Classifying different movement of human body based on EEG data using Machine Learning Algorithms.

by

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Declaration

This is certified that the project is done by us under the course "Project (ICE 498)". The project of Classify different movement of human body based EEG data using machine learning algorithms has not been submitted elsewhere for the requirement of any degree or any other purpose except for publication.

Signature-

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Acceptance

This project paper is submitted to the **Department of Electronics and Communications Engineering, East West University** id submitted in partial fulfillment of the requirements for the degree of B.Sc in ICE under complete supervision of the undersigned.

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We are very grateful for the motivation and simulation from my friends and seniors.

Finally, our most heartfelt gratitude goes to our beloved parents, brothers and sister for their endless support, continuous inspiration.

Abstract

In this paper, we propose an automated computer platform for the purpose of classifying Electroencephalography (EEG) signals associated with left and right hand movements using a hybrid system that uses advanced feature extraction techniques and machine learning algorithms. It is known that EEG represents the brain activity by the electrical voltage fluctuations along the scalp, and Brain-Computer Interface (BCI) is a device that enables the use of the brain's neural activity to communicate with others or to control machines, artificial limbs, or robots without direct physical movements. In our research work, we aspired to find the best feature extraction method that enables the differentiation between left and right executed fist movements through various classification algorithms. The EEG dataset used in this research was created and contributed to PhysioNet by the developers of the BCI2000 instrumentation system. Data was preprocessed using the EEGLAB MATLAB toolbox and artifacts removal was done using AAR. Data was epoched on the basis of Event-Related (De) Synchronization (ERD/ERS) and movement-related cortical potentials (MRCP) features. Mu/beta rhythms were isolated for the ERD/ERS analysis and delta rhythms were isolated for the MRCP analysis. The Independent Component Analysis (ICA) spatial filter was applied on related channels for noise reduction and isolation of both artifactually and neutrally generated EEG sources. The final feature vector included the ERD, ERS, and MRCP features in addition to the mean, power and energy of the activations of the resulting Independent Components (ICs) of the epoched feature datasets. The datasets were inputted into two machine- learning algorithms: NFL, Fuzzy Logic and Support Vector Machines (SVMs). Intensive experiments were carried out and optimum classification performances of obtained using NFL, Fuzzy Logic and SVM, respectively. This research shows that this method of feature extraction holds some promise for the classification of various pairs of motor movements, which can be used in a BCI context to mentally control a computer or machine.

Contents

Chapter 1

Introduction

Chapter outlines

- Introduction
- Motivation
- Outlines of Thesis

1.1 Introduction

A Brain Computer Interface (BCI) is a system that takes inputs from the brain, for example EEG, and translates it to commands on a computer. This is usually done by classification, where several commands are trained. The training consists of the user executing the different commands. The goal is then to build a system which uses this information to classify future commands. This work will not look into model-based EEG classification. This has been done for seizure detection [Chong, 2013] where the signals are much stronger than for ordinary brain activity. It is not assumed to be impossible to use a model-based approach for normal signals, but such possibilities were not explored. Instead of making a new literature study, results will be presented from Hwang et al. [Hwang et al., 2013] that reviews the literature from 2007 to 2011. It does not include the most recent research but should still be sufficient for giving an overview of the field. An illustration of a complete BCI system can be seen in Figure 2.1. The first step is signal acquisition where data is acquired, for example via EEG. Next features are extracted from the data and commands are decided based on those features. Memory classification is not a BCI system since there are no commands executed. Everything up the the command execution is however the same, and the execution of commands is generally not the hard part of building a BCI system. Memory classification will hence be treated as a BCI system throughout this report.

1.2 Motivation:

The human body is very capable of interacting with its surrounding. It can share its thoughts by speaking and move around via muscles. In some cases this is not possible due to disabilities or injuries. In other cases it would be beneficial if the brain could interact directly with its surrounding without first having to go through the rest of the body. For example activating an emergency button at the moment the brain wants to could be faster than the person physically having to press it. This might sound like science fiction but the technology is not that far away. One way for the neurons in the brain to communicate is through electrical activity. Those electrical activities will change depending of what the brain is trying to accomplish. If that activity can be measured and interpreted, the intentions of a person could be read without relying on the rest of his body. One such method for measuring brain activity is electroencephalography (EEG). It measures the mean membrane potential of populations of neurons through a series of electrodes, usually attached to the scalp, see Figure 1.1. These devices have been around for a long time and have been used to assist in the diagnosis of epilepsy and sleep disorders by looking at the electroencephalographic activity. This has already been aided by automatic classification of the data where it has been found that certain EEG activities occur before the onset of seizures [Berg et al., 2010]. It can also be used to monitor the mental state of pilots [The pilot brain], pilot quadcopters [LaFleur et al., 2013], control of humanoid robots [Chae et al., 2012] or controlling exoskeletons for disabled persons [Schaap, 2016]. A system that reads signals from the brain and then interprets the signals to make decisions or execute commands is called a Brain Computer Interface (BCI) and this is an emerging research field.

1.3 Outline of Thesis

Chapter 2: Contains the literature review on the different body movement based on EEG data using machine learning algorithm.

Chapter 3: Contains the total procedure or methodology behind this work.

Chapter 4: Comprehends the brief discussions about the segmentation its type and nature, difference and application. Finally, it's result.

Chapter 5: Concludes the total work with clear explanation of applicability, benefits, limitations of the proposed schemes. The scope of future work is also analyzed in section.

Chapter 2

Literature Review

Chapter outlines

- Introduction
- Literature review
- Summary

2.1 Introduction:

Our previous work was focused on the single-trial offline classification of right index hand,leg movement direction by means of the movement-related EEG signal. The aim of our study was to verify the necessity of using the EEG time context information for classification of very closely localized and similar movements. In this case both movements are accompanied with activation of the close parts of the cerebral cortex. As movements are performed on the same side of the body it is not possible to use the power difference between left and right senzorimotor area SVMs, FL, NFL, which is usually used in common problem of left/right hand movement classification. Our SVM, FL, NFL classification system utilizes movement- related changes in the spectrum of the recorded EEG – Event Related De synchronization (ERD) and Event Related Synchronization (ERS) [1,2]. SVMs, FL, NFL were used for their advantages in physiological compatibility, ease of the interpretation and utilization of the context information [1]. We compare our system to common systems used in left/right hand movement classification [3,4].

2.2 Literature Review

The idea of BCI was originally proposed by Jaques Vidal in [11] where he proved that signals recorded from brain activity could be used to effectively represent a user's intent. In [12], the authors recorded EEG signals for three subjects while imagining either right or left hand movement based on a visual cue stimulus. They were able to classify EEG signals into right and left hand movements using a neural network classifier with an accuracy of 80% and concluded that this accuracy did not improve with increasing number of sessions.

The author of [13] used features produced by Motor Imagery (MI) to control a robot arm. Features such as the band power in specific frequency bands (alpha: 8-12Hz and beta: 13- 30Hz) were mapped into right and left limb movements. In addition, they used similar features with MI, which are the Event Related De synchronization and Synchronization (ERD/ERS) comparing the signal's energy in specific frequency bands with respect to the mentally relaxed state. It was shown in [14] that the combination of ERD/ERS and Movement-Related Cortical Potentials (MRCP) improves EEG classification as this offers an independent and complimentary information.

In [15], a hybrid BCI control strategy is presented. The authors expanded the control functions of a P300 potential based BCI for virtual devices and MI related sensorimotor rhythms to navigate in a virtual environment. Imagined left/right hand movements were translated into movement commands in a virtual apartment and an extremely high testing accuracy results were reached.

A three-class BCI system was presented in [16] for the translation of imagined left/right hands and foot movements into commands that operates a wheelchair. This work uses many spatial patterns of ERD on mu rhythms along the sensory-motor cortex and the resulting classification accuracy for online and offline tests was 79.48% and 85.00%, respectively. The authors of [17] proposed an EEG-based BCI system that controls hand prosthesis of paralyzed people by movement thoughts of left and right hands. They reported an accuracy of about 90%.

A single trial right/left hand movement classification is reported in [18]. The authors analyzed both executed and imagined hand movement EEG signals and created a feature vector consisting of the ERD/ERS patterns of the mu and beta rhythms and the coefficients of the autoregressive model. Artificial Neural Networks (ANNs) is applied to two kinds of testing datasets and an average recognition rate of 93% is achieved.

The strength of BCI applications depends lies in the way we translate the neural patterns extracted from EEG into machine commands. The improvement of the interpretation of these EEG signals has become the goal of many researchers; hence, our research work explores the possibility of multi-trial EEG classification between left and right hand movements in an offline manner, which will enormously smooth the path leading to online classification and reading of any executed movements, leading us to what we can technically call “Reading Minds”.

3.3 Summary:

Traditional methods perform best after the application of dimensionality reduction, and, at least during visual perception tasks, when trained across subjects. LSTM based deep learning models are able to out perform traditional methods. With the application of transfer learning, all deep learning models tested were superior to traditional techniques, and the gap between LSTM methods and traditional techniques widened considerably.

It is currently difficult to exceed the performance of traditional machine learning techniques with deep learning techniques. It took many iterations of model architectures and hyperparameters, along with weeks of computing time to find architectures that outperformed the traditional results initially. However, with the continued exploration of deep learning in the classification of EEG and better guidelines, this time could be drastically reduced. Furthermore, the benefits provided by transfer learning may be significant enough to allow classification of problems traditional techniques fail on.

Chapter 3

Methodology

Chapter outlines

- Introduction
- EEG
- Neuro Fuzzy Classification
- Fuzzy Logic
- Support Vector Machine

3.1 Introduction:

A Brain Computer Interface (BCI) is a system that takes inputs from the brain, for example EEG, and translates it to commands on a computer. This is usually done by classification, where several commands are trained. The training consists of the user executing the different commands. The goal is then to build a system which uses this information to classify future commands. This work will not look into model-based EEG classification. This has been done for seizure detection [Chong, 2013] where the signals are much stronger than for ordinary brain activity. It is not assumed to be impossible to use a model-based approach for normal signals, but such possibilities were not explored. Instead of making a new literature study, results will be presented from Hwang et al. [Hwang et al., 2013] that reviews the literature from 2007 to 2011. It does not include the most recent research but should still be sufficient for giving an overview of the field. An illustration of a complete BCI system can be seen in Figure 2.1. The first step is signal acquisition where data is acquired, for example via EEG. Next features are extracted from the data and commands are decided based on those features. Memory classification is not a BCI system since there are no commands executed. Everything up the the command execution is however the same, and the execution of commands is generally not the hard part of building a BCI system. Memory classification will hence be treated as a BCI system throughout this report.

3.2 EEG

Electroencephalography (EEG) is an electrophysiological monitoring method to record electrical activity of the brain. It is typically noninvasive, with the electrodes placed along the scalp, although invasive electrodes are sometimes used such as in electrocorticography. EEG measures voltage fluctuations resulting from ionic current within the neurons of the brain. In clinical contexts, EEG refers to the recording of the brain's spontaneous electrical activity over a period of time, as recorded from multiple electrodes placed on the scalp. Diagnostic applications generally focus either on event-related potentials or on the spectral content of EEG. The former investigates potential fluctuations time locked to an event like stimulus onset or button press. The latter analyses the type of neural oscillations (popularly called "brain waves") that can be observed in EEG signals in the frequency domain.

EEG is most often used to diagnose epilepsy, which causes abnormalities in EEG readings. It is also used to diagnose sleep disorders, depth of anesthesia, coma, encephalopathies, and brain death. EEG used to be a first-line method of diagnosis for tumors, stroke and other focal brain disorders, but this use has decreased with the advent of high-resolution anatomical imaging techniques such as magnetic resonance imaging (MRI) and computed tomography (CT). Despite limited spatial resolution, EEG continues to be a valuable tool for research and diagnosis. It is one of the few mobile techniques available and offers millisecond-range temporal resolution which is not possible with CT, PET or MRI.

Derivatives of the EEG technique include evoked potentials (EP), which involves averaging the EEG activity time-locked to the presentation of a stimulus of some sort (visual, somatosensory, or auditory). Event-related potentials (ERPs) refer to averaged EEG responses that are time-locked to more complex processing of stimuli; this technique is used in cognitive science, cognitive psychology, and psychophysiological research.

3.2.1 EEG data

Electroencephalography (EEG) is an electrophysiological monitoring method to record electrical activity of the brain. It is typically noninvasive, with the electrodes placed along the scalp, although invasive electrodes are sometimes used such as in electrocorticography.

EEG test used to diagnose

An electroencephalogram (EEG) is a noninvasive test that records electrical patterns in your brain. The test is used to help diagnose conditions such as seizures, epilepsy, head injuries, dizziness, headaches, brain tumors and sleeping problems. It can also be used to confirm brain death.

3.2.2 EEG signal

The electroencephalogram (EEG) is a recording of the electrical activity of the brain from the scalp. The recorded waveforms reflect the cortical electrical activity. Signal intensity: EEG activity is quite small, measured in microvolts (mV).

The test itself will take about 30-60 minutes. Placing the electrodes usually takes 20 minutes, but can take up to an hour, so the entire procedure may take about one to 2 hours. If you have an ambulatory EEG, brain activity is recorded for 24 hours or more.

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3.2.3 EEG results

The EEG recording must be analyzed by a neurologist, who then sends the results to your doctor. It is important to make a follow-up appointment with your doctor. In many cases, the test results are sent to your doctor within 48 hours of the test. Treatment depends on the diagnosis.

An electroencephalogram (EEG) is a test used to evaluate the electrical activity in the brain. ... An EEG can be used to help detect potential problems associated with this activity. An EEG tracks and records brain wave patterns. Small flat metal discs called electrodes are attached to the scalp with wires

An electroencephalogram (EEG) is a test used to find problems related to electrical activity of the brain. An EEG tracks and records brain wave patterns. Small metal discs with thin wires (electrodes) are placed on the scalp, and then send signals to a computer to record the results.

3.2.4 Abnormal brain activity

Seizure Disorders and Epilepsy. Abnormal electrical activity in the brain can cause seizures. When a person has repeated seizures, this condition is called epilepsy. Diagnosis and treatment of these disorders often requires consultation with a neurologist.

Abnormal EEG mean

This means that sometimes the EEG is described as 'abnormal' (that is 'not normal' brain activity) but does not 'prove' that the person has epilepsy. ... Also, many people who do have epilepsy will only have 'abnormal' activity on the EEG if they have a seizure at the time the test is happening.

EEG detect dementia

An electroencephalogram (EEG) may be done to detect abnormal brain-wave activity. Although the EEG is usually normal in people with mild Alzheimer's disease and many other types of dementia, EEG abnormalities do occur in delirium and Creutzfeldt-Jakob disease, which is a cause of dementia.

3.2.5 EEG test

How you prepare

Wash your hair the night before or the day of the test, but don't use conditioners, hair creams, sprays or styling gels. ...

If you're supposed to sleep during your EEG test, your doctor might ask you to sleep less or avoid sleep the night before your test.

Current EEG systems can have as few as four electrodes [11] or as many as 256 electrodes. Until recently, the use of EEG has been limited to stationary settings (i.e., settings where the subject is seated or prone) because of the susceptibility of EEG electrodes to movement and electromyographic artifacts [12-14].

Normal EEG

The electroencephalogram (EEG) is the depiction of the electrical activity occurring at the surface of the brain. ... Frequency (Hertz, Hz) is a key characteristic used to define normal or abnormal EEG rhythms. Most waves of 8 Hz and higher frequencies are normal findings in the EEG of an awake adult.

Sharp waves on an EEG

Epileptiform transients such as spikes and sharp waves are the interictal marker of a patient with epilepsy and are the EEG signature of a seizure focus. Nonepileptiform abnormalities are characterized by alterations in normal rhythms or by the appearance of abnormal ones.

