filter. Notch Filter is designed such that it eliminates a particular frequency component from the signal under observation. Unlike, Band-pass filter which removes a range of frequencies, notch filters are highly frequency selective. They are widely used to remove power line noises from the signals.

3.1.3 Rejection method:

This is a simple method in which the contaminated signal is simply discarded. But it also results in loss of information. For this method to work, the signal is first divided into different frequency bands using the various decomposition methods available like wavelet transform, Short-time Fourier transform, etc. Once, the signal is decomposed into desired frequency levels, the sub-signals with artifacts can be discarded.

3.1.4 Subtraction method:

Every noisy signal can be represented as a combination of original signal and the noisy signal. Subtraction method, simply subtracts the noisy part from the contaminated signal. For better results the noisy signal should be modelled as close to the actual noisy signal. Since, it is difficult to model the noise, available probability density distributions like Gaussian, Rayleigh, etc. can be employed. Subtraction method is applied for removing the artifacts produced by eye movement.

3.1.5 Simple amplitude threshold:

This is a relatively simple method in which the threshold value for positive and negative peaks is set. Data out of this range is considered artifact. The threshold value should be chosen carefully, so that the actual data without noise is not affected. Any data value exceeding the set threshold value will be saturated to that particular threshold value. It is also known as Saturation Method. EEG data lies in range of $-100\mu V$ to $100\mu V$ and hence, data outside this range can be considered as artefact.

3.1.6 Wavelet Transform (WT):

Wavelet Transform is a method to represent the signal in time-frequency domain. It has better time-frequency resolution as compared to Fourier Transform and Short Time Fourier Transform. Wavelet Transform is used in various researches to remove signal artifacts. In Discrete Wavelet Transform (DWT), the signal is passed through a series of low pass and high-pass filters and the signal is decomposed into various frequency bands. After, decomposing the signal, thresholding is applied to remove the signal with artefact and the artefact free signal is again added to reconstruct the EEG signal.

3.1.7 Gradient Criterion:

Gradient is a mathematical operator which computes the point-to-point difference of value of signal with respect to inter-sample time. This technique can be employed to remove artifacts from the signal.

3.1.8 Joint Probability:

This method employs computing the probability of occurrence of a given value of point in time in a specific channel and segment relative to global probability of occurrence of such value.

3.1.9 Independent component analysis (ICA):

ICA performs blind source separation to split components that have statistical difference. This technique is based on linear decomposition of the signal containing artifacts. The ICA method is based on assumptions that the time series data recorded on the scalp:

- are spatially stable signals of activities which are not occurring in the part of brain, and are due to artificial sources.
- the summation of potentials arising from scalp, body, brain is linear at electrodes.
- propagation delay from source to the electrodes is negligible.

The equation describing ICA working is as follows: W.x=U where W is the un-mixing matrix, x is the EEG signal and U is the source of generation of signal. This un-mixing matrix W decomposes or linearly un-mixes the multi-channel EEG data into sum of temporally independent and spatially fixed components. The rows of output, U=Wx , are the time courses of activation of the ICA components. The columns of the inverse matrix, inv(W), give the relative projection strengths of the respective components at each of the scalp sensors. These scalp weights give the scalp topography of each signal and provide source location. Some useful Heuristics:

- Eye movement should project mainly to frontal sites with a low-pass time course.
- Eye blinks should project to the frontal sites and have large activation.
- Temporal muscle activity should project to temporal sites with a spectral peak above 20Hz.

After determining the artefacts based on the source location, remove the artefacts and reconstruct the signal. The signal will be free from artefacts.

3.2 SIGNAL PROCESSING TECHNIQUES

In order to gain more information about the data, we transform the data from one domain to another. There are several transforms available in literature in order to do so. In this section we will be focusing on the transforms that convert time domain data to frequency domain and vice-versa.

3.2.1 Fourier Transform (FT)

Fourier Transform is a mathematical technique that transforms the time domain signal f(t) into frequency domain signal $F(\omega)$ and vice versa.

Although Fourier Transform is easier to implement, we cannot acquire the time and frequency values of the signal simultaneously, i.e., if we are working in the time domain, there is no information about the frequency domain and vice versa. Also Fourier Transform cannot be used when the signal is non-stationary. Non-stationary signals are those whose frequency vary with time. Fourier Transform of a signal is represented as:

$$F(\omega) = \int_{-\infty}^{\infty} f(t) \exp^{-j\omega t} \, dt \tag{3.1}$$

$$f(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} F(w) \exp^{i\omega t} \, d\omega \tag{3.2}$$

For discrete time signals Discrete Fourier Transform (DFT) is used and is implemented using the Fast Fourier Transform (FFT) algorithm. FFT is a commonly used technique to compute spectral analysis of EEG signals.

3.2.2 Short Time Fourier Transform (STFT)

Since the natural signals are all non-stationary signals; hence, they cannot be handled by Fourier Transform. Short-Time Fourier Transform overcomes this limitation. STFT is a sequence of Fourier Transform of windowed signals. In STFT, there is a sliding window whose length is such that each sub-signal in that window is stationary. As a result, the Fourier Transform can be applied to each sub-signal. STFT of a signal x(t) with window function $w(t-\tau)$ is represented as :

$$STFTx(t)(\tau,\omega) = X(\tau,\omega) = \int_{-\infty}^{\infty} x(t)\omega(t-\tau)\exp^{-j\omega t} dt \tag{3.3}$$

The problem with STFT is that one cannot determine the exact time-frequency representation of a signal. This principle is named as the Heisenberg Uncertainty Principle. One cannot determine what spectral components exist at what time instance. What one can know is the time intervals in which a certain band of frequencies exist, which is a resolution problem. In STFT, our window is of finite length. Thus it covers only a portion of the signal, which causes the frequency resolution to get poorer. We no longer know the exact frequency components that exist in the signal, we only know a band of frequencies that exist. If the length of the window in the STFT is selected as infinite, then it behaves just like Fourier Transform and we will be having perfect frequency resolution but zero time resolution. Since the signals are non-stationary so in order to apply FT window size should be finite. Since, the window length of STFT is fixed a prior, there always exist a trade-off in the time-frequency resolution. This limitation is overcome by the Wavelet Transform.

3.2.3 Wavelet Transform

Wavelets are functions that have “wave” above and below the x-axis, and have the following properties:

- varying frequency
- are of limited duration
- have an average value of zero

In order to obtain simultaneous time and frequency resolution, the wavelet transform is used. A wavelet function is characterized by a scaling parameter ’a’ and translation parameter ’b’. By changing the value of ’a’ mother wavelet is represented at different scales and by changing the value of ’b’ mother wavelet is translated in the right and left directions.

Types of Wavelet Transforms:

Continuous Wavelet Transform:

In this, first of all, a mother wavelet is chosen, then at a particular scale, it is translated along the entire EEG signal x(t). At each and every time instant the correlation between mother wavelet and signal x(t) is determined. The same procedure is repeated by changing the value of the scaling 'a' parameter.

$$X\omega(a,b) = \frac{1}{|a|^{1/2}} \int_{-\infty}^{\infty} x(t)\phi(\frac{t-b}{a})dt \tag{3.4}$$

Discrete Wavelet Transform:

The DWT of a signal x(n) is determined by passing the signal through a series of filters where g(n) is the high-pass filter and h(n) is the low pass filter. At each stage the scale value and the data points available in the EEG signals are reduced to half. The output is obtained in terms of detailed and approximation coefficients. As a result, the signal x(n) is represented in the form of coefficients D_1, D_2, D_3, A_3.

Although, wavelet transform has better time-frequency resolution in comparison to STFT

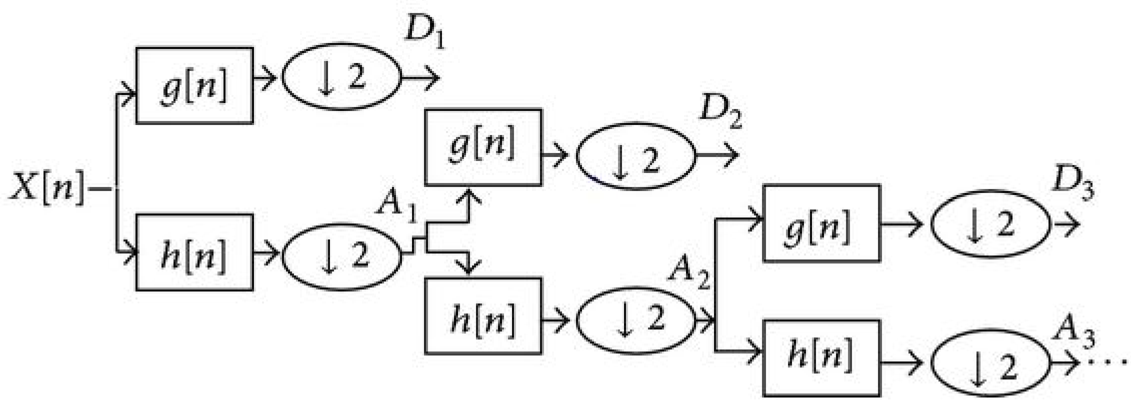

Figure 3.1: Filter method

as the window size is flexible, it still has some limitations. In order to apply the transform on the signal x(t) one has to fix the basis function $\phi(t)$ in advance i.e. one has to select the mother wavelet in-advance. Since, the real signals are unpredictable it may happen that the chosen wavelet may not perform as expected. These transforms are non-adaptive. In contrast adaptive transforms are the one, which change their parameters according to the signal. One of the transform belonging to class of adaptive transform is Hilbert Huang Transform which is discussed in the below section.

3.2.4 Hilbert Huang Transform (HHT)

Hilbert-Huang Transform is a two step method, used for the analysis of non-linear and non-stationary signals.

- The first step, comprise of evaluating the Empirical Mode Decomposition (EMD) of the time series data in order to obtain sub-signals which are also represented in time known as Intrinsic Mode Functions (IMFs).
- The second step, is to compute instantaneous frequency of IMFs by applying the Hilbert Spectral Analysis (HSA).
- These two steps when combined represent the signal in time-frequency domain.

EMD and HSA which characterize the HHT are discussed below.

Empirical Mode Decomposition

Empirical Mode Decomposition (EMD) separates a signal in several Intrinsic Mode Functions (IMFs). This method is termed empirical because it is an algorithm which has no strong mathematical proof, in contrast with theoretical decomposition like that based on the Fourier Transform. So it has some advantages when dealing with complicated real-life signals, which are often non-stationary. For non-stationary signals, applying a band-pass filter over a certain frequency range may not be ideal, as it will likely attenuate some aspects of the signal you want to preserve. In EMD, the data is represented in time-domain only. IMFs are the fancy names given to the signal components identified by EMD because they satisfy the following criteria:

- In the whole data set, the number of extrema and the number of zero-crossings must either be equal or differ at most by one.
- At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

Resultant IMFs therefore are generally monotonic between their peaks (above 0) and troughs (below 0). Therefore, the Hilbert transform, which is commonly used to extract the instantaneous phase and amplitude of a signal, will yield clean results. This strategy of applying EMD and Hilbert transform to get instantaneous frequency of a non-stationary function is called the Hilbert-Huang Transform.

Determining EMD of a Signal x(t)

1. Find the local extrema of x(t).
2. Find the maximum envelope e+(t) of x(t) by fitting a natural cubic spline through the local maxima. Then, repeat this step to find the minimum envelope, e(t), by using the local minima.
3. Compute an approximation to the local average:
$$m(t) = (e + (t) + e(t))/2 \tag{3.5}$$
4. Find the proto-mode function:
$$pi(t) = x(t) - m(t) \tag{3.6}$$
5. Check if pi(t) is an IMF. The properties for a signal to be considered as an IMF are given below.
    - The number of extrema and the number of zero crossings may differ by no more than one.
    - The local average is zero. The thresholds chosen to set this condition are critical to avoid over or under-training.
    - To avoid the extraction of accidental IMFs, the conditions must be accomplished in at least two to three consecutive iterations (three in our case).

6. If pi(t) is not an IMF, repeat the EMD sifting process by setting:

$$x(t) = pi(t) \tag{3.7}$$

If pi(t) is an IMF then set:

$$IMFi(t) = pi(t) \tag{3.8}$$

EMD generate finite number of Intrinsic Mode Functions (IMFs). IMF are time-varying single frequency functions. Highest frequency component is captured by first IMF and as the number of IMFs increase the frequency variation decreases.

Hilbert Spectral Analysis

The second step of HHT is Hilbert transform that produces an orthogonal pair for each IMF that is phase shifted by 90 degrees. Each IMF set and its orthogonal pair can be used to estimate the instantaneous variation in magnitude and frequency of the IMF with respect to time. Thus, HHT is very useful to extract information from nonlinear and non-stationary time series data such as EEG. Instantaneous Frequency obtained using Hilbert Transform are represented as give below.

$$w(t) = \frac{1}{2\pi}\frac{d\theta(t)}{dt} \tag{3.9}$$

$$\theta(t) = arctan(\frac{Hx(t)}{x(t)}) \tag{3.10}$$

where $H[.]$ is the Hilbert Transform, θ is the phase and $x(t)$ is the IMF.