EEG machines work

During an EEG, small electrodes and wires are attached to your head. The electrodes detect your brain waves and the EEG machine amplifies the signals and records them in a wave pattern on graph paper or a computer screen (Fig. 1). Figure 1. A sample EEG recording showing a focal spike typical of a seizure.

3.2.6 EEG costing

For patients not covered by health insurance, an EEG typically costs $200-$700 or more for a standard EEG -- or up to $3,000 or more if extended monitoring is required. For example, Garden City Hospital in Michigan charges $749 for an EEG, but offers the test for $199 through a special program for uninsured patients.

Having an EEG is not painful. It may be slightly uncomfortable having the electrodes attached, but the electrodes do not produce any sensation — they only record your brain's activity.

But your doctor may order one to look for signs of seizures, which can cause symptoms similar to those associated with migraine or other types of headaches. ... An EEG can show that something's not right in the brain, but it doesn't pinpoint the exact problem that might be causing a headache.

How long it takes to get EMG results

The nerve conduction part of the test usually takes longer than the needle exam because one needs to make calculations and measurements during it. On average, if one extremity is studied, the nerve conductions take anywhere between 15 and 30 minutes. The needle exam for one extremity usually takes 15 to 20 minutes.

Device used to measure people's brain waves

Biofeedback headsets measure your brain waves, using EEG. They're small bands that sit easily on your head and measure activity through sensors. EEG stands for Electroencephalography, but you'll be forgiven for not remembering that.

What happens to the brain during a seizure?

During a seizure, there are bursts of electrical activity in your brain, sort of like an electrical storm. This activity causes different symptoms depending on the type of seizure and what part of the brain is involved. ... Seizures are episodic (they come and go) and they can be unpredictable

What does EEG measure?

EEG measures voltage fluctuations resulting from ionic current within the neurons of the brain. In clinical contexts, EEG refers to the recording of the brain's spontaneous electrical activity over a period of time, as recorded from multiple electrodes placed on the scalp

Eating before an EEG

Do not eat or drink anything with caffeine in it for 12 hours before the test. This includes cola, energy drinks, and chocolate.

Sleeping during an EEG

A sleep-deprived EEG can show up subtle seizures, including absence, myoclonic or focal (partial) seizures. Before you have a sleep-deprived EEG test, your doctor may ask you not to go to sleep at all the night before. ... You may then fall asleep or doze while the EEG is still recording the activity in your brain.

EEG show autism

New EEG Test to Diagnose Children with Autism. ... The EEG test, usually lasts some 30-40 minutes, and has been used to identify epilepsy and is also used as a front line diagnosis for brain damage after a stroke or brain tumor.

3.2.7 Method

Computer electroencephalograph Neurovisor-BMM 40

In conventional scalp EEG, the recording is obtained by placing electrodes on the scalp with a conductive gel or paste, usually after preparing the scalp area by light abrasion to reduce impedance due to dead skin cells. Many systems typically use electrodes, each of which is attached to an individual wire. Some systems use caps or nets into which electrodes are embedded; this is particularly common when high-density arrays of electrodes are needed.

Electrode locations and names are specified by the International 10–20 systems for most clinical and research applications (except when high-density arrays are used). This system ensures that the naming of electrodes is consistent across laboratories. In most clinical applications, 19 recording electrodes (plus ground and system reference) are used. A smaller number of electrodes are typically used when recording EEG from neonates. Additional electrodes can be added to the standard set-up when a clinical or research application demands increased spatial resolution for a particular area of the brain. High-density arrays (typically via cap or net) can contain up to 256 electrodes more-or-less evenly spaced around the scalp.

Each electrode is connected to one input of a differential amplifier (one amplifier per pair of electrodes); a common system reference electrode is connected to the other input of each differential amplifier. These amplifiers amplify the voltage between the active electrode and the reference (typically 1,000–100,000 times, or 60–100 dB of voltage gain). In analog EEG, the signal is then filtered (next paragraph), and the EEG signal is output as the deflection of pens as paper passes underneath. Most EEG systems these days, however, are digital, and the amplified signal is digitized via an analog-to-digital converter, after being passed through an anti-aliasing filter. Analog-to-digital sampling typically occurs at 256–512 Hz in clinical scalp EEG; sampling rates of up to 20 kHz are used in some research applications.

During the recording, a series of activation procedures may be used. These procedures may induce normal or abnormal EEG activity that might not otherwise be seen. These procedures include hyperventilation, photic stimulation (with a strobe light), eye closure, mental activity, sleep and sleep deprivation. During (inpatient) epilepsy monitoring, a patient's typical seizure medications may be withdrawn.

The digital EEG signal is stored electronically and can be filtered for display. Typical settings for the high-pass filter and a low-pass filter are 0.5–1 Hz and 35–70 Hz respectively. The high-pass filter typically filters out slow artifact, such as electrogalvanic signals and movement artifact, whereas the low-pass filter filters out high-frequency artifacts, such as electromyographic signals. An additional notch filter is typically used to remove artifact caused by electrical power lines (60 Hz in the United States and 50 Hz in many other countries).

The EEG signals can be captured with open source hardware such as OpenBCI and the signal can be processed by freely available EEG software such as EEGLAB or the Neurophysiological Biomarker Toolbox.

As part of an evaluation for epilepsy surgery, it may be necessary to insert electrodes near the surface of the brain, under the surface of the dura mater. This is accomplished via burr hole or craniotomy. This is referred to variously as "electrocorticography (ECoG)", "intracranial EEG (I-EEG)" or "subdural EEG (SD-EEG)". Depth electrodes may also be placed into brain structures, such as the amygdala or hippocampus, structures, which are common epileptic foci and may not be "seen" clearly by scalp EEG. The electrocorticographic signal is processed in the same manner as digital scalp EEG (above), with a couple of caveats. ECoG is typically recorded at higher sampling rates than scalp EEG because of the requirements of Nyquist theorem—the subdural signal is composed of a higher predominance of higher frequency components. Also, many of the artifacts that affect scalp EEG do not impact ECoG, and therefore display filtering is often not needed.

A typical adult human EEG signal is about 10 µV to 100 µV in amplitude when measured from the scalp and is about 10–20 mV when measured from subdural electrodes.

Since an EEG voltage signal represents a difference between the voltages at two electrodes, the display of the EEG for the reading encephalographer may be set up in one of several ways. The representation of the EEG channels is referred to as a montage.

Each channel (i.e., waveform) represents the difference between two adjacent electrodes. The entire montage consists of a series of these channels. For example, the channel "Fp1-F3" represents the difference in voltage between the Fp1 electrode and the F3 electrode. The next channel in the montage, "F3-C3", represents the voltage difference between F3 and C3, and so on through the entire array of electrodes.

Referential montage

Each channel represents the difference between a certain electrode and a designated reference electrode. There is no standard position for this reference; it is, however, at a different position than the "recording" electrodes.

3.2.8 Limitations

EEG has several limitations. Most important is its poor spatial resolution. EEG is most sensitive to a particular set of post-synaptic potentials: those generated in superficial layers of the cortex, on the crests of gyri directly abutting the skull and radial to the skull. Dendrites, which are deeper in the cortex, inside sulci, in midline or deep structures (such as the cingulate gyrus or hippocampus), or producing currents that are tangential to the skull, have far less contribution to the EEG signal.

EEG recordings do not directly capture axonal action potentials. An action potential can be accurately represented as a current quadrupole, meaning that the resulting field decreases more rapidly than the ones produced by the current dipole of post-synaptic potentials. In addition, since EEGs represent averages of thousands of neurons, a large population of cells in synchronous activity is necessary to cause a significant deflection on the recordings. Action potentials are very fast and, as a consequence, the chances of field summation are slim. However, neural backpropagation, as a typically longer dendritic current dipole, can be picked up by EEG electrodes and is a reliable indication of the occurrence of neural output.

Not only do EEGs capture dendritic currents almost exclusively as opposed to axonal currents, they also show a preference for activity on populations of parallel dendrites and transmitting current in the same direction at the same time. Pyramidal neurons of cortical layers II/III and V extend apical dendrites to layer I. Currents moving up or down these processes underlie most of the signals produced by electroencephalography.

Therefore, EEG provides information with a large bias to select neuron types, and generally should not be used to make claims about global brain activity. The meninges, cerebrospinal fluid and skull "smear" the EEG signal, obscuring its intracranial source.

It is mathematically impossible to reconstruct a unique intracranial current source for a given EEG signal, as some currents produce potentials that cancel each other out. This is referred to as the inverse problem. However, much work has been done to produce remarkably good estimates of, at least, a localized electric dipole that represents the recorded currents. [citation needed]

Normal activity

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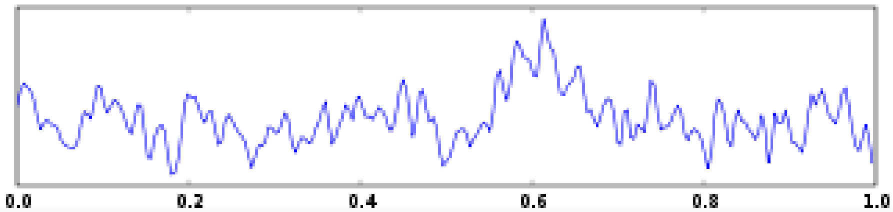

One second of EEG signal

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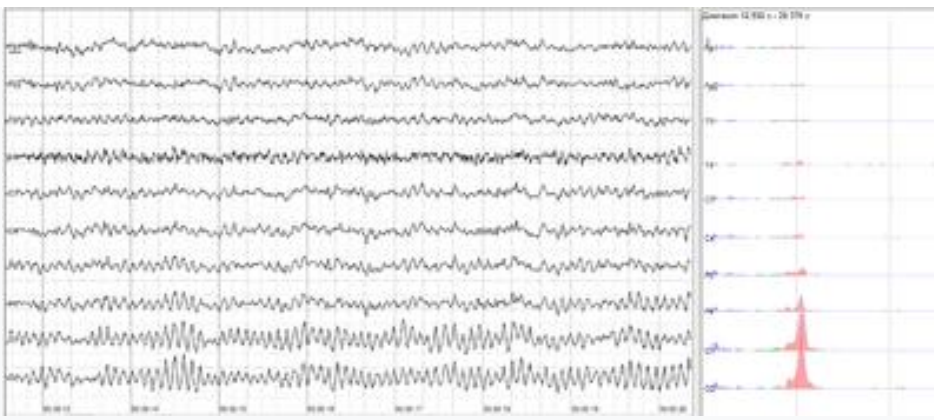
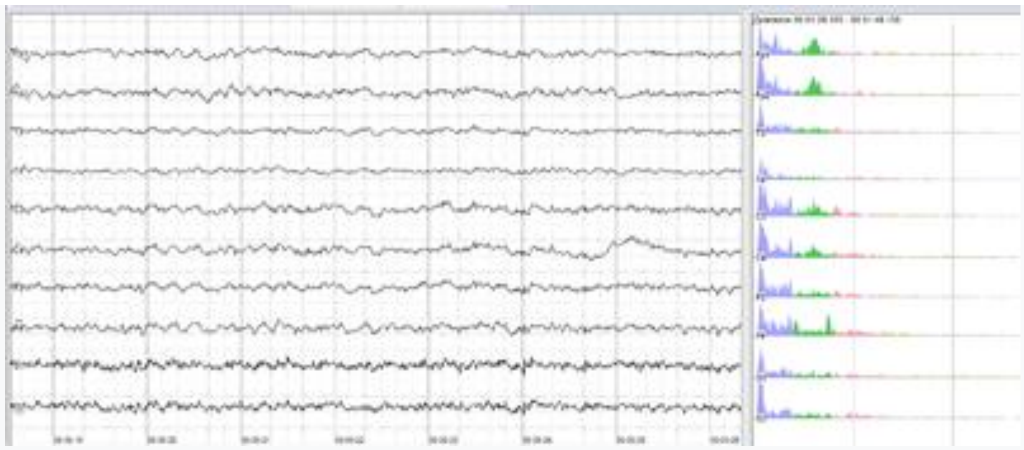
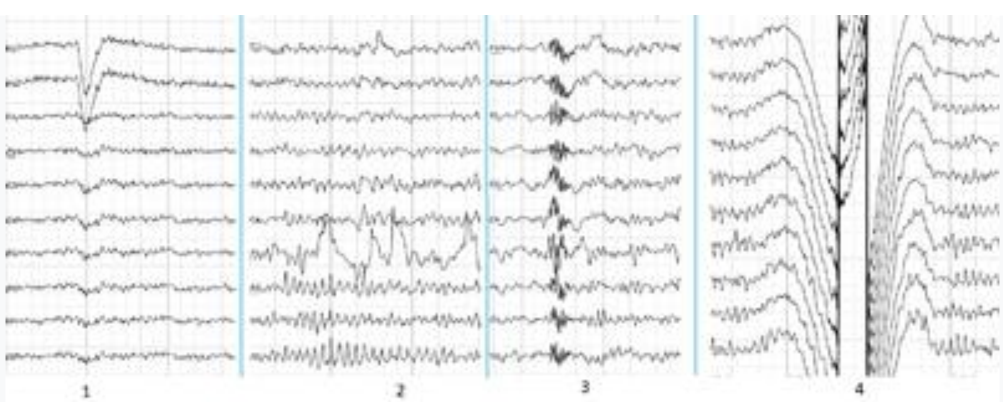


The sample of human EEG with prominent resting state activity – alpha-rhythm. Left: EEG traces (horizontal – time in seconds; vertical – amplitudes, scale 100 μV). Right: power spectra of shown signals (vertical lines – 10 and 20 Hz, scale is linear). Alpha-rhythm consists of sinusoidal-like waves with frequencies in 8–12 Hz range (11 Hz in this case) more prominent in posterior sites. Alpha range is red at power spectrum graph.

- 

The sample of human EEG with in resting state. Left: EEG traces (horizontal – time in seconds; vertical – amplitudes, scale 100 μV). Right: power spectra of shown signals (vertical lines – 10 and 20 Hz, scale is linear). 80–90% of people have prominent sinusoidal-like waves with frequencies in 8–12 Hz range – alpha rhythm. Others (like this) lack this type of activity.

- 

The samples of main types of artifacts in human EEG. 1: Electrooculographic artifact caused by the excitation of eyeball's muscles (related to blinking, for example). Big-amplitude, slow, positive wave prominent in frontal electrodes. 2: Electrode's artifact caused by bad contact (and thus bigger impedance) between P3 electrode and skin. 3: Swallowing artifact. 4: Common reference electrode's artifact caused by bad contact between reference electrode and skin. Huge wave similar in all channels.

The EEG is typically described in terms of rhythmic activity and (2) transients. The rhythmic activity is divided into bands by frequency. To some degree, these frequency bands are a matter of nomenclature (i.e., any rhythmic activity between 8–12 Hz can be described as "alpha"), but these designations arose because rhythmic activity within a certain frequency range was noted to have a certain distribution over the scalp or a certain biological significance. Frequency bands are usually extracted using spectral methods (for instance Welch) as implemented for instance in freely available EEG software such as EEGLAB or the Neurophysiological Biomarker Toolbox. Computational processing of the EEG is often named quantitative electroencephalography (qEEG).

Most of the cerebral signal observed in the scalp EEG falls in the range of 1–20 Hz (activity below or above this range is likely to be artifactual, under standard clinical recording techniques). Waveforms are subdivided into bandwidths known as alpha, beta, theta, and delta to signify the majority of the EEG used in clinical practice.