3.2.5 Comparison of different Transforms

Transform/Features	FT	WT	HHT
Basis	a priori	a priori	adaptive
Representation	Energy-Frequency	Energy-Time-Frequency	Energy-Time-Frequency
Non-linear data	No	No	No
Non-stationary data	No	Yes	Yes
Frequency	Global frequency	Regional frequency	Local frequency

Chapter 4

FEATURES

Broadly there are three different types of features:

- Time Domain Features
- Frequency Domain Features
- Time-Frequency Domain Features

The main difference lies in the fact that one can directly compute the features if the time-series EEG data available i.e, in Time Domain, whereas when computing features in Frequency domain or in Time-Frequency domain one needs to first apply some transform in order to convert the data from one domain to another and then on the transformed data features are computed. This chapter describes the different features that can be calculated on the EEG data for different domains.

4.1 TIME DOMAIN FEATURES

Time Domain features represent the data distribution in terms of a single value. A distribution consisting of large data points can be represented in terms of it's mean and standard deviation which are the two most widely used time domain features. Different Time domain features computed on EEG signals are described in this section.

4.1.1 Mean

Mean value of a signal $x(t)$ represents the average value of the signal about which rest of the data points are distributed. values smaller than mean value are present on the left side of mean and the values which are larger than mean value are present on the right of the mean or centre value. In other words, the entire dataset can be distributed around the mean value of the dataset. Mean value of the signal x(t) is defined as sum of all the values present in the signal divided by the number of values present in the signal.

$$\mu = \frac{1}{t}\sum_{i=0}^{t} x(i) \tag{4.1}$$

4.1.2 Standard Deviation

Standard deviation describes the deviation of values from the centre point or the mean value of the dataset. A low standard deviation means the values are close to the average value and a high standard deviation means that the values are more spread-out. It is calculated by first computing the deviation of values present in the signal x(t) from the mean value μ, squaring the difference of the deviations and then taking the average of it.

$$\sigma = \sqrt{\frac{1}{t}\sum_{i=0}^{t}(x(i) - \mu)^2} \tag{4.2}$$

4.1.3 Maximum and Minimum Value

Maximum and minimum values gives information about the peak values that are present in the dataset.

$$x_{max} = max(x(t)) \tag{4.3}$$

$$x_{min} = min(x(t)) \tag{4.4}$$

Where x(t) represent the series of data.

4.1.4 Peak to Peak value

Peak to Peak represent the range in which all the values lie. It is also a statistical parameter which helps to represent the entire EEG data in terms of a single value. Peak to Peak value can be computed as:

$$x_{p_p} = x_{max} - x_{min} \tag{4.5}$$

4.1.5 Sample Entropy

Entropy is a non-linear feature which quantifies the complexity of time-series data. It is a measure of uncertainty or the chaos of the system. For an ordered system the value of entropy is zero. For EEG signals, entropy quantifies the repeatabilty of the waveform pattern. It also describes the information present in the signal. Entropy computed on time-series data is known as sample entropy.

For computing entropy, the entire EEG signal is divided into smaller segments using a window of specific length and then the similarity of particular segment to the rest of segments is computed. In other words, probability of occurrence of segment under consideration is computed.

4.1.6 Kurtosis and Skewness

EEG data of normal and healthy people has a normal distribution and such a distribution can be represented in terms of two statistical parameters that are mean and standard deviation. In order to well define the distribution two more parameters which are kurtosis and skewness are computed as they characterize the location and variability of the dataset. Kurtosis determines that whether the data is high tailed or low tailed, in other words whether the dataset has out liners or not.

On the other hand, skewness is the measure of asymmetry of data distribution about the mean value. The data distribution can be right skewed or left skewed. These parameters are mathematically represented as:

$$\text{Skewness} = \frac{\sum_{i=1}^{N}(x_i - \mu)^3/N}{\sigma^3} \tag{4.6}$$

$$\text{kurtosis} = \frac{\sum_{i=1}^{N}(x_i - \mu^4/N}{\sigma^4} \tag{4.7}$$

4.1.7 Hjorth Parameters

There are three different Hjorth parameters namely Activity, Mobility, and complexity which determine the statistical properties of the time series. Activity represents the variance of signal in time domain or signal power. Mobility is defined as the ratio of activity of the derivative of the signal to the activity of the signal. It represents the centre frequency or the proportion of standard deviation of power spectrum. Complexity is defined as the ratio of Mobility of the derivative of the signal to the mobility of the signal. It represents the variation of frequency content of a signal. Mathematically, these parameters are represented as:

$$Activity = \sigma^2(x(t)) \tag{4.8}$$

$$Mobility = \frac{\sigma(\frac{d(x(t))}{dt})}{\sigma(x(t))} \tag{4.9}$$

$$Complexity = \frac{Mobility(\frac{d(x(t))}{dt})}{Mobility(x(t))} \tag{4.10}$$

4.2 FREQUENCY DOMAIN FEATURES

Unlike Time domain where features can be directly computed on EEG time series, when working in frequency domain the EEG data is first converted from amplitude versus time to amplitude versus frequency representation. This can be achieved by using transforms such as Fourier Transform, cosine transform etc. Once, we have data in frequency domain various features can be computed which are known as Frequency domain features.

4.2.1 Power Spectral Density

Power spectral density (PSD) represents the signal variations or energy as a function of frequency. Since EEG Signals are characterized by different waves with varying frequency values, PSD plot is used to determine which of the frequency bands are more active in a particular task or situation. Like, when working on emotion detection using EEG signals it is observed that theta, and beta values are more profound as compared to rest of the bands.

PSD is computed using the Welch's method [20], where the entire data is first divided into small segments, with a maximum overlap of half the values in the segment. After that Periodogram is computed on each segment and the average value of periodogram is calculated. Periodogram is computed using the magnitude square of the Fast Fourier Transform (FFT) of segment taken one at a time.

4.2.2 Band Power

Band-power represents which particular EEG band is active at a given time. For example, when considering sleep studies the delta band power is high when the person is asleep but the same band-power decreases when the person is wide awake. So, band-power plays an important role in determining which bands are particularly active in specific tasks.

When PSD is computed on a single band for example, PSD of a signal having frequency range of 0.5Hz-4Hz gives the band-power of that signal. In similar way, band-power for delta, theta, alpha, beta and gamma bands can be calculated.

4.2.3 Relative Band Power

Yet another important feature in frequency domain is the relative band power. It characterizes the contribution of a particular band with respect to all the bands. For example, beta/alpha ratio is a well known index of mental arithmetic tasks. Relative band power is computed as :

$$Relative\ Power = \frac{Absolute\ Power\ of\ band}{Total\ Power} \tag{4.11}$$

4.2.4 Spectral Entropy

Spectral entropy represents the complexity of the system. In order to compute the spectral entropy, firstly the PSD of entire EEG signal is computed and then PSD of particular band is calculated. Then normalized PSD of a band is computed by dividing the PSD of particular band by PSD of EEG signal. Spectral entropy is represented as:

$$SE = -\sum_{f=0.5}^{30} P(f) log[P(f)] \tag{4.12}$$

where P(f) is the normalized PSD.

4.2.5 Correlation

Correlation of EEG signal is defined as the distance between pair of electrodes. Since, each electrode is placed at a different location and captures the signal related to that particular brain region, correlation can be used as a feature to determine the physical distance between the pair of electrodes like Fp1 and Fp2.

4.3 TIME-FREQUENCY DOMAIN FEATURES

Recent studies are focusing on the time-frequency aspect of signals as they help in determining the time at which a particular frequency is present. It is specially helpful in studies where the response time is to be determined in response to a stimulus. In order to determine the time-frequency domain features simultaneous information of time-frequency and amplitude is required which can be obtained using Wavelet Transform (WT) and Hilbert-Huang Transform (HHT). Both of these transforms decompose the signal into sub-signals, each sub-signal represents a particular frequency range. Hence, features belonging to time and frequency domain can be computed on these sub-signal thus, giving rise to the time-frequency domain features. Some of the time-frequency features are described

4.3.1 Variance

Variance of each and every sub-signal is computed as it represent the deviation from the mean value. It is one of the most used feature in BCI.

4.3.2 Shannon Entropy

Entropy is the measure of information stored in the signal. It is computed on the data that is obtained after applying time-frequency transform.

4.3.3 Lempel Ziv Complexity

Lempel Ziv Complexity (LZC) quantifies the complexity of a signal. It is analyzed in terms of spatio-temporal patterns. It computes the number of different segments that are present in a signal.

4.3.4 Average Instantaneous Frequency

One of the widely used feature in time-frequency domain is average instantaneous frequency. Since, the value of frequency is present at all instants of time, average value of instantaneous frequency is used. It represents the center or mean frequency of the signal. Average value of instantaneous frequency is calculated for each and every sub-signal.

$$f_{avg} = \frac{1}{N} \sum_{i=0}^{N} x(i) \tag{4.13}$$

4.3.5 Maximum Instantaneous Frequency

Maximum instantaneous frequency represents the bandwidth of the signal. It is represented as the maximum value of frequency that is present in the signal.

$$f_{max} = max(X(\omega)) \tag{4.14}$$

where $X(\omega)$ represents the signal in frequency domain.

Chapter 5

FEATURE SELECTION METHODS

It happen sometimes that the number of features become too large and not all features contribute much to the accuracy of the algorithm. In other words, some of the features can be removed without affecting the classification accuracy. There are various methods present which works in this direction and are known as Feature Selection Methods. These methods reduce the computational cost, curse of dimensionality, and in some cases improve the classification accuracy of the model. Also a feature set consisting of large number of irrelevant feature can increase the computational time and may cause over-fitting. Over-fitting occurs when training accuracy of a model is much higher than the testing accuracy. Broadly there are three categories of selection methods:

- Filter Based Method: This method uses some metric like correlation between features and output to filter out features.
- Wrapper-based: It selects a set of features by considering the problem as a search problem.
- Embedded: These methods use algorithms which have selection methods embedded in them.

All these methods can be further divided into sub-types depending on whether the output variable is continuous or categorical. Some of the widely used feature selection Methods are described in this section.

5.1 PEARSON CORRELATION

This method belongs to the class of filter-based method. It determines the correlation between output or target values and the features extracted from the dataset. After computing correlation top N features are selected.

$$r = \frac{\sum(x-\bar{x})(y-\bar{y})}{\sqrt{\sum(x-\bar{x})^2\sum(y-\bar{y})^2}} \tag{5.1}$$

5.2 CHI-SQUARE

This method is also a filter-based method but, the output variable is categorical. In this method the metric chi-square is computed in order to select relevant features from the feature set. Features with the best chi-square value are selected.

$$\chi = \frac{(Observed\, frequency - Expected\, frequency)^2}{Expected\, frequency} \tag{5.2}$$

5.3 FISHER CRITERIA

This method selects those features which effectively separate two classes. Fscore is computed and the larger the value of Fscore the better is the feature.

$$Fscore(d) = \frac{(\mu_i - \mu_j)^2}{(\sigma_i)^2 - (\sigma_j)^2} \tag{5.3}$$

where μ is the mean value for two class i and j, and σ is the standard deviation corresponding to 'd' feature. The numerator term represents the between class variance and the denominator is with-in class variance. The value of Fscore will be high when numerator is large and denominator value is small. Features having high Fscore value are selected.

5.4 ANALYSIS OF VARIANCE (ANOVA)

ANOVA is a variance based method. It determines the sensitivity of the features to distinguish between classes. This test computes two parameters F-statistic which is the ratio of mean squares and p-statistic which is the Cumulative Distribution Function (CDF) of F. This test considers a hypothesis,H_0 all mean values are equal and H_1 not all mean values are equal. On the basis of the value obtained from F-statistic this hypothesis is accepted or rejected. Larger the value of F-statistic better is the feature.

5.5 RECURSIVE FEATURE ELIMINATION (RFE)

This method belongs to the class of wrapper-based method. It is a recursive method where the set of features becomes smaller and smaller with each iteration. At each iteration the feature set is pruned until the desired number of features are achieved.

Chapter 6

Machine Learning Algorithms

Machine learning is a concept which allows the machines like computer, phones, etc. to learn from experiences and examples. Broadly, machine learning algorithms are divided into three different types namely Supervised, Unsupervised and Reinforcement Learning.