3.2.9 EEG SIGNAL ACQUISITION:

EEG (Electroencephalogram) is a non-invasive simple method used to quantize or measure the electrical activity in the brain which is a result of the voltage fluctuations resulting from the neurons of the brain. The signals are extensively used for detecting epilepsy, sleep disorders, coma brain death etc. In this paper we focus on the division of the signals for sleep analysis and disorders. The brain is actively working at all times even while we are asleep and the brain activity during different stages of the sleep can be realized by the presence of some characteristic brain waves. They are majorly classified into five frequency bands namely the alpha, theta, beta, gamma and delta. The waves lie in the frequencies ranging from 0 to 35Hz approximately and the signals are of the order of micro volts. All other signals which include EMG, EOG, ECG waves or disturbances caused due to blinking, body movement etc. have to be treated as noise or artifacts as they are popularly known and have to be filtered appropriately both in the digital and analog domain. The presence of the signals in lower frequencies makes filtering a very tedious and difficult task. Early amplification also results in the loss of the real signals to noise and other artifacts which are of the order of mille volts as opposed to EEG signals which are of the order of uV (typically less than 100uV

ANALOG FILTERING

Rejection of the dc offset is necessary before amplification to produce the required dynamic range. A very simple approach to doing the same is to use a capacitor which can block dc content and allow all frequencies ranging till 3570Hz.A series of analog filters (high pass and low pass) can also be used to limit the frequencies between the ranges of 1Hz to 35-70Hz.The high pas filter typically filters out slow artifacts such as electro galvanic signals and movements. A notch filter is used to limit the artifacts caused due to electrical power lines, it is typically of the frequency 60Hz in the US and 50Hz in many other countries.

3.2.10 PCA analysis

Principal component analysis of raw data

Syntax

coeff = pca(X)

coeff = pca(X,Name,Value)

[coeff,score,latent] = pca(___)

[coeff,score,latent,tsquared] = pca(___)

[coeff,score,latent,tsquared,explained,mu] = pca(___)

coeff = pca(X) returns the principal component coefficients, also known as loadings, for the n-by-p data matrix X. Rows of X correspond to observations and columns correspond to variables. The coefficient matrix is p-by-p. Each column of coeff contains coefficients for one principal component, and the columns are in descending order of component variance. By default, pca centers the data and uses the singular value decomposition (SVD) algorithm.

example

coeff = pca(X,Name,Value) returns any of the output arguments in the previous syntaxes using additional options for computation and handling of special data types, specified by one or more Name,Value pair arguments.

For example, you can specify the number of principal components pca returns or an algorithm other than SVD to use.

example

[coeff,score,latent] = pca(___) also returns the principal component scores in score and the principal component variances in latent. You can use any of the input arguments in the previous syntaxes.

Principal component scores are the representations of X in the principal component space. Rows of score correspond to observations, and columns correspond to components.

The principal component variances are the eigenvalues of the covariance matrix of X.

example

[coeff,score,latent,tsquared] = pca(___) also returns the Hotelling's T-squared statistic for each observation in X.

example

[coeff,score,latent,tsquared,explained,mu] = pca(___) also returns explained, the percentage of the total variance explained by each principal component and mu, the estimated mean of each variable in X.

Principal Components of a Data Set

Try This Example

Load the sample data set.

load hald

The ingredients data has 13 observations for 4 variables.

Find the principal components for the ingredients data.

coeff = pca(ingredients)

coeff = *4×4*

-0.0678	-0.6460	0.5673	0.5062
-0.6785	-0.0200	-0.5440	0.4933
0.0290	0.7553	0.4036	0.5156
0.7309	-0.1085	-0.4684	0.4844

The rows of coeff contain the coefficients for the four ingredient variables, and its columns correspond to four principal components.

Feature extraction:

In machine learning, pattern recognition and in image processing, feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. Feature extraction is a dimensionality reduction process, where an initial set of raw variables is reduced to more manageable groups (features) for processing, while still accurately and completely describing the original data set.

When the input data to an algorithm is too large to be processed and it is suspected to be redundant (e.g. the same measurement in both feet and meters, or the repetitiveness of images presented as pixels), then it can be transformed into a reduced set of features (also named a feature vector).

Determining a subset of the initial features is called feature selection.

The selected features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data.

We usually use **mean, median, average** for feature extraction. The whole data are classified in such as x1, x2, x3…… and bf1, bf2, bf3…. Categories. We collect the data and extract them in two parts. One is real data and the other one is imaginary data. In every section we rearrange the data sequence **in left hand, right hand, right foot, right foot**.

Then we saw that in every data set we have **36x16** matrix of data.

We get the average value of every data in **1x16** matrix set using excel.

Thus we got **14** different average value of every part of human being. The final matrix is 56x16.

We identified the different average values with different number such as 1, 2, 3… to execute the code very easily.

edu ▸ thesis paper ▸ For CNN

Variables - eeg_data

sub1_iLF | eeg_data

56x17 double

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	-1.1900	-1.3073	-1.1647	-1.2479	3.6359	3.9994	3.5631	3.8176	0.8928	0.9820	0.8749	0.9374	2.8549	3.1404	2.7978	2.9977	1
2	-2.8800	-3.1646	-2.8194	-3.0208	4.4529	4.8982	4.3638	4.6755	3.0215	3.3236	2.9611	3.1726	-0.4192	-0.4611	-0.4108	-0.4402	1
3	0.3100	0.3402	0.3031	0.3247	1.3169	1.4486	1.2906	1.3828	1.9218	2.1139	1.8833	2.0178	2.8480	3.1328	2.7911	2.9904	1
4	0.5100	0.5647	0.5031	0.5391	-0.8716	-0.9587	-0.8541	-0.9152	2.4974	2.7472	2.4475	2.6223	1.1767	1.2944	1.1532	1.2356	1
5	2.1800	2.4025	2.1404	2.2933	2.5137	2.7650	2.4634	2.6393	2.3994	2.6394	2.3514	2.5194	-0.2712	-0.2983	-0.2658	-0.2848	1
6	0.5800	0.6371	0.5676	0.6081	-1.2426	-1.3668	-1.2177	-1.3047	1.9403	2.1343	1.9015	2.0373	2.2807	2.5088	2.2351	2.3947	1
7	-0.5100	-0.5659	-0.5042	-0.5402	4.2127	4.6339	4.1284	4.4233	1.9403	4.4155	3.9338	4.2148	4.8045	5.2850	4.7085	5.0448	1
8	1.9900	2.1852	1.9469	2.0859	0.5980	0.6578	0.5860	0.6279	0.2403	0.2643	0.2355	0.2523	-3.3526	-3.6879	-3.2856	-3.5203	1
9	1.1100	1.2232	1.0897	1.1676	1.4905	1.6395	1.4607	1.5650	2.6983	2.9681	2.6443	2.8332	1.2285	1.3514	1.2040	1.2900	1
10	-1.9400	-2.1289	-1.8967	-2.0321	2.4398	2.6838	2.3910	2.5618	1.9047	2.0952	1.8666	2.0000	6.4684	7.1153	6.3390	6.7918	1
11	-1.2400	-1.3595	-1.2112	-1.2977	-0.6528	-0.7181	-0.6398	-0.6855	0.0548	0.0603	0.0537	0.0576	1.5858	1.7443	1.5541	1.6651	1
12	2.5800	2.8354	2.5261	2.7065	0.0507	0.0558	0.0497	0.0532	0.8847	0.9732	0.8670	0.9289	-0.8659	-0.9525	-0.8486	-0.9092	1
13	-0.2100	-0.2329	-0.2075	-0.2223	2.2095	2.4305	2.1654	2.3200	2.1466	2.3612	2.1036	2.2539	1.6151	1.7766	1.5828	1.6959	1
14	-0.0200	-0.0200	-0.0178	-0.0191	0.9689	1.0658	0.9495	1.0173	1.7062	1.8768	1.6721	1.7915	1.6448	1.8093	1.6119	1.7270	1
15	2.9343	3.2277	2.8756	3.0810	-2.5530	-2.8083	-2.5019	-2.6806	-2.4624	-2.7087	-2.4132	-2.5855	0.3680	0.4048	0.3606	0.3864	2
16	2.1136	2.3249	2.0713	2.2192	0.7422	0.8164	0.7273	0.7793	-2.4030	-2.6433	-2.3549	-2.5231	2.1351	2.3486	2.0924	2.2418	2
17	-0.5636	-0.6200	-0.5523	-0.5918	0.1577	0.1735	0.1545	0.1656	-1.2493	-1.3742	-1.2243	-1.3118	1.2515	1.3767	1.2265	1.3141	2
18	0.1655	0.1821	0.1622	0.1738	-1.5274	-1.6802	-1.4969	-1.6038	-1.3931	-1.5324	-1.3652	-1.4627	0.8137	0.8951	0.7974	0.8544	2
19	-0.7412	-0.8153	-0.7264	-0.7782	2.8399	3.1239	2.7831	2.9819	6.4174	7.0592	6.2891	6.7383	3.2887	3.6176	3.2229	3.4531	2
20	4.7639	5.2402	4.6686	5.0021	-0.0319	-0.0351	-0.0312	-0.0335	-1.5429	-1.6972	-1.5121	-1.6201	1.3199	1.4518	1.2935	1.3858	2
21	0.0212	0.0234	0.0208	0.0223	2.6469	2.9116	2.5940	2.7793	-1.5429	1.7937	1.5980	1.7122	2.5789	2.8368	2.5273	2.7078	2
22	0.4626	0.5089	0.4533	0.4857	-0.2367	-0.2604	-0.2320	-0.2486	3.2628	3.5891	3.1976	3.4260	0.0548	0.0602	0.0537	0.0575	2
23	0.8616	0.9477	0.8443	0.9046	-2.2018	-2.4220	-2.1578	-2.3119	-5.1775	-5.6952	-5.0739	-5.4363	6.0355	6.6391	5.9148	6.3373	2
24	-0.5819	-0.6401	-0.5703	-0.6110	0.2743	0.3018	0.2688	0.2880	0.8306	0.9136	0.8140	0.8721	1.8284	2.0112	1.7918	1.9198	2
25	-0.6846	-0.7531	-0.6709	-0.7189	-0.8828	-0.9711	-0.8652	-0.9270	1.3274	1.4602	1.3009	1.3938	4.5102	4.9612	4.4199	4.7357	2
26	1.7501	1.9251	1.7151	1.8376	-0.2511	-0.2762	-0.2460	-0.2636	2.3722	2.6094	2.3248	2.4908	3.7632	4.1395	3.6879	3.9513	2
27	0.7817	0.8599	0.7661	0.8208	-0.0681	-0.0749	-0.0668	-0.0715	-0.2181	-0.2399	-0.2137	-0.2290	0.8600	0.9460	0.8428	0.9030	2
28	0.9685	1.0654	0.9492	1.0170	-0.0864	-0.0950	-0.0847	-0.0907	0.0662	0.0728	0.0649	0.0695	2.2497	2.4746	2.2047	2.3621	2
29	-0.5471	-0.6018	-0.5362	-0.5744	0.7275	0.8002	0.7129	0.7638	0.5740	0.6315	0.5626	0.6027	-0.9025	-0.9928	-0.8845	-0.9477	3
30	0.3547	0.3902	0.3476	0.3725	1.6542	1.8196	1.6211	1.7369	5.5697	6.1267	5.4583	5.8482	2.5345	2.7880	2.4838	2.6612	3
31	0.9268	1.0195	0.9083	0.9731	1.4479	1.5926	1.4189	1.5203	-1.1490	-1.2639	-1.1260	-1.2064	-1.0187	-1.1205	-0.9983	-1.0696	3
32	0.5859	0.6445	0.5742	0.6152	2.5809	2.8390	2.5292	2.7099	-0.1198	-0.1318	-0.1174	-0.1258	-1.4054	-1.5459	-1.3773	-1.4756	3
33	0.6976	0.7673	0.6836	0.7325	-0.0650	-0.0715	-0.0637	-0.0682	0.9313	1.0244	0.9127	0.9779	0.2810	0.3091	0.2754	0.2950	3
34	0.3169	0.3486	0.3106	0.3327	2.3417	2.5759	2.2949	2.4588	-0.6883	-0.7571	-0.6745	-0.7227	0.5629	0.6192	0.5516	0.5910	3
35	-0.6786	-0.7464	-0.6650	-0.7125	-0.5006	-0.5507	-0.4906	-0.5256	2.0424	2.2466	2.0015	2.1445	3.1694	3.4864	3.1060	3.3279	3
36	2.6318	2.8950	2.5791	2.7634	3.0305	3.3335	2.9698	3.1820	2.0424	-3.7057	-3.3014	-3.5372	-3.2450	-3.5695	-3.1801	-3.4072	3

Then we use this average value as matlab file in ANN, FUZZY, NFC etc. classification.

3.3.1 NEURO FUZZY CLASSIFICATION:

Neuro-fuzzy classification systems offer means to obtain fuzzy classification rules by a learning algorithm. It is usually possible to find a suitable fuzzy classifier by learning from data, but it can be hard to obtain a classifier that can be interpreted conveniently. However, the main reason for using fuzzy methods for classification is usually to obtain an interpretable classifier. In this paper we discuss the learning algorithms of NEFCLASS, a neuro-fuzzy approach for data analysis.

- A neuro-fuzzy system is a fuzzy system that is trained by a learning algorithm (usually) derived from neural network theory. The (heuristically) learning procedure operates on local information, and causes only local modifications in the underlying fuzzy system. The learning process is not knowledge based, but data driven

- A neuro-fuzzy system can be viewed as a special 3-layer feedforward neural network. The units in this network use t-norms or t-conorms instead of the activation function common in neural networks. The first layer represents input variables, the middle (hidden) layer represents fuzzy rules and the third layer represents output variables. Fuzzy sets are encoded as (fuzzy) connection weights. This view of a fuzzy system illustrates the data flow within the system, and its parallel nature. However, this neural network view is not a prerequisite for applying a learning procedure, it is merely a convenience

- A neuro-fuzzy system can always (i.e. before, during and after learning) be interpreted as a system of fuzzy rules. It is both possible to create the system out of training data from scratch, and it is possible to initialize it by prior knowledge in form of fuzzy rules.

- The learning procedure of a neuro-fuzzy system takes the semantical properties of the underlying fuzzy system into account. This results in constraints on the possible modifications applicable to the system parameters

- A neuro-fuzzy system approximates an n-dimensional (unknown) function that is partially given by the training data. The fuzzy rules encoded within the system represent vague samples, and can be viewed as vague prototypes of the training data. A neuro-fuzzy system should not be seen as a kind of (fuzzy) expert system, and it has nothing to do with fuzzy logic in the narrow sense [Kruse et al., 1994].

For NFC we use the same EEG data which was given in feature extraction. There is the NFC code for matlab workspace.

```
%
clc;
clear all;
close all;
load CNN_EEG_data.mat
%iris.dat has 150 samples, 4 features and 3 classes.
%Here, the data is equally divided to train and test sets
input=sub1_RH1(1:2:end,1:16);
test=sub1_RH1(2:2:end,1:16);
target_tr=sub1_RH1(1:2:end,17);
target_te=sub1_RH1(2:2:end,17);


%first classifier
%[fismat,outputs,recog_tr,recog_te,labels,performance]=scg_nfc(input,target_tr,test,target_te,ep
och,class,clustersize);
[fismat,outputs,recog_tr,recog_te,labels,performance]=scg_nfc(input,target_tr,test,target_te,100,
3,1);



%second classifier
%[fismat,outputs,recog_tr,recog_te,labels,performance]=scg_pow_nfc(input,target_tr,test,target_
te,epoch,class,clustersize);
[fismat1,outputs,recog_tr,recog_te,labels,performance]=scg_pow_nfc(input,target_tr,test,target_t
e,100,3,1);
```

```
%third classifier
%[fismat,outputs,recog_tr,recog_te,labels,performance]=scg_nfclass_speedup(input,target_tr,test
,target_te,stepsize,class,clustsize);
[fismat3,outputs,recog_tr,recog_te,labels,performance]=scg_nfclass_speedup(input,target_tr,test,
target_te,100,3,1);



%feature selection
%[fismat,feature,outputs,recog_tr,recog_te,labels,performance]=nfc_feature_select(input,target_t
r,test,target_te,epoch,class,clustersize);
[fismat4,feature,outputs,recog_tr,recog_te,labels,performance]=nfc_feature_select([input;test],[ta
rget_tr;target_te],test,target_te,1000,3);


%Classification with selected features
[fismat5,outputs,recog_tr,recog_te,labels,performance]=scg_pow_nfc(input(:,feature.selected),ta
rget_tr,test(:,feature.selected),target_te,100,3,2);
```

Command window:

the classification with NFC is realizing initial recognation rate= 28.5714 initial perform= 0.607143

epoch 25   recog 28.5714 recog_test 25 performans   0.589551

epoch 50   recog 28.5714 recog_test 25 performans   0.589551

the classification with NFC_LH is realizing

initial recognation rate= 28.5714 initial perform= 0.607143

epoch 25   recog 28.5714 recog_test 25 performans   0.607143

epoch 50   recog 28.5714 recog_test 25 performans   0.607143

initial recognation rate= 28.5714 initial perform= 0.571429

epoch 25   recog_train 28.5714 recog_test 25 performance   0.571428

epoch 50   recog_train 28.5714 recog_test 25 performance   0.571428

The gradient does not change, and the program is broken

initial recognation rate= 26.7857 initial perform= 0.581611

epoch 25   recog_train 26.7857 recog_test 25 performance   0.557738

epoch 50   recog_train 26.7857 recog_test 25 performance   0.557738

the classification with NFC_LH is realizing

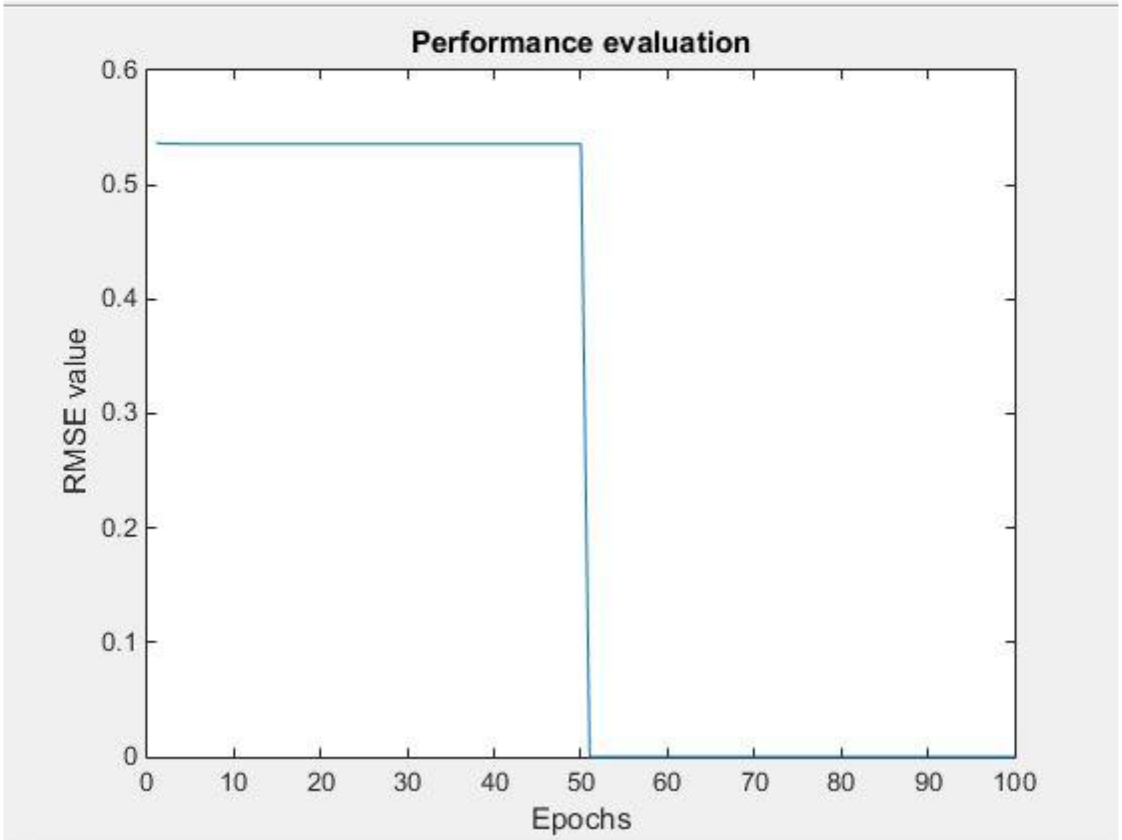
initial recognation rate= 32.1429 initial perform= 0.536864

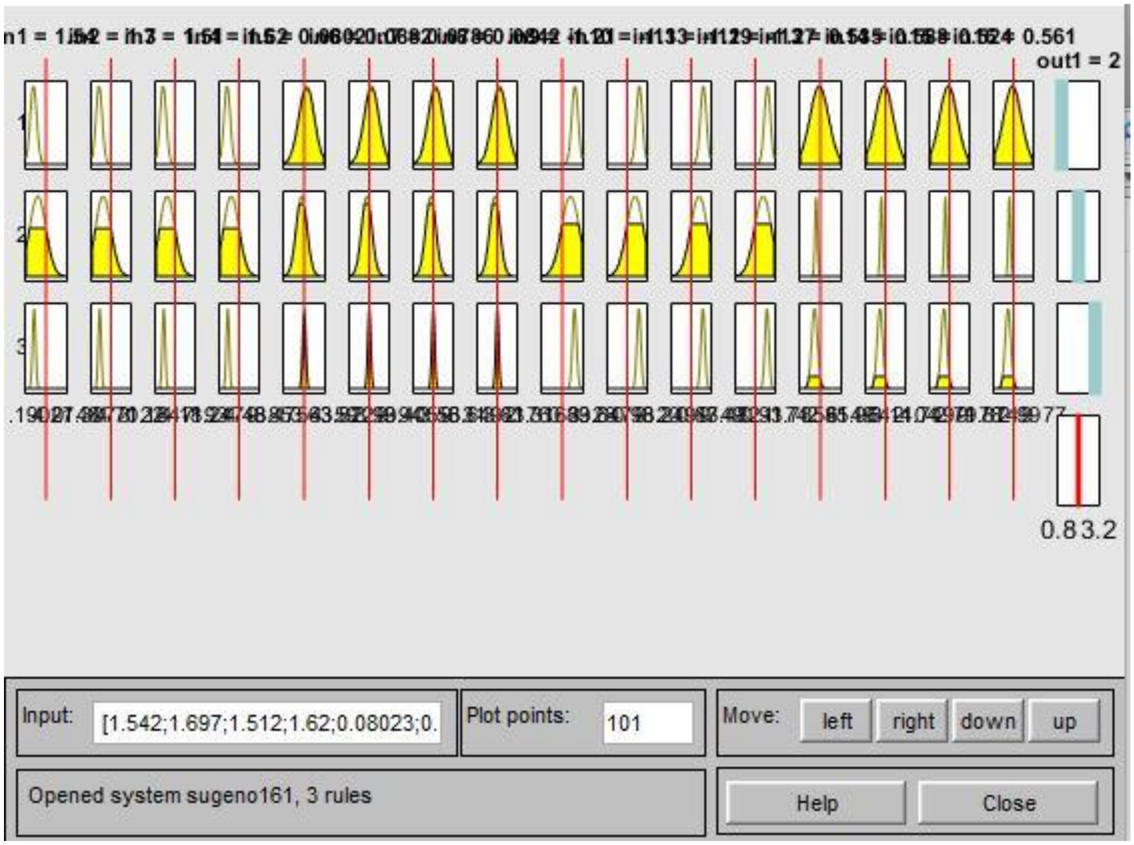
epoch 25   recog 32.1429 recog_test 25 performans   0.535815

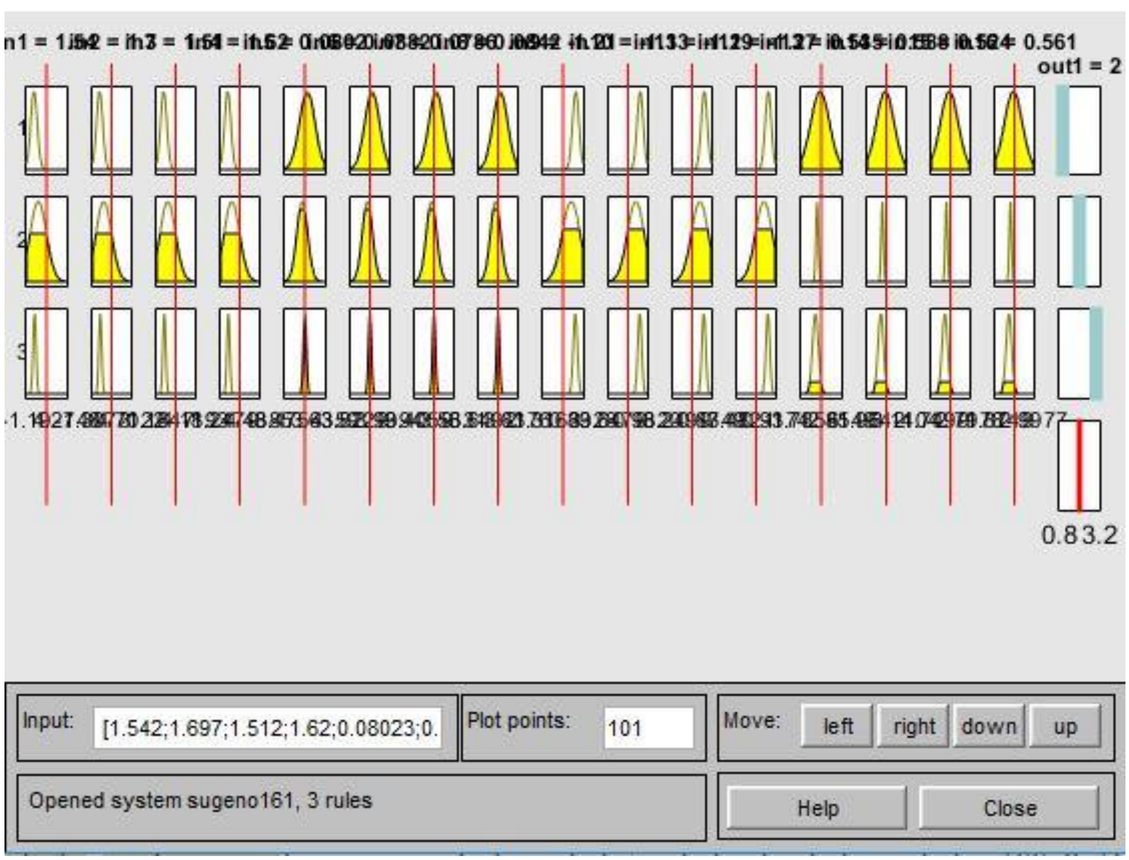
epoch 50   recog 32.1429 recog_test 25 performans   0.535815

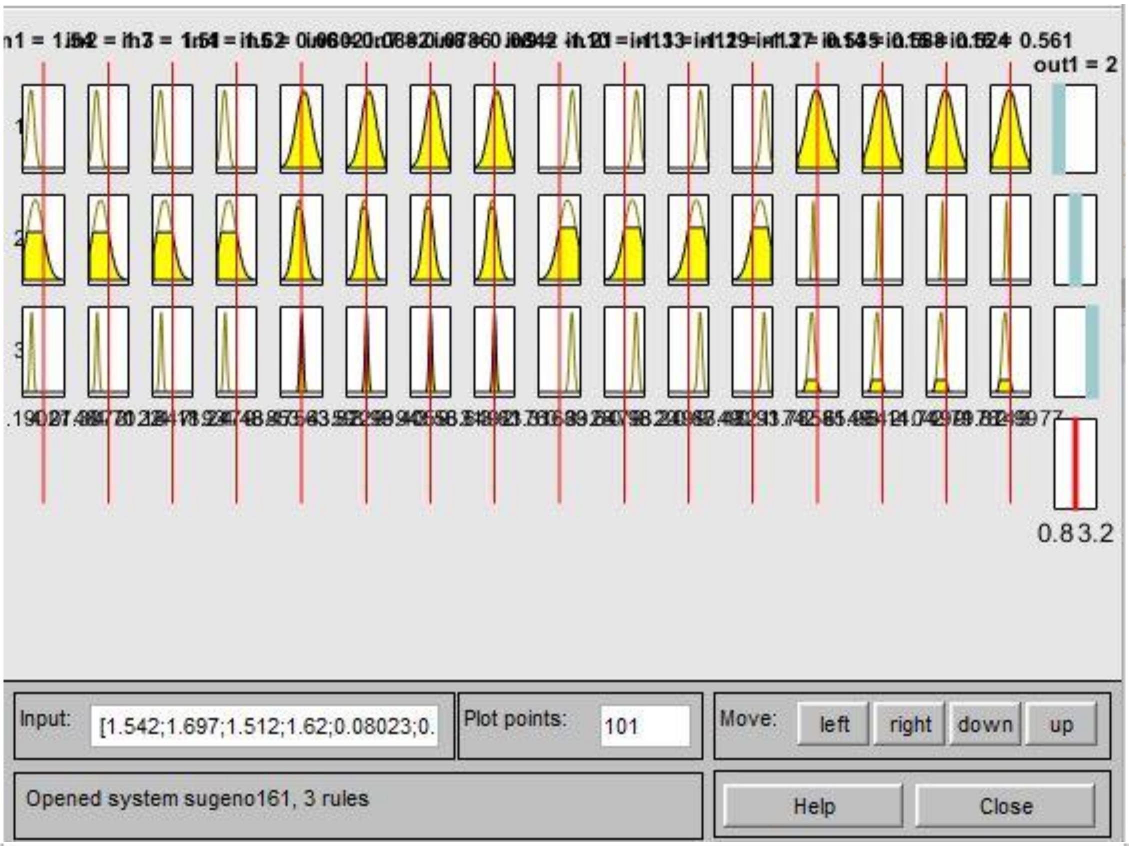
>>

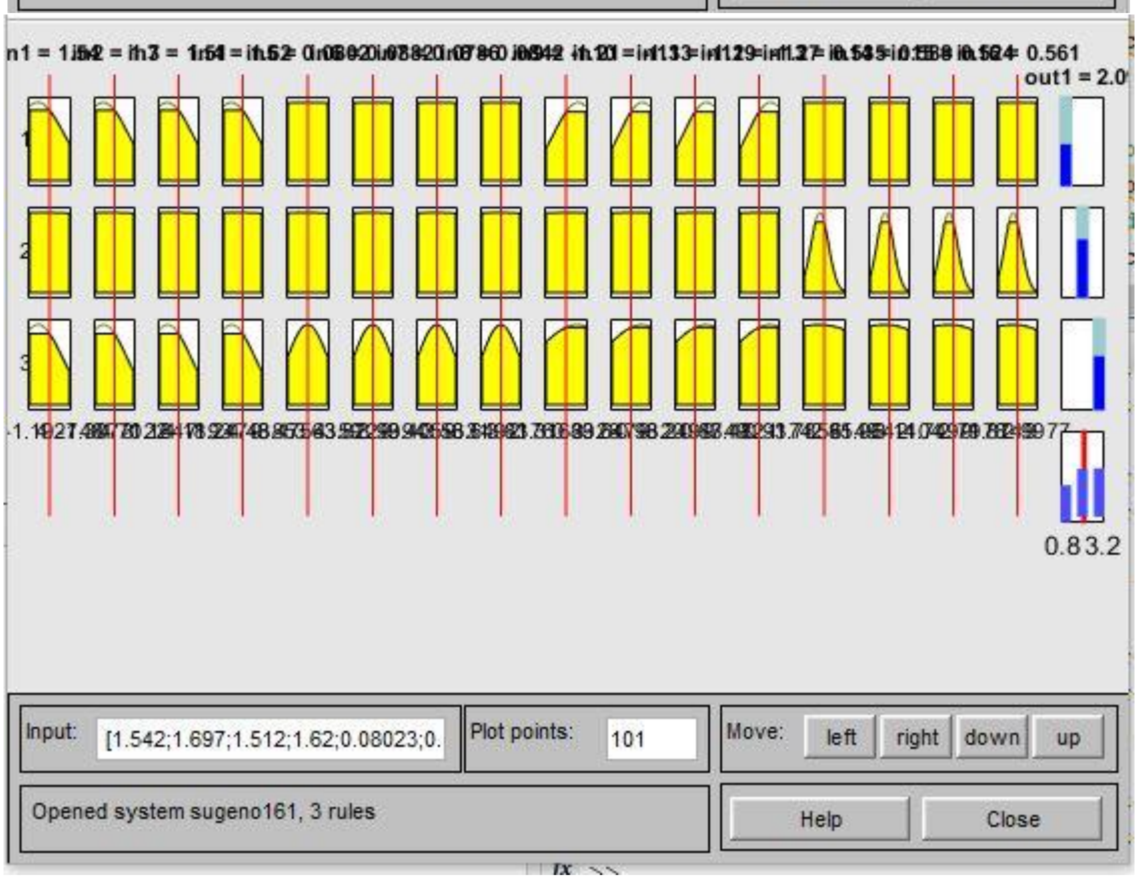
Output figure:

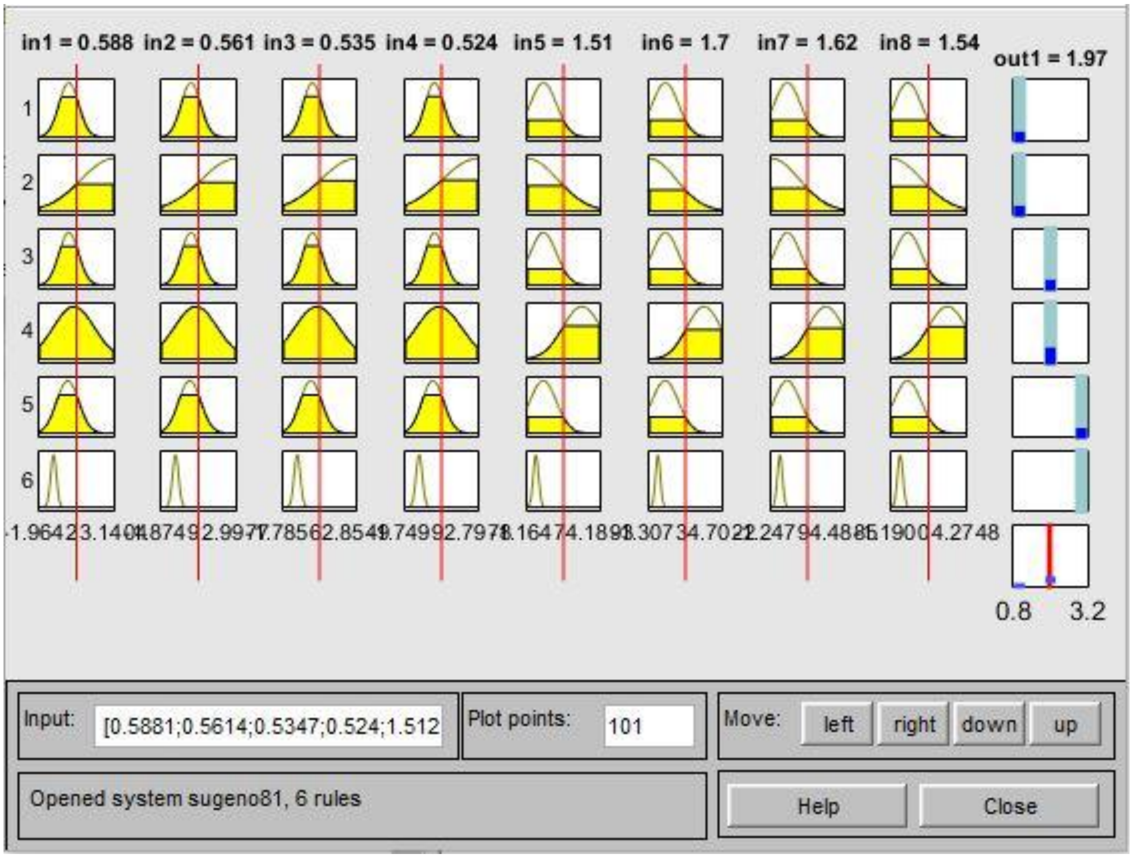

Performance evaluation
RMSE value
Epochs
0
0.1
0.2
0.3
0.4
0.5
0.6
0
10
20
30
40
50
60
70
80
90
100


out1 = 2
0.8 3.2
Input:
[1.542;1.697;1.512;1.62;0.08023;0.
Plot points:
101
Move:
left
right
down
up
Opened system sugeno161, 3 rules
Help
Close


out1 = 2
0.8 3.2
Input:
[1.542;1.697;1.512;1.62;0.08023;0.
Plot points:
101
Move:
left
right
down
up
Opened system sugeno161, 3 rules
Help
Close


out1 = 2
0.8
3.2
Input:
[1.542;1.697;1.512;1.62;0.08023;0.
Plot points:
101
Move:
left
right
down
up
Opened system sugeno161, 3 rules
Help
Close


0.8
3.2
Input:
[1.542;1.697;1.512;1.62;0.08023;0.
Plot points:
101
Move:
left
right
down
up
Opened system sugeno161, 3 rules
Help
Close


in1 = 0.588
in2 = 0.561
in3 = 0.535
in4 = 0.524
in5 = 1.51
in6 = 1.7
in7 = 1.62
in8 = 1.54
out1 = 1.97
1
2
3
4
5
6
0.8
3.2
Input:
[0.5881;0.5614;0.5347;0.524;1.512
Plot points:
101
Move:
left
right
down
up
Opened system sugeno81, 6 rules
Help
Close

3.4.1 Introduction:

Emotions play an important role in our daily lives influencing decisions [1], reasoning and attention [2]. Emotions have been associated with the wellbeing of people [3] and their quality of life [4]. Researchers have also indicated that emotions are associated with the body immune system. Experimental results show that people who typically report experiencing negative emotions are at greater risk of disease than those who typically report positive emotions [5]. Furthermore, people with a more negative affective style (negative emotional state) have a weaker immune response than those with a more positive affective style (positive emotional state) [6]. A recent publication has also indicated that people who frequently experience positive emotions live longer and healthier lives [7]. All these findings have enticed researchers to better understand human emotions and make good for use in areas such as human-computer interaction and affective computing.

Researchers have detected emotions from individuals' heart rate, skin conductance, pupil dilation, tone of voice, facial expression and EEG using various techniques. Most of these techniques emerge from the machine learning and pattern recognition fields. Classification algorithms such as k-nearest neighbors (kNN) [8], Naïve Bayes [8], neural network [9], support vector machines (SVM) [10] and others [11], [12] have been used in detection of emotions. Fuzzy logic based methods, which are widely used in the area of control, have also been used in emotion detection [13]–[15]. Fuzzy based emotion classifications from EEG have also been proposed due to its advantage of assigning patterns into more than one class with certain degree of membership. In [16] the authors proposed EEG-based emotion classification using fuzzy clustering algorithms (Fuzzy K-Means and Fuzzy C- Means), and [17] presented a method of extracting emotion from the EEG using incremental neural fuzzy inference system.

In this paper, a new fuzzy based classification algorithm of positive and negative emotion from EEG is presented. In previous contributions both the fuzzy rules and fuzzy membership functions were generated from the data. In this work, however, fuzzy rules are defined based on research showing that there is a correlation of negative and positive emotions with activation of the right and left hemispheres of the human head. The algorithm has three main advantages: (1) direct use of intuitive rules that can be obtained from the literature or from expertise and additionally, new rules can be added as required, (2) the classification output gives two types of information: type of emotion and the strength of that emotion, and (3) it has low computation times and hence is suitable for portable devices and for real time applications.

This paper is organized as follows. Section 2 presents the methodology providing the background on Fisher's discriminate analysis (FDA) and fuzzy logic systems followed by the implementation of the algorithm. Section 3 presents the testing and evaluation methods of the proposed algorithm and finally Section 4 presents the results and conclusions.

Fuzzy Logic: Fuzzy logic is a method of rule-based decision making used for expert systems and process control. Fuzzy logic differs from traditional Boolean logic in that fuzzy logic allows partial membership in a set. Traditional Boolean logic is two-valued in the sense that a member either belongs to a set or does not. Values of one and zero represent the membership of a member to the set with one representing absolute membership and zero representing no membership. Fuzzy logic allows partial membership, or a degree of membership, which might be any value along the continuum of zero to one.

3.4.2 Fuzzy Classification:

Fuzzy classes reflect reality better and allow decision makers or analytics to describe input attributes and output classes more intuitively using linguistic variables, overlapping classes and approximate reasoning. Objects that belong to more than one class are treated in all classes where they have partial membership.

In order to solve a fuzzy classification problem within a knowledge-based fuzzy inference system (FS) it is necessary to fuzzy attributes, determine all IF-THEN rules (rule base), process them and to provide result in a usable and understandable form. More about fuzzy classification is in (Hudec and Vujošević, 2005).

The advantages of fuzzy systems are as follows. They § enable the creation of logical inference system based on human mind including uncertainties in membership degrees to the appropriate fuzzy sets. § support the inference process based on “IF-THEN” rules. § enable accessible, understandable and easy to use and modify knowledge base.

There are many fuzzy system software capable to solve classification tasks, for example MATLAB or FLOPS. These software have been produced to solve a wide area of tasks but they are complicated for users. In order to solve a classification task, the decision maker needs the assistance to prepare the input data from database into proper format for the FS and to present the results into a useful and understandable form. This part could be programmed but it is not a trivial task. The decision maker also needs assistance to set the most suitable mathematical functions inside the FS.

Fuzzy System:

A fuzzy system is a system of variables that are associated when using fuzzy logic. A fuzzy controller uses defined rules to control a fuzzy system based on the current values of input variables. Fuzzy systems consist of three main parts: linguistic variables, membership functions, and rules.

Fuzzification:

Fuzzy logic uses linguistic variables instead of numerical variables. The process of converting a numerical variable (real number or crisp variable) into a linguistic variable (fuzzy number) is called fuzzification. The simplest form of membership function is the triangular membership function and it is used in Figure as the reference.

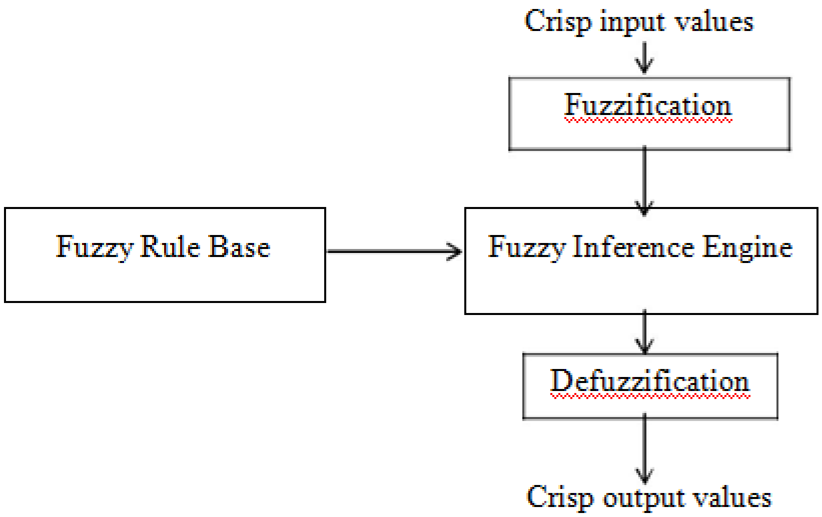


Figure: Fuzzy logic block diagram

Membership Function:

1. Trapezoidal Membership Function
2. Gaussian Membership Function
3. Bell Shape Membership Function
4. Sigmoidal Membership Function
5. S Membership Function

6. E Membership Function

7. Triangular Membership Function

Defuzzification:

There are a few 'Defuzzification' methods by which fuzzy to crisp value conversion could have been obtained, if a closed loop system is preferred.

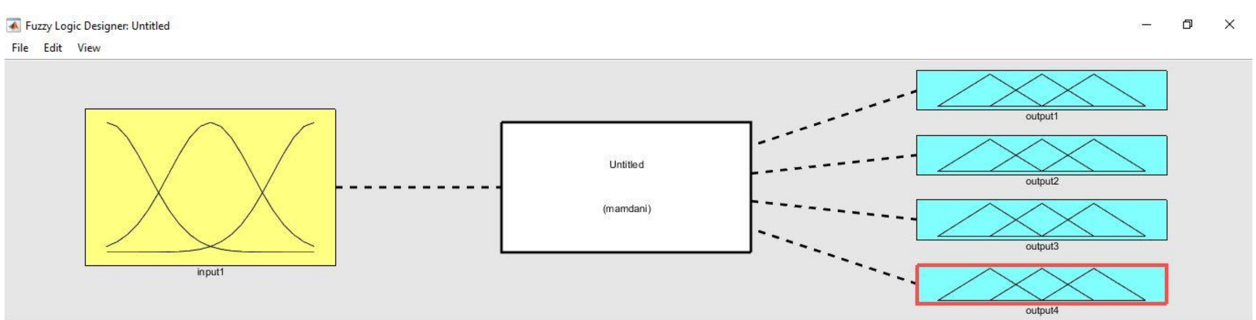
The reverse of fuzzification is called defuzzification. The use of FLC inference engine produces the required output in a linguistic form. Riley et al (1997) and Renwang et al (2010) and discussed about vibration monitoring and fuzzy algorithms. According to this citation on real world equipment, the linguistic variables have to be transformed to crisp output. The centre of weight method is the best well-known defuzzification method and it is used in this work.