- Supervised Learning is the one where learning is done in presence of a teacher or mentor who guides and help you get-through. In similar way, while applying supervised learning the output values are known in advance or in other words the dataset is labelled so, the machine tries to learn from the training data and once done it makes prediction on the testing data. Supervised learning is further categorized in two sub-types Regression and Classification. When the output value is continuous it is Regression based supervised learning but, when the output is categorical like yes or no, 0 or 1 it belongs to the class of Classification based supervised learning.
- Unsupervised learning does not take place in presence on teacher, the student learns from experience. In other words, the dataset is not labelled, the machine tries to find some patterns or relationship among the data and cluster the data according to the similarity.
- Reinforcement Learning uses the reward system. The machine learns from its experiences. If the the answer is correct it gets reward and if not it is penalized. Depending on the number of rewards the machine learns the correct behavior and trains it self.

This chapter discusses the various Supervised Learning algorithms.

6.1 SUPPORT VECTOR MACHINE

A Support Vector Classifiers (SVC) is a type of soft margin classifier. The name SVC comes from the fact that observations or values on the edge and within the soft margin are known as support vectors. For 2-D data the svc is a line. For 3-D data svc is a plane. They can also be used for multi-dimensional data. The goal of SVC is to maximize the margin i.e., the distance of hyper-plane separating the four or more classes from the points in the respective classes. SVC depends on its support vectors. SVC can handle out-liners and, since they allow mis-classification, this algorithm can also handle overlapping data. When the data is inseparable or the data-points are overlapping, then Support Vector Machines (SVM) are used. It takes the data in low dimension and transforms it into a high-dimension where the data can be easily separated with the help of SVC. Support vector machines use the kernel function or the polynomial function to systematically find the SVC in higher dimensions.

6.1.1 Polynomial Kernel Function

Polynomial kernel is represented as :

$$(a * b + r)^d \tag{6.1}$$

Where a and b are the two classes, r is the polynomial coefficient and d is the degree of polynomial. The value of r and d is determined by cross-validation and once the values are set the values present in classes a and b are mapped to higher dimension.

6.1.2 Radial Basis Function Kernel

The most commonly used kernel is the Radial Kernel, also known as the Radial Basis Function (RBF) Kernel which is represented as:

$$e^{-\gamma(a-b)^2} \tag{6.2}$$

where a and b refers to two different classes, the value of parameterγ is determined by cross-validation. RBF finds SVC in infinite dimensions.

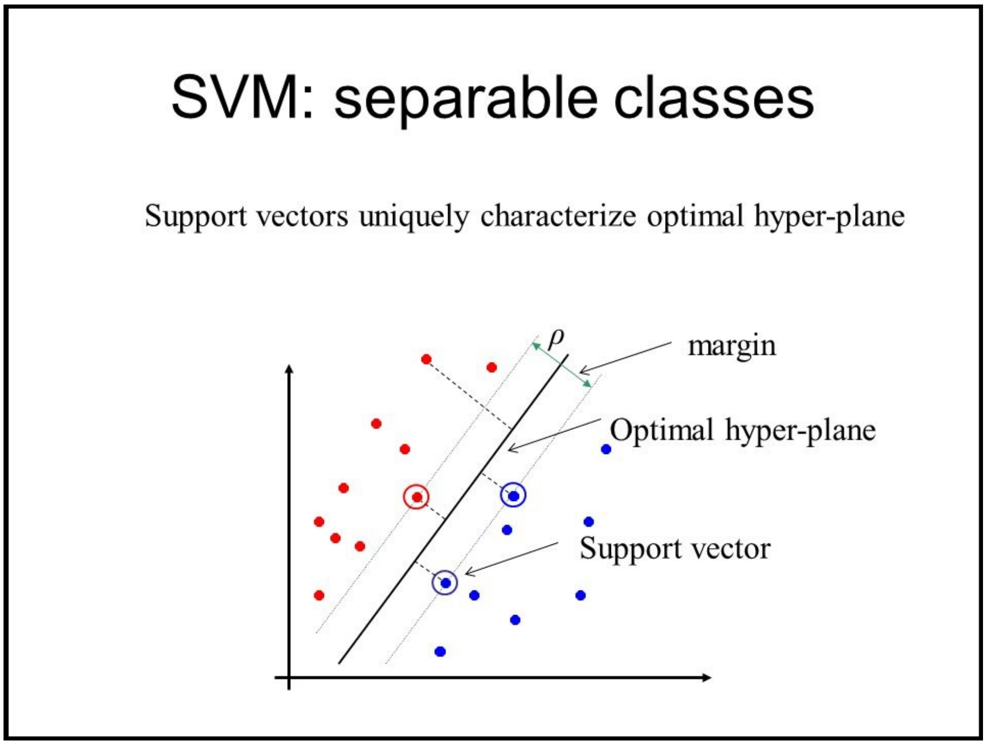

Figure 6.1: SVM applied on separable data

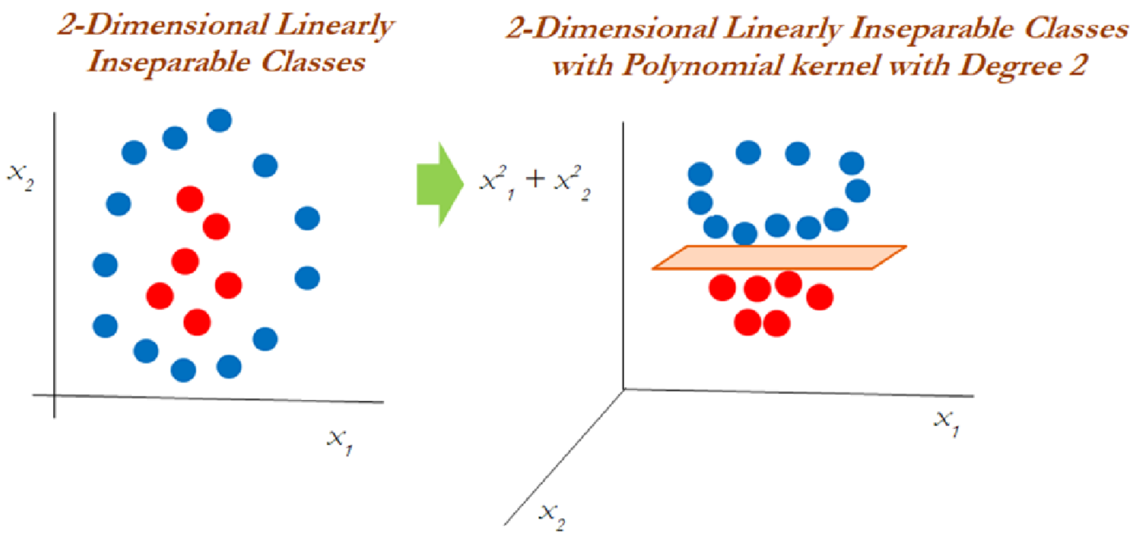

Figure 6.2: SVM applied on Inseparable data

6.2 K-NEAREST NEIGHBOR'S

KNN algorithm is employed when the following conditions are true:

- the data set is small
- the dataset is labeled
- the dataset is noise-free

We start with a dataset with known categories, then cluster the data using well known clustering techniques like k-means algorithm, principal component analysis. Then a new test data is applied whose category is not known. The new data point is classified by looking at the nearest neighbor's. If k in the nearest neighbor's is equal to 1, then we only use the nearest neighbor to define the category. If k=5, then 5 neighbor's are considered. We simply pick the category that gets the maximum votes.
Low value of k like k=1 or k=2 can be noisy and subject to the effects of out liners. Large value for k smooth over things, we don't want k to be so large that a category with only a few samples in it will always be out voted by other categories.

6.3 DECISION TREE

Decision Tree is a supervised learning technique. It solves the classification problem based on labeled examples. It starts from the root node, then depending on the number of attributes the root node is divided into internal node. Each branch corresponds to the attribute value. Each leaf node assigns a continuous variable or categorical variable. This classification method is used when the person needs to know the reason behind the decision taken. It works well in non-linear data fitting cases. Each node of the tree acts as a test case for the attribute and each branch or edge that descends from the node represent the possible answers to the test case. If a dataset has N different attributes of features then which one should to be used as root node depends on different selection measures. Some of the commonly used measures are Entropy, Information Gain, Gini Index, etc.

6.4 NAIVE BAYES

Naive Bayes is a machine learning algorithm which has probabilistic nature and is based on the popular Bayes Theorem.

$$P(y|X) = \frac{P(X|y)P(y)}{P(x)} \tag{6.3}$$

Bayes Theorem is used to determine the probability of occurrence of an event y when X has occurred. X is called the evidence and y is called as hypothesis. In other words, y is the class variable and X is the feature.

If there are n number of features Bayes Theorem can be rewritten as:

$$P(y|x_1, x_2, ..., x_i) = \frac{P(x_1|y)P(x_2|y)...P(x_n)P(y)}{P(x_1)P(x_2)....P(x_n)} \tag{6.4}$$

where y is the class variable and $x_1, x_2, ..., x_n$ are the features. The first assumption is all the features are independent i.e. one feature does not affect the other and the second assumption is every feature has equal affect on the output.

The algorithm is easy to implement and works fast but in real time scenarios the features or predictors are dependent and hence, it degrades the performance of naive bayes.

Chapter 7

METHODOLOGY

The flow chart below describes the methodology adopted in this work.

7.1 MATERIALS

This study utilises the EEG During Mental Arithmetic Tasks dataset [8] to classify the stress states. This dataset is publicly available on PhysiobankThere were initially 66 healthy participants comprising of 19 men and 47 women. But the data of 30 out of 66 participants was discarded because of artefacts and poor quality. As a result the data of 36 participants was provided comprising of 9 were men and 27 women. All the participants were healthy right handed candidates, having no history of any mental illness, verbal and non-verbal disabilities.

7.1.1 Experiment

The participants were involved in mental arithmetic task where they had to perform serial subtraction of two numbers. This is a single trial study comprising of the four-digit minuend and two-digit subtrahend. The questions were communicated verbally. The entire experiment was split-up into three phases: adaption, rest phase and active phase. Participants were given 3 mins to adapt to the environment. The resting phase lasted for about 3 mins where the participants were told to relax and rest with their eyes closed.

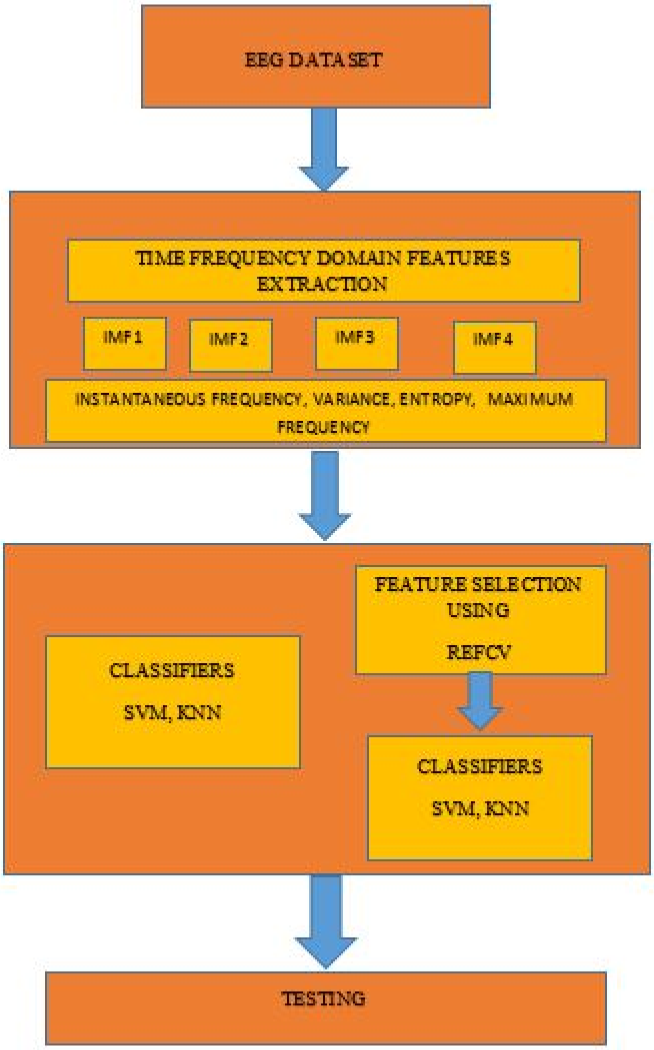

Figure 7.1: Flowchart of the methodology used

Participants were made to perform serial subtraction in 4 mins.

7.1.2 Data Acquisition

The EEG data was recorded using the Neurocom 23-channel system. The placement of electrodes was done according the 10-20 International System [7]. The sampling frequency of the device was 500 Hz. Channels belonging to different regions of brain are described below.