1. Max membership principle
2. Centroid method
3. Weighted average method
4. Mean max membership
5. Centre of sums
6. Centre of largest area
7. First (or last) of maxima

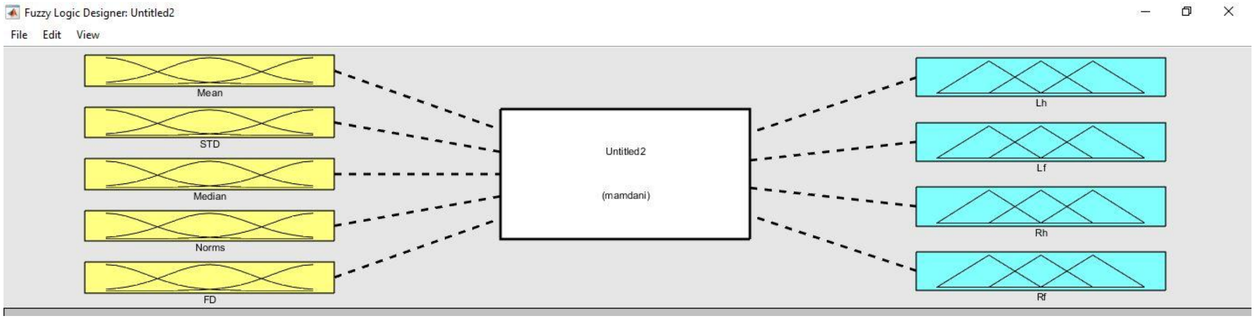
3.4.3 Methodology:

FDA [18] is a common and robust method for reducing high dimension data into a lower dimension subspace using a projection matrix, W. As it was pointed out by Fukunaga [12], there are equivalent variants of FDA to find the projection matrix that maximizes the feature separation criteria. In this paper, the following FDA method was used [12].The between-class scatter matrix, and $S\ T = \sum (xj - \mu)(xj - \mu) \top N\ j$=1 (3) is the total scatter matrix, C is the total number of classes, ni is the sample number of the class i, μi is the mean of the class i, μ is the global mean, N is the total number of training samples in matrix X with elements xj, $\forall j$ = 1, 2, . . N and the symbol $\top$ is the transpose. The new algorithm in this paper uses FDA to reduce the high dimension feature space into low dimension space. As FDA is a supervised dimension reduction method, W was computed using labeled training samples. Then W is updated continuously to take into account changes that might occur over time in the stream of unlabeled samples. In order to update S B (see eqn. 2) using unlabeled samples, μi was kept constant, as proposed in [19]. S T , on the other hand, was updated every time a new sample, $x(t)$ was acquired. We have used matlab code and finished task step by step. We have shown following step below:

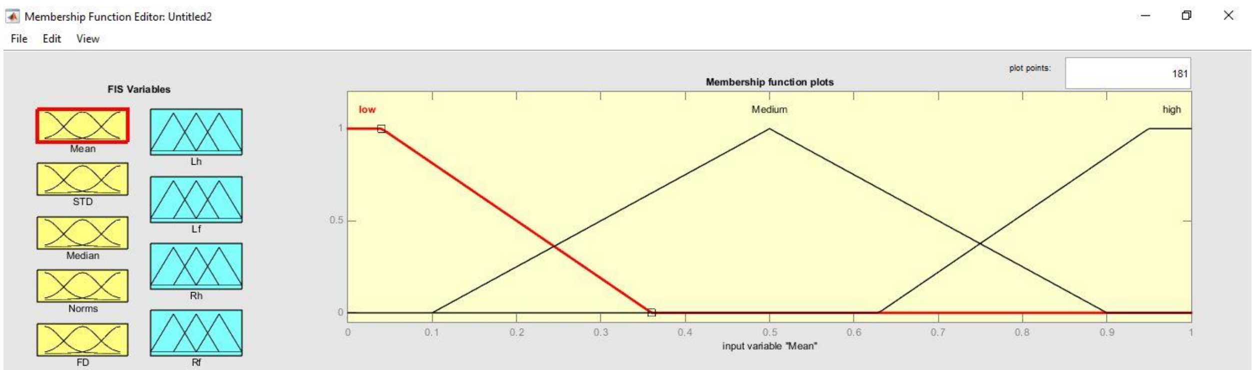
Step1:



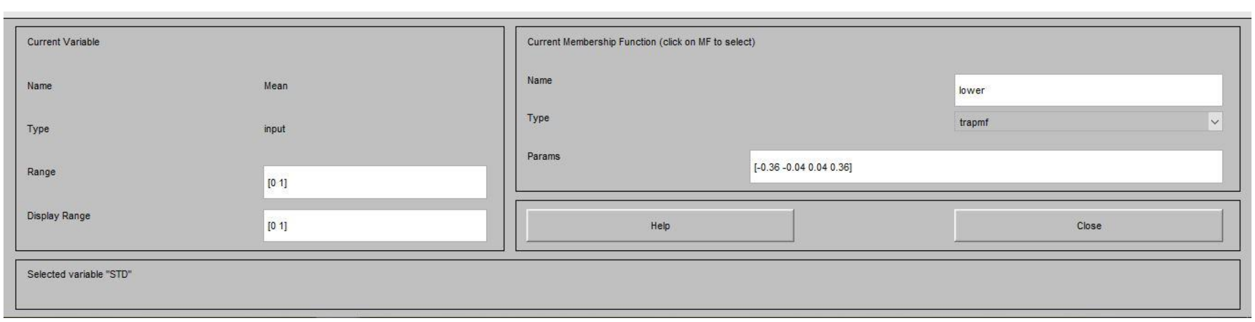
Step2:


Fuzzy Logic Designer: Untitled2
File
Edit
View
Mean
STD
Median
Norms
FD
Untitled2
(mamdani)
Lh
Lf
Rh
Rf

Step3:


Membership Function Editor: Untitled2
File
Edit
View
FIS Variables
Mean
STD
Median
Norms
FD
Lh
Lf
Rh
Rf
plot points:
181
Membership function plots
low
Medium
high
input variable "Mean"

Step4:


Current Variable
Name
Mean
Type
input
Range
[0 1]
Display Range
[0 1]
Current Membership Function (click on MF to select)
Name
lower
Type
trapmf
Params
[-0.36 -0.04 0.04 0.36]
Help
Close
Selected variable "STD"

Fuzzy rule based classification:

In standard pattern recognition, classes are mutually exclusive [21], that is, a sample or pattern is assumed to belong to only one of the classes. However, in fuzzy classification, a pattern can belong to several classes with a certain degree of membership. In this paper, the fuzzy classifier of the following form will be used [22]:

$$IF\ x1\ is\ A1\ AND\ \ldots\ xm\ is\ An\ THEN\ C\ is\ Y \qquad (7)$$

where x1, .. xm are features, A1,.. An and Y are linguistic variables (e.g. small, medium, and large), C is the class. The number of IF-THEN rules depends on the number of linguistic variables and the number of features. For example, if there are m linguistic variables for each feature and n number of features, then there are mn possible number of rules. There two reasons fuzzy logic classification was chosen: (1) it has intuitive linguistic rules which are easy to understand and be obtained from experts and in the literature, (2) emotions are subjective and continuously varying and this variation can be well reflected using the degree of membership property of fuzzy classification.

Proposed fuzzy logic based emotion classification:

This algorithm was developed based on a valence-arousal emotion classification model which is widely used in the literature. Based on this model, it has been reported that the right hemisphere of the brain is more active during negative emotions (low valence) and the left hemisphere is more active during positive emotions (high valence) [23]–[25]. This has been supported by experimental results in the literature. Trainor et al [26] reported that both joy and happiness emotions showed relatively greater left frontal alpha activation whereas both fear and sadness showed greater right alpha activation. In other words, the alpha wave of the left hemisphere decreases with positive emotions and that of the right hemisphere decreases with negative emotions. In [27] the authors reported that there existed a left and right difference in the relative power of the alpha wave for left and right hemispheres and the alpha wave decreased only at the right side in the happy state. Also, in [28] alpha power was greater in the left than in the right frontal region during experience of negative emotions. These findings and others reported in the literature can be used to devise rules which can be used as a fuzzy classifier to classify emotions from the EEG signal. The highlighted text above are good indicators of the linguistic variables of the fuzzy system. Therefore, the table of rules (see Table 1) was developed using two input features (one from the left hemisphere (LEFT), the other from the right hemisphere (RIGHT) and one output (VALENCE). Three linguistic variables: low, medium, and high were used for the input features and five linguistic variables: very low, VL, low, L, medium, M, high, H, and very high, VH, were used for the valence. The membership functions corresponding to these linguistic variables are shown in Figure 1 and 2 for input features and valence respectively.

Table 1: IF-THEN fuzzy rules used for emotion classification

		RIGH		
		LOW	MEDIUM	HIGH
LEFT	LOW	M	L	VL
	MEDIUM	H	M	L
	HIGH	VH	H	M

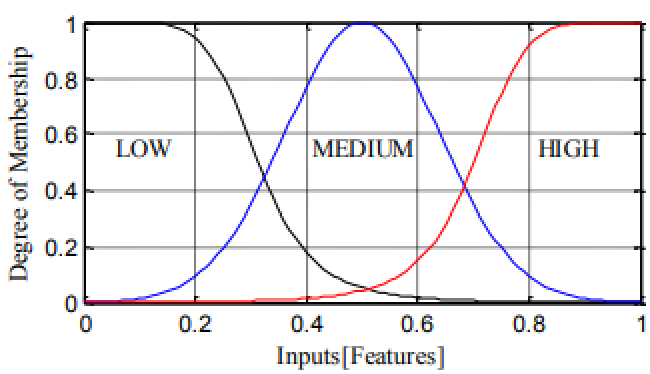


Figure 1. Input membership functions

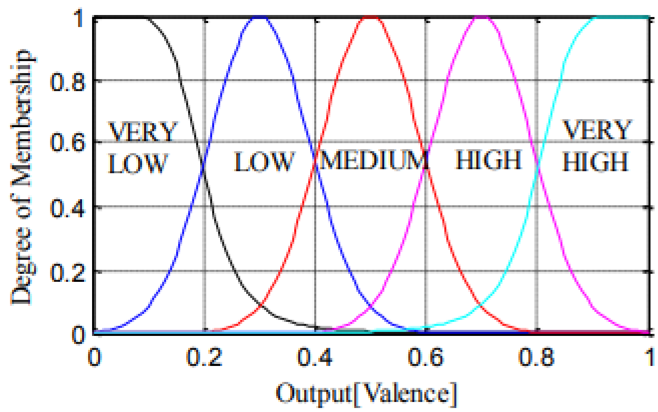


Figure 2. Output membership functions

To put this in context, if it is assumed that the signal power from the EEG alpha band is taken from FP1 (electrode at frontal left hemisphere) and FP2 (at frontal right hemisphere) channels, then based on equation 7, example of rules from Table 1 could be linguistically interpreted as: Rule 1: If left alpha power is low and right alpha power is high, then valence is very low. Rule 2: If left alpha power is medium and right alpha power is high, then valence is low. The fuzzy logic based emotion classification algorithm, FLEC, was implemented using FDA for feature dimension reduction and Fuzzy logic using the rules shown in Table 1 for classification and was implemented using Mamdani-type inference system [29]. The FLEC algorithm can be summarized as follows:

Signal acquisition and feature extraction:

The algorithm was tested using real EEG data which was obtained from a dataset for the analysis of human affective states managed by Queen Mary University of London [30]. The data was acquired from 32 participants while watching music video clips to induce different emotions. Each participant in the experiment watched 40 one minute long music video clips while his or her physiological signals being recorded using a 32 channel EEG. Then, participants rated each video in terms of arousal, valence, like/dislike, dominance and familiarity. More details and the EEG dataset can be obtained from [8] and [30].

In this experiment 14 asymmetrical channel pairs, named according to the 10-20 International standard of electrode placements [31], { *(FP1,FP2), (AF3,AF4), (F3,F4), (F7,F8), (FC3,FC4), (FC1,FC2), (C3,C4), (T7,T8), (CP5,CP6), (CP1,CP2) , (P3,P4), (P7,P8), (PO3,PO4), (O1,O2)*} were used. From each channel, the alpha band (8 Hz to 12 Hz) was filtered using a finite impulse response filter with 127 filter coefficients. Then the following statistical features were extracted from the obtained alpha band: mean, standard deviation, mean of the absolute values of the first differences, mean of the absolute values of the second differences. Formulae for computing these features can be found in [32]. In addition, the signal power of the alpha band was also computed as a feature.

In this paper, we also propose a new feature that will be referred as the oscillation feature. This was obtained by finding all local maxima and local minima of the signal and this gives an insight of how signal power is related to oscillations and activation and inactivation of certain areas of the brain. Therefore, the correlation of the signal power and oscillation features is an indication that both features originate from the same emotion activity. This feature is obtained using an algorithm shown below:

Get the signal x(t), with t = 1,2,…N samples

Set local minima, Lmin = 0

Set local maxima, Lmax = 0

FOR t = 1 to N-2

IF x(t) > x(t+1) AND x(t+2) > x(t+1)

THEN Lmin = Lmin +1

IF x(t) <x(t+1) AND x(t+2) < x(t+1)

THEN Lmax = Lmax +1

END FOR

Then, the oscillation feature, *O,* was calculated as in eqn. 8

3.4.4 Feature selection and classification:

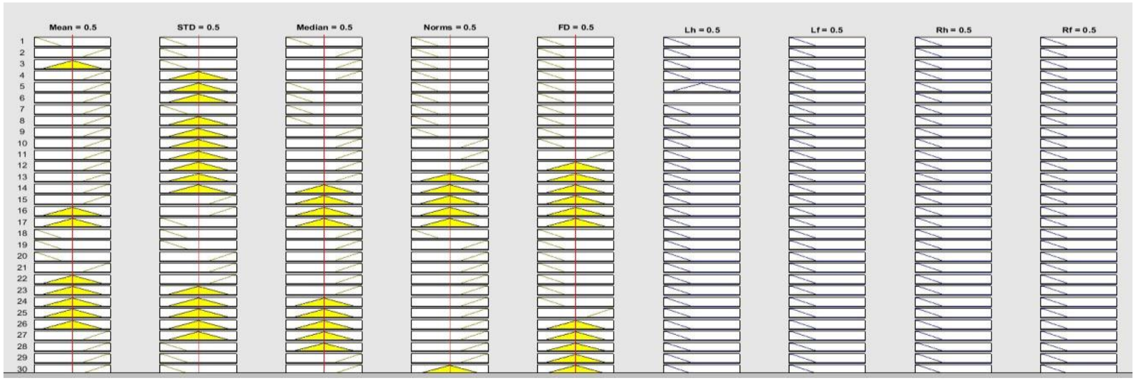
For each video trial there were six features per channel and so a total of twelve features per channel pair. To reduce the classification computation cost without compromising the accuracy, we reduced the number of features from twelve to four. This was done by computing the FDA ratio for all possible combinations of features ($^{12}C4 = 495$) and those with the highest discrimination ratio were chosen. It was observed that feature combinations which contained the signal power and oscillation features had higher discrimination ratios than other features. Thus the power and oscillation features of the alpha band from each channel were used for classification.

To test the performance of the proposed algorithm, subject independent classification was performed on all video trials using our classification algorithm, FLEC, and its performance was compared using standard classifiers such as Naïve Bayes, Matlab inbuilt support vector machine (SVM), and LIBSVM [34] which are widely used for emotion classifications [10]. For every channel pair, classification was performed for all subjects and a 10-fold cross validation was used to determine and compare the performance of each of the four classification methods.

3.4.5 Result:

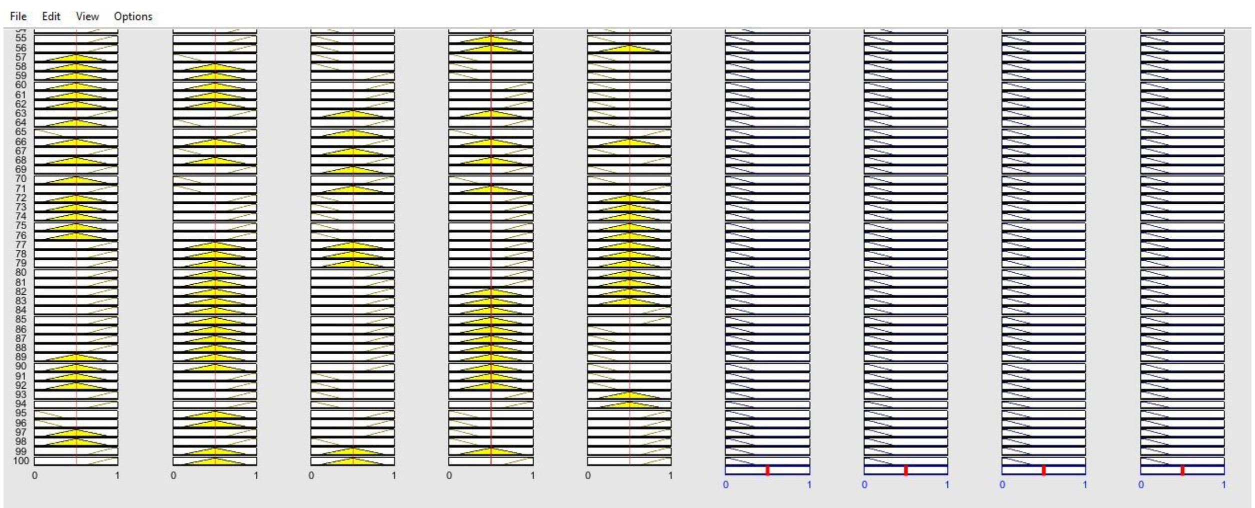
At the end part we have seen result.

Step5:



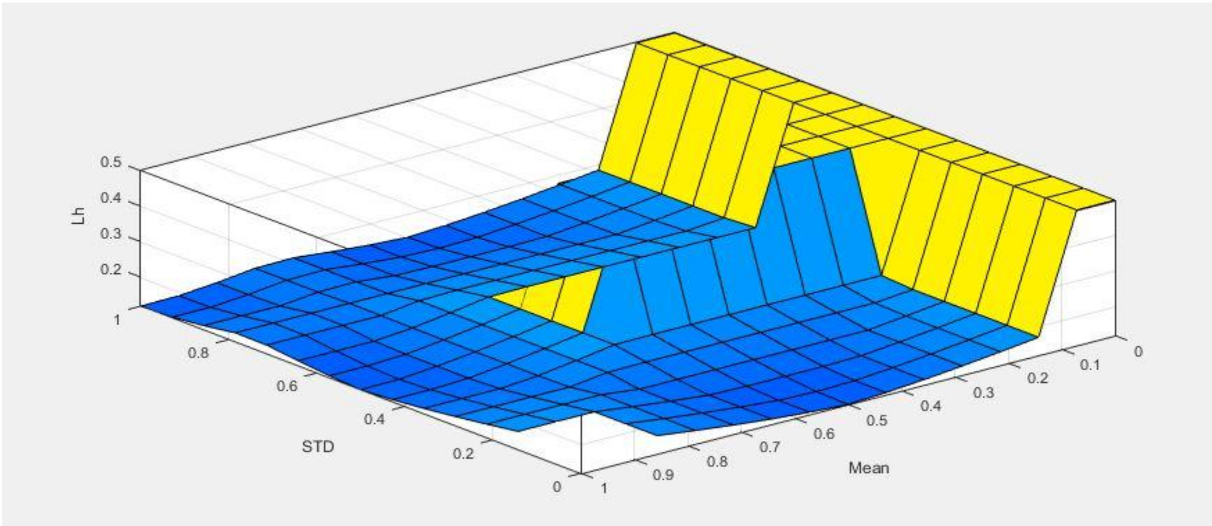
Step6 :

Result with Crisp Value:



Step7:

The surface view of result:



Lh
0.5
0.4
0.3
0.2
1
0.8
0.6
0.4
STD
0.2
0
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Mean

3.5.1 Introduction:

Electroencephalography (EEG) is the prominent technology for identifying the brain abnormalities in many challenging applications in the field of medicine, which includes Seizures, Alzheimer Disease, Coma, Brain death, Dysarthria [1]. Paralyzed peoples are not having muscle control. In order to capture the brain signals for analyze the activity of the brain [2].

EEG signals will be generally represented in high dimensional features space and it is very difficult to interpret. Machine learning methods are helpful for interpreting high dimensional feature sets and analyze the characteristics of brain patterns. Support Vector Machine is one of the popular Machine Learning methods for classifying EEG signals. SVM aims to maximize the margin in order to avoid the risk of over fitting data and minimize the misclassification error.

In conventional methods like multilayer perceptron, complexities are controlled depends on number of features used where as in SVM complexities are independent from dimensionality. Optimization problem occurs due to conversion of data into high dimensional feature space and it can be resolved by using inner product of Kernel methods [3]. Classification was done using support vector machines (SVM). Section 2 describes the SVM. In Section 3, data set was introduced. In Section 4, feature selection algorithms were presented. Section 5 summarizes the results and conclusions.

3.5.2 Support Vector Machine:

Support Vector Machine was initiated by Vapnik and Cortes for two group classification problem. SVM is applied in many applications like EEG signal classification, cancer identification, bioinformatics, seizure prediction, face recognition and speech disorder.

Support Vector Machine techniques [4] can be classified into three types namely, linearly separable, Linearly Inseparable and Non-linearly separable as shown in Figure 1.

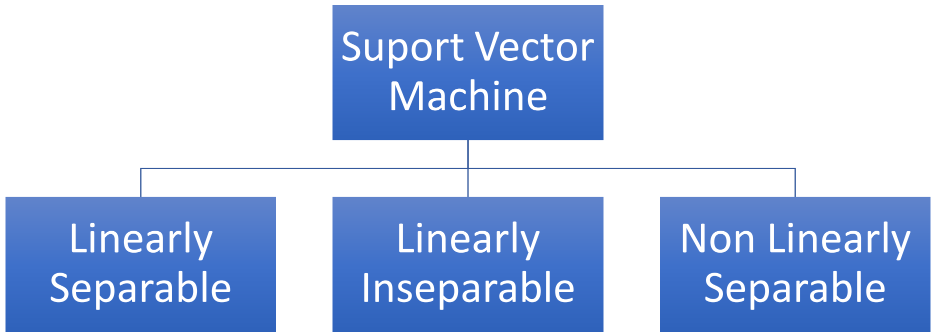


Figure 1: Types of Classification

SVM is used to construct the optimal hyperplane with largest margin for separating data between two groups. For two dimensional data, single hyper plane is enough to separate the data into two groups such as +1 or -1. Two hyper planes are needed to separate the data points for three dimensional data. SVM constructs hyper plane for separating the sample data based on the target categories. For two dimensional data, there are number of possible linear separators (hyper planes) and need to find the optimal hyper plane which has maximum margin width. The lines are drawn parallel to optimal hyper plane (solid line) and mark the distance between the hyper plane and the data points. The distance between the dotted lines is called as margin. Some of the sample data points which lie on the hyper planes are called as Support Vectors (SVs) refer Figure 2. These SVs are essential for calculating the margin width.

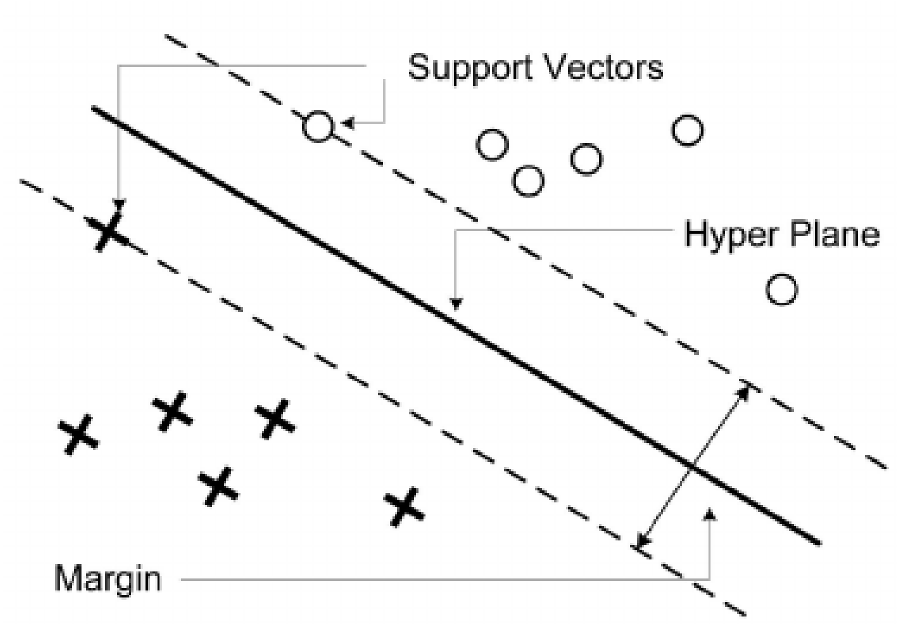


Figure 2: Support Vector Machine Diagram

Linearly Separable:

Usually, there are many such separating planes. SVMs therefore try to find a hyperplane that maximizes the margin between the points closest to the plane respectively (called support vectors)[4].

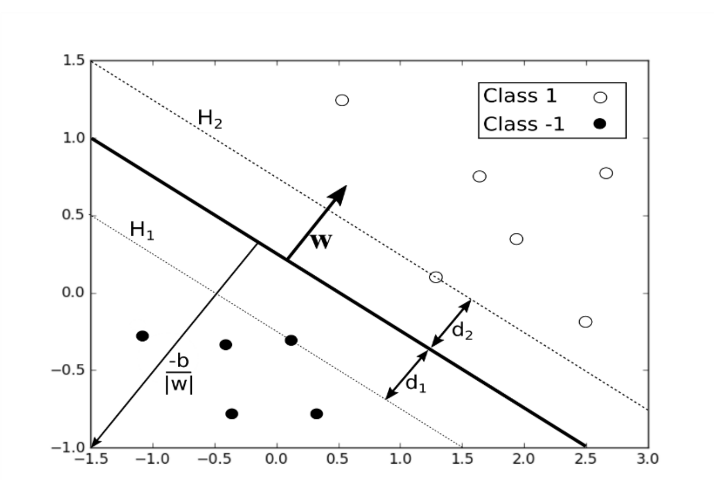


Figure 1: Hyperplane through two linearly separable classes

Linearly Inseparable:

In most real-world scenarios, data from different classes can't be separated linearly. In that case, the above Support Vector Machine Classifier can't converge and we need to introduce means to deal with the inseparable case. The only difference between this optimization problem and the above one is the parameter, constraining the absolute size of the are so-called slack variables that form a penalty term that will penalize wrongly classified samples: the farther the distance of a wrongly classified sample from the separating hyper plane, the largest will be [5].

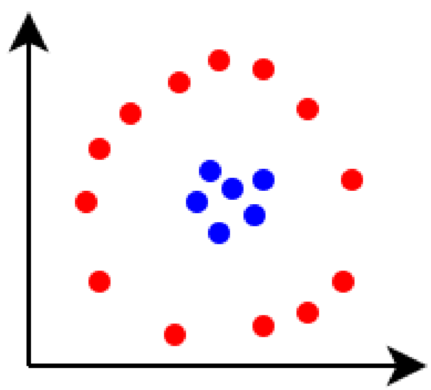


Figure 2: Linearly Inseparable

Non-Linearly Separable:

Both of the described algorithms (linearly separable and linearly inseparable classification) build linear Support Vector Machines, resulting in flat hyperplanes separating the feature space. A very convenient way of expanding the model is to map the data into a space of higher-dimension by applying kernel functions [6].

This diagram shows a very simple example of data that are not linearly separable but very easily separable by transforming the data into the third dimension. Just imagine the blue points having a different "height" than the red points [7].

The kernel trick owe their name to the use of kernel functions, which enable them to operate in a high-dimensional, implicit feature space without ever computing the coordinates of the data in that space, but rather by computing the inner products between the images of all pairs of data in the feature space.

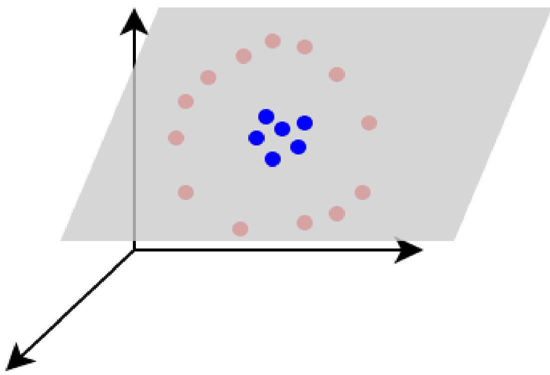


Figure 3: Non-linear Separable

SVM for Classification:

SVM is a useful technique for data classification. Even though it's considered that Neural Networks are easier to use than this, however, some times unsatisfactory results are obtained. A classification task usually involves with training and testing data, which consist of some data instances [9]. Each instance in the training set contains one target values and several attributes. The goal of SVM is to produce a model, which predicts target value of data instances in the testing set, which are given only the attributes [10]. Classification in SVM is an example of Supervised Learning. Known labels help indicate whether the system is performing in a right way or not. This information points to a desired response, validating the accuracy of the system, or be used to help the system learn to act correctly. A step in SVM classification involves identification as which are intimately connected to the known classes. This is called feature selection or feature extraction. Feature selection and SVM classification together have a use even when prediction of unknown samples is not necessary. They can be used to identify key sets which are involved in whatever processes distinguish the classes [10].

3.5.3 SVM for Regression:

SVMs can also be applied to regression problems by the introduction of an alternative loss function [10] [11]. The loss function must be modified to include a distance measure. The regression can be linear and non linear. Linear models mainly consist of the following loss functions, e-intensive loss functions, quadratic and Huber loss function. Similarly to classification problems, a non-linear model is usually required to adequately model data. In the same manner as the non-linear SVC approach, a non-linear mapping can be used to map the data into a high dimensional feature space where linear regression is performed. The kernel approach is again employed to address the curse of dimensionality. In the regression method there are considerations based on prior knowledge of the problem and the distribution of the noise. In the absence of such information Huber's robust loss function, has been shown to be a good alternative [10] [12].

3.5.4 Support Vector Classification for EEG Signals:

Support Machine is mainly applied for classifying normal and seizure activity from the continuous recording EEG signals. Feature vectors are generated for both seizure and non seizure activity. RBF kernal function can be choosen as classifier for generating optimal decision boundaries [6]. Feature vectors can be constructed from empirical mode decomposition which decomposes the EEG signal into amplitude and frequency modulated components. Parameters like area and mean frequency of the components are estimated and given as input for LS-SVM. Least square support vector machine with radial basis kernel function can be used for classification of seizure and non seizure activity [7].

EEG signals can be decomposed into different frequency bands with the help of Discrete Wavelet Transform. Features can be generated from entropy, energy and standard deviation and used to train SVM for classifying seizure and non seizure activity [8].

Support Vector Machine classification can be used to classify different kinds of mental tasks like thinking to move left hand, thinking to move right hand, performing mathematical operation and thinking to a carol. Power Spectrum method is applied for extracting features from preprocessed signals and given as training data for SVM. For testing, single channel may be given to classify [9].

SVM also considered for feature selection process. SVM with Gaussian Kernel is used for neonatal feature selection. Various features like mean and standard deviation are extracted from SVM classifier. Training data identifies the optimal hyperplane for neonatal data. [10].

EEG signals can be used to detect the brain tumors with proper testing and training. EEG signal artifacts are removed using adaptive filter method and spectral methods are applied for extracting different spectral bands of frequencies. These features are given to SVM classifier for classifying tumor [11].

SVM can be used to classify emotion detection from EEG signals. Fractal dimension (FD) values of EEG signals are extracted from both hemisphere and allow recognizing emotions with different levels of arousal and valence values. Support vector machine kernel classifier is used to classify the emotions based on positive and negative values of arousal and valence features [12].

3.5.5 EEG Data:

Description of the Dataset:

The EEG dataset used in this research was created and contributed to PhysioNet [19] by the developers of the BCI2000 [20] instrumentation system.The dataset consists of more than 1500 EEG records, with different durations (one or two minutes per record), obtained from 109 healthy subjects. Subjects were asked to perform different motor/imagery tasks while EEG signals were recorded from 64 electrodes along the surface of the scalp. Each subject performed 14 experimental runs:

A one-minute baseline runs (with eyes open)

A one-minute baseline runs (with eyes closed)

Three two-minute runs of each of the four following tasks:

- The left or right side of the screen shows a target. The subject keeps opening and closing the corresponding fist until the target disappears. Then he relaxes.
- The left or right side of the screen shows a target. The subject imagines opening and closing the corresponding fist until the target disappears. Then he relaxes.
- The top or bottom of the screen. A target appears on either. The subject keeps opening and closing either both fists (in case of a top-target) or both feet (in case of a bottom-target) until the target disappears. Then he relaxes.
- The top or bottom of the screen A target appears on either. The subject imagines opening and closing either both fists (in case of a top-target) or both feet (in case of a bottom-target) until the target disappears. Then he relaxes.