- Symmetrical Anterior Frontal (Fp1, Fp2)
- Frontal (F3, F4, Fz, F7, F8)

- Central (C3, C4, Cz)
- Parietal (P3, P4, Pz)
- Occiptal (O1, 02)
- Temporal (T3, T4, T5, T6)

7.2 PRE-PROCESSING

Since, raw EEG data consists of artefacts which is basically interference of signals having source other than brain, they have to be minimized so as to have accurate classification. The dataset used in this study is pre-processed using a 30 Hz low pass filter in order to remove the high-frequency noise. Also a notch filter is used to remove the power line noise. Along with that, ICA was applied to remove the artefacts due to eye blink, muscle movement.

7.3 PLOT OF EEG SIGNAL FOR REST AND ACTIVE PHASE

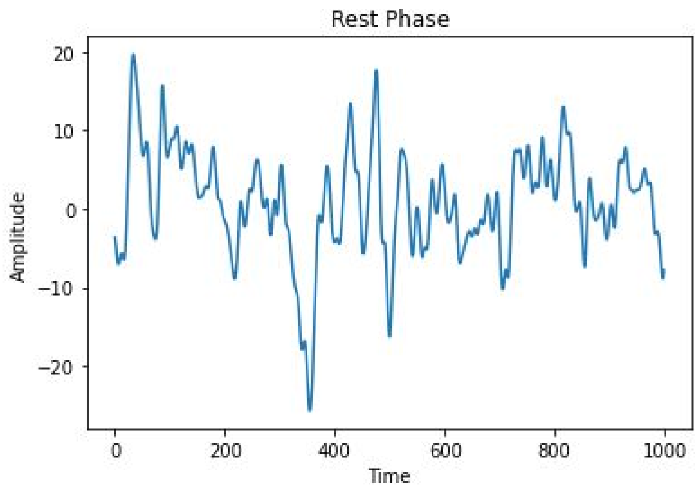

Figure 7.2: EEG data of participant 1 for channel 1 during rest phase

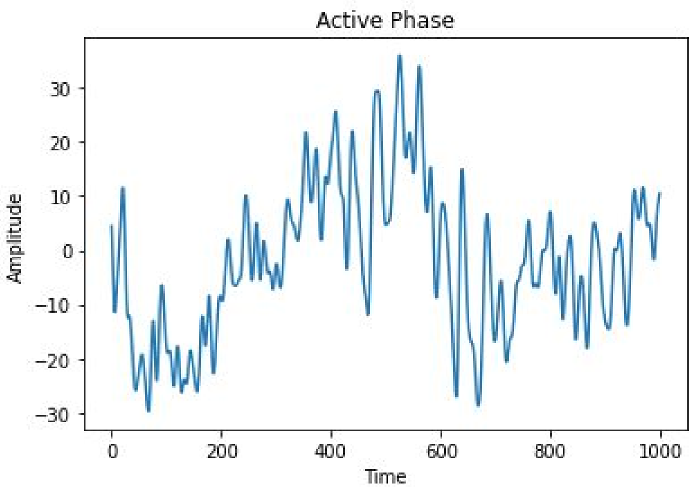

Figure 7.3: EEG data of participant 1 for channel 1 during active phase

It can be seen from Figure 7.2 and 7.3 that EEG signals differ for the two phases for the same participant and channel. These signals can vary between participants depending on the amount of stress induced. This study confines itself for subject independent model.

7.4 FEATURE EXTRACTION

In recent studies, the focus has shifted to time-frequency domain features as they represent the signal in multiple domain. The information related to both time and frequency is useful in EEG related studies and hence, this study determines the time-frequency domain features. For computing the features, Hilbert huang algorithm is used which is an adaptive algorithm that handles the non-linear and non-stationary data efficiently. HHT is described in the chapter titled Signal processing methods. For computing the HHT two different python modules are used namely PyEMD (for computing IMFs) and Scipy.hilbert (for determining instantaneous frequency). After computing HHT the first four IMFs are considered as they represent the beta, alpha, theta, and delta bands. The decomposed signal is shown below in Figure 7.4.
The decomposed signal are also in time domain i.e. amplitude versus time plot. The signal length remains same as that of the original signal. In order to determine the frequency values Hilbert Spectral Analysis is done. The combination of these two methods represents the data in time-frequency domain. The different time-frequency domain features computed in this study are:

- Average instantaneous frequency
- Maximum instantaneous frequency
- Variance of IMFs
- Sample Entropy of IMFs

In order to compute variance, average and maximum value 'Numpy' library of python is used. For determining entropy 'EntroPy' module is used. These features are explained in detail in the chapter titled Features. The size of complete feature set is 16 features*20 channels which is 320 features in total.

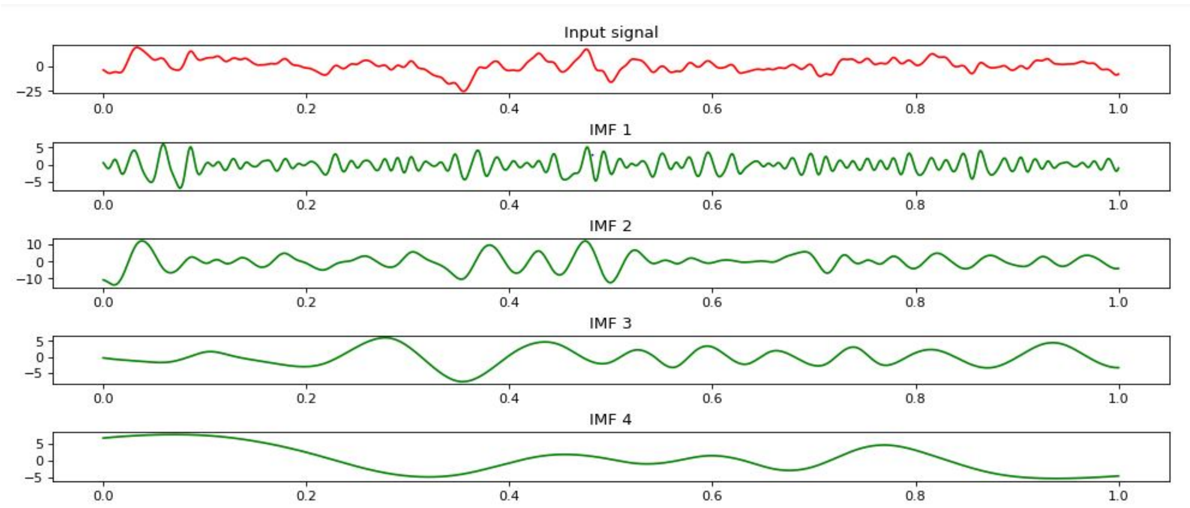

Figure 7.4: IMFs obtained from EEG Signal from participant 1 data for channel 1 during rest phase

7.5 FEATURE SELECTION

Since, the number of features is large and also all features may not contribute in the accuracy of the system to classify stress states as rest or active, feature selection techniques are used. In this study Recursive Feature Elimination using Cross-validation (RFECV) technique is employed. RFECV is a modified version of Recursive Feature Elimination (RFE) method. Both the methods are recursive in nature but in RFECV the features selected are cross-validated a number of times and it provides a refined set of features as compared to RFE. In order to implement RFECV in python, the $sklearn.feature\_selection$ is used and RFECV is imported from this python module.

7.6 CLASSIFIER

In this work, both the complete feature set as well as the features selected after applying RFECV are given as separate inputs to the classifiers. Supervised machine learning classifiers namely SVM and K-NN are used in order to classify the stress states as rest and active. Both the classifiers showcase excellent performance when used for two-class classification problems, they take care of out-liners and are computationally effective and easy to implement. The value of K for K-NN is chosen as 5. The dataset is labelled. Rest phase is labelled as '0' and active phase is labelled as '1'. The scikit-learn [21] module of python is used to implement SVM and K-NN. This work uses $sklearn.model\_selection.StratifiedKFold$ method available in python to split the data into training and testing sets. Different values of K fold is used to determine the classification accuracy.

Chapter 8

RESULT

8.1 EXPERIMENTAL RESULTS

In this section, the Accuracy and F1 score are compared for two scenarios:

- When the entire feature set is giving as input to the classifier.
- When subset of features selected by the feature selection technique is given as input to the classifiers.

The Accuracy and F1 score are represented as:

$$Accuracy\,Score = \frac{TP + TN}{TP + FP + TN + FN} \tag{8.1}$$

$$F1\,Score = \frac{2 * Precision * Recall}{Precision + Recall} = \frac{2 * TP}{2 * TP + FP + FN} \tag{8.2}$$

Here, TP, FP, FN, $and\,TN$ represent the True Positive, False Positive, False Negative, and True Negative respectively, are computed from the confusion matrix for the predictions.

8.1.1 Accuracy and F1 Score for Complete Feature Set

Results obtained by giving the complete feature set consisting of 320 features as input to the classifiers namely SVM and K-NN are shown in table below.

Table 8.1: Classification Results for complete Feature Set with K fold value=6

Classifiers	Training		Testing	
	Accuracy(%)	F1 score(%)	Accuracy(%)	F1 score(%)
SVM	100	100	90.27	90.36
K-NN	65.27	45.63	62.5	35.31

Table 8.2: Classification Results for complete Feature Set with K fold value=10

Classifiers	Training		Testing	
	Accuracy(%)	F1 score(%)	Accuracy(%)	F1 score(%)
SVM	100	100	91.6	90.6
K-NN	70.6	57.14	63.92	41.67

8.1.2 Accuracy and F1 Score for Subset of Features

Results obtained by giving the significant features as input to the classifiers which were obtained after after applying RFECV method are summarized in table below. By applying RFECV the number of reduced from 320 to just 95. This implies that only one-third features play a role in determining the classification accuracy.

Table 8.3: Classification Results for Time-Frequency domain Features after applying RFECV with k fold value=6

Classifiers	Training		Testing	
	Accuracy(%)	F1 score(%)	Accuracy(%)	F1 score(%)
SVM	100	100	98.61	98.48
K-NN	72.5	61.95	69.44	54.67

Table 8.4: Classification Results for Time-Frequency domain Features after applying RFECV with k fold value=10

Classifiers	Training		Testing	
	Accuracy(%)	F1 score(%)	Accuracy(%)	F1 score(%)
SVM	99.84	99.84	100	100
K-NN	79.16	73.15	76.42	67.14

8.1.3 Comparison of Proposed work with Existing work

This section compares the results of existing work with our proposed method. It can be seen from the table below that the proposed work out-performs the work of [14, 17, 18], which also computed the time-frequency domain features.
Ahammed et al. [19] used the same dataset as we have, and achieved a maximum accuracy of 90% whereas our work achieves a maximum accuracy of 100%.

Table 8.5: Comparison of Results with other works

Paper	Feature Domain	Classifier	Accuracy
Sharma et al. [14]	Time-Frequency	SVM	92.86%
Vanitha et al. [18]	Time-Frequency	SVM	89.07%
Diez et al. [17]	Time-Frequency	LD	91%
Ahammed et al. [19]	Time	SVM	90%
Our work	**Time-Frequency**	**SVM**	**100%**

Chapter 9

CONCLUSION AND FUTURE WORK

Employing HHT for determining Time-Frequency domain features for stress level classifications obtains a maximum accuracy of about 100% and F1 Score of 100% . It can be seen from the comparison table that time-frequency domain features perform better than the time domain and frequency domain features when used for stress related studies. Also, feature selection techniques not only reduces the computational time and dimensionality of feature set but also enhances the accuracy. Thus the system can be made more efficient by applying feature selection techniques and it also helps in determining the features which works well in these studies and hence can be employed for the designing of real-time stress detection and prediction systems.

Since, this study limits itself to EEG based single trial and subject independent classification, in future we can look into the avenue of subject dependent classification as in [22]which can then be helpful in designing customized systems as the training and testing data will be subject dependent.

Also, conducting multiple trials of the same procedure not only increases the size of dataset which is beneficial as the bias will reduce, but also makes the procedure more effective in classifying stress.

In future, different physiological signals like heart rate, eye blinks, etc. can be used along with EEG Signals for enhancing the accuracy and determining the efficiency of other physiological signals in determining stress levels.

Since, in this study the dataset comprises of EEG Signals of only 36 participants, which is insufficient for generalizing the results for mass public. We can create our dataset, conducting the trial on large number of subjects 100 or more and creating a system which can help in real-time stress detection and prediction.

Also, in future we can compare the performance of time domain, frequency domain and time-frequency domain features by computing them on the same dataset and deep learning techniques can also be applied to make stress classification process more efficient.

This study employs SVM and K-NN as classifiers which belongs to the class of machine learning classifiers, in future we can delve into deep learning classifiers which shows promising results in EEG related studies [23].

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.1 List of Publications

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Publication awaiting acceptance response:

- Cognitive Workload Detection using EEG Signals: Analysis of Features and Feature Selection Methods, Elsevier Journal, Biomedical Signal Processing and Control.