The 64-channels EEG signals were recorded according to the international 10-20 system (excluding some electrodes) as seen in Fig. 2.

The author of [17] used features produced by Motor Imagery (MI) to control a robot arm. Features such as the band power in specific frequency bands (alpha: 8-12Hz and beta: 13- 30Hz) were mapped into right and left limb movements. In addition, they used similar features with MI, which are the Event Related Desynchronization and Synchronization (ERD/ERS) comparing the signal's energy in specific frequency bands with respect to the mentally relaxed state. It was shown in [18] that the combination of ERD/ERS and Movement-Related Cortical Potentials (MRCP) improves EEG classification as this offers an independent and complimentary information.

In [15], a hybrid BCI control strategy is presented. The authors expanded the control functions of a P300 potential based BCI for virtual devices and MI related sensorimotor rhythms to navigate in a virtual environment. Imagined left/right hand movements were translated into movement commands in a virtual apartment and an extremely high testing accuracy results were reached.

A three-class BCI system was presented in [16] for the translation of imagined left/right hands and foot movements into commands that operates a wheelchair. This work uses many spatial patterns of ERD on mu rhythms along the sensory-motor cortex and the resulting classification accuracy for online and offline tests was 79.48% and 85.00%, respectively. The authors of [17] proposed an EEG-based BCI system that controls hand prosthesis of paralyzed people by movement thoughts of left and right hands. They reported an accuracy of about 90%.

A single trial right/left hand/leg movement classification is reported in [18]. The authors analyzed both executed and imagined hand movement EEG signals and created a feature .

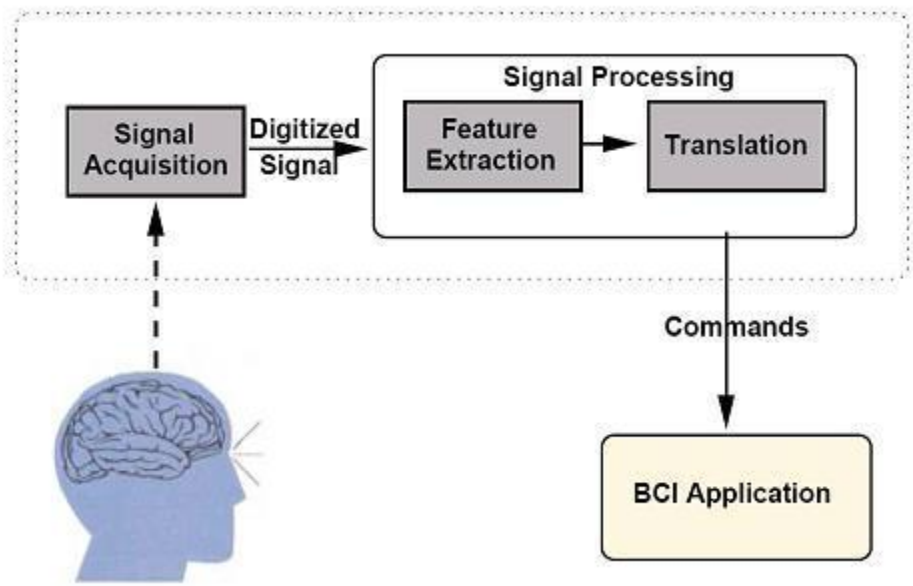


Fig. 1. Feature extraction and translation into machine commands

The Sub set use din the Current Work

From this dataset, we selected the three (two-minute) runs of the first task described above (opening and closing the left/right fist based on a target that appears on left or right side of the screen). These runs include EEG data for executed hand movements.

We created an EEG data subset corresponding to the first six subjects (S001, S002, S003, S004, S005, and S006) including three runs of executed movement specifically per subject for a total of 18 two-minute records.

3.5.6 EEG Signals for Feature Extraction:

Channel Selection:

According to [22], many of the EEG channels appeared to represent redundant information. It is shown in [37] that the neural activity that is correlated to the executed left and right hand movements is almost exclusively contained within the channels C3, C4, and CZ of the EEG channels of Fig. 2. This means that there is no need to analyze all 64 channels of data.

On the other hand, only eight electrode locations are commonly used for MRCP analysis covering the regions between frontal and central sites (FC3, FCZ, FC4, C3, C1, CZ, C2, and C4) [14]. These channels were used for the Independent Component Analysis (ICA) discussed later in the current section (Fig. 3).

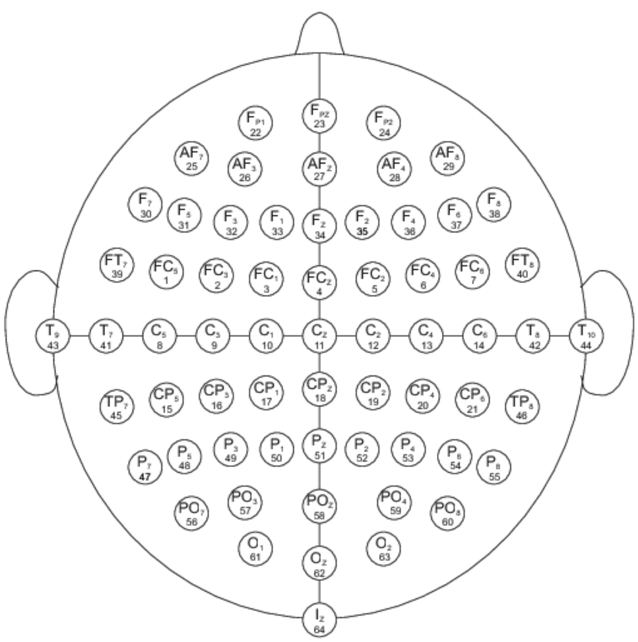


Fig. 2. Electrodes of the International 10-20 system for EEG

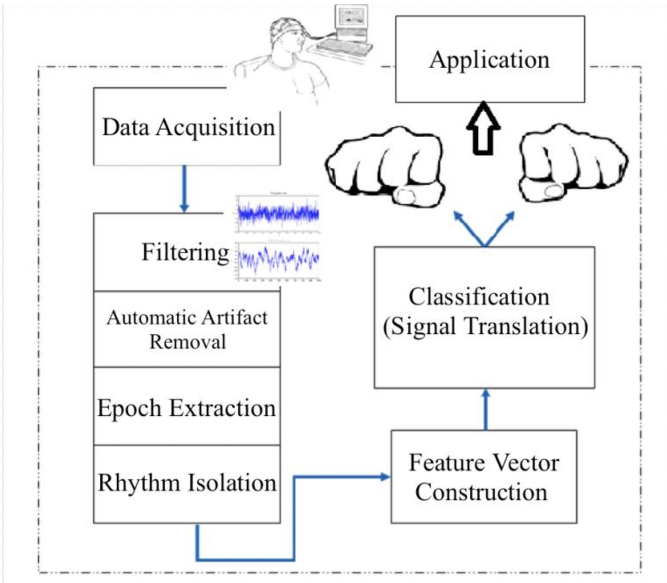


Fig. 3. Schematic diagram for the proposed system

Filtering:

Because EEG signals are known to be noisy and non- stationary, filtering the data is an important step to get rid of unnecessary information from the raw signals. EEGLAB [40], which is an interactive MATLAB toolbox, was used to filter EEG signals.

A band pass filter from 0.5 Hz to 90 Hz was applied to remove the DC (direct current) shifts and to minimize the presence of filtering artifacts at epoch boundaries. A Notch filter was also applied to remove the 50 Hz line noise.

Automatic Artifact Removal (AAR):

The EEG data of significance is usually mixed with huge amounts of useless data produced by physiological artifacts that masks the EEG signals [40]. These artifacts include eye and muscle movements and they constitute a challenge in the field of BCI research. AAR automatically removes artifacts from EEG data based on blind source separation and other various algorithms.

The AAR toolbox [41] was implemented as an EEGLAB plug-in in MATLAB and was used to process our EEG data subset on two stages: Electrooculography (EOG) removal using the Blind Source Separation (BSS) algorithm then Electromyography (EMG) Removal using the same algorithm [26].

Epoch Extraction (Splitting)

After the AAR process, the continuous EEG data were epoched by extracting data epochs that are time locked to specific event types.

When no sensory inputs or motor outputs are being processed, the mu (8–12 Hz) and beta (13–30 Hz) rhythms are said to be synchronized [21]. These rhythms are electrophysiological features that are associated with the brain's normal motor output channels [21]. While preparing for a movement or executing a movement, a desynchronization of the mu and beta rhythms occurs which is referred to as ERD and it can be extracted 1-2 seconds before onset of movement (as depicted in Fig. 4). Later, these rhythms synchronize again within 1-2 seconds after movement, and this is referred to as ERS.

On the other hand, delta rhythms can be extracted from the motor cortex, within the pre-movement stage, and this is referred to MRCP. The slow (less than 3 Hz) MRCP is associated with an event-related negativity that occurs 1-2 seconds before the onset of movement [44, 45].

In our experiments, we extracted time-locking events with type = 3 (left hand) or type = 4 (right hand) with different epoch limits and types of analysis:

- ERD analysis: epoch limits from -2 to 0 seconds.
- ERS analysis: epoch limits from 4.1 to 5.1 seconds.
- MRCP analysis: epoch limits from -2 to 0 seconds.

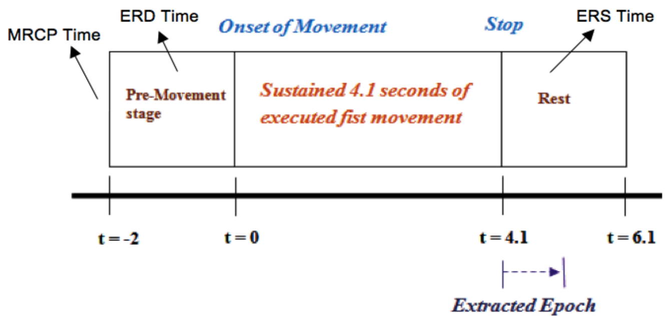


Fig. 4. Epoch Extraction (ERS/ERD and MRCP)

Independent Component Analysis (ICA):

After the AAR process, ICA was used to parse the underlying electrocortical sources from EEG signals that are affected by artifacts [36]. Data decomposition using ICA changes the basis linearly from data that are collected at single scalp channels to a spatially transformed virtual channel basis. Each row of the EEG data in the original scalp channel data represents the time course of accumulated differences between source projections to a single data channel and one or more reference channels [48].

EEGLAB was used to run ICA on the described epoched datasets (left and right ERD, ERS, and MRCP) for the channels FC3, FCZ, FC4, C3, C1, CZ, C2, and C4.

Principal Component Analysis:

Principal component analysis (PCA) is a form of signal analysis that identifies the principal components of multivariate data and uses these components to reduce the dimension of the data. Principal components contain statistically significant information about the data and can be defined as the variance in that data [49]. In other words, PCA identifies the components that contribute the most to the variance in the data as these components are most important to recreating the data.

Principal components are ranked in order if their decreasing contribution to the variance in the data with first principal component containing information contributing maximally to the variance in the data and subsequent principal components ranked in order. The primary purpose of PCA is to find a new set of axes so that when the data is projected on these axes, the projected points have maximum variation in a way that the projected data points are widely spread out[50 For a given data set where i = 1... m, each is an n dimensional dataset. So when this data is reduced to a k-dimensional data where k<n, the reduction in dimension is done to reduce noise, visualize higher dimensional data into reduced number of dimensions, and to compress high dimensional data to save time and computational complexities.

To perform PCA, the eigenvectors and eigenvalues of the covariance matrix of the normalized data are obtained. The eigenvalues and their associated eigenvectors are ranked in order of magnitude so to reduce n-dimensional data; eigenvectors associated with the first k eigenvalues are chosen which form the new principal axes for dataset .

The covariance matrix S can be reduced to a diagonal matrix D by pre and post multiplication with an orthonormal matrix U The diagonal elements of D make up the variances of the new data and form the eigenvalues of the covariance matrix S. The columns of U constitute the eigenvectors for the corresponding eigenvalues. These eigenvalues determine the percentage of the total variance that any given principal component represents. To simplify this approach, the singular value decomposition (SVD) works directly with the data matrix X that is decomposed into D and the principal components matrix U. Using SVD, the eigenvalues describe the variance accounted for by the associated principal components that are ordered by

size and can be meaningful in identifying the number of principal components that are really significant. These principal components can then be used to reduce the data set as those contributing the least to the variance in the data can be eliminated.

EEG data is considered to be a large dataset and the purpose of reducing the dimension, while allowing minimal information loss as most of the data is in the lower dimensional space, is to use it as input to machine learning systems such as support vector machines.

3.5.7 Optimization and Results:

In all experiments, 80% samples were randomly selected and used for training and the remaining

20% for testing. This was repeated 10 times, and in each time the datasets were randomly mixed.

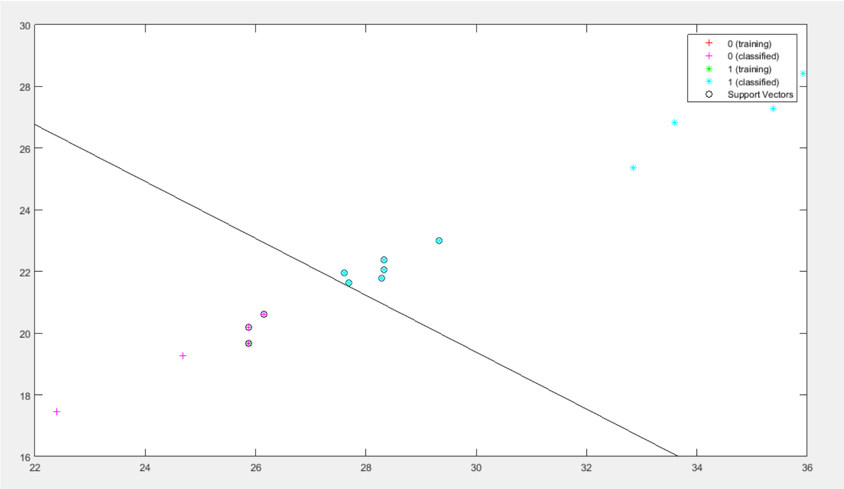


Figure: Hyperplane for 15 signals of 2-level.

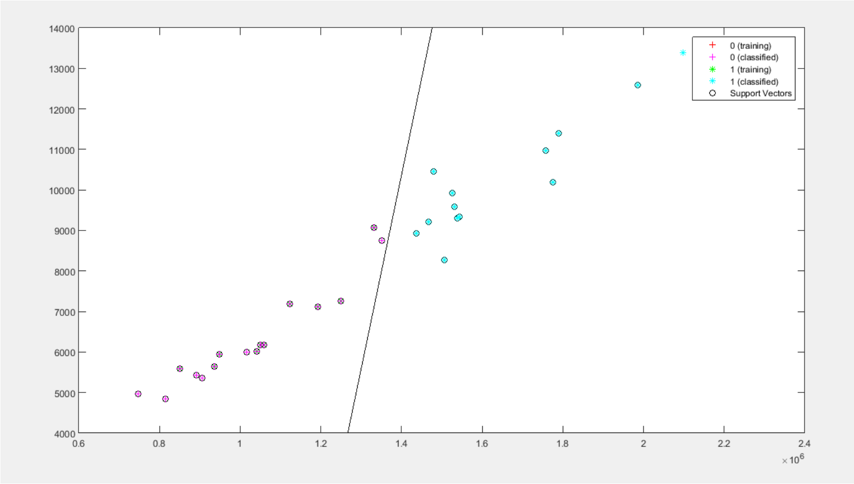


Figure: Hyperplane for 30 signals of 2-level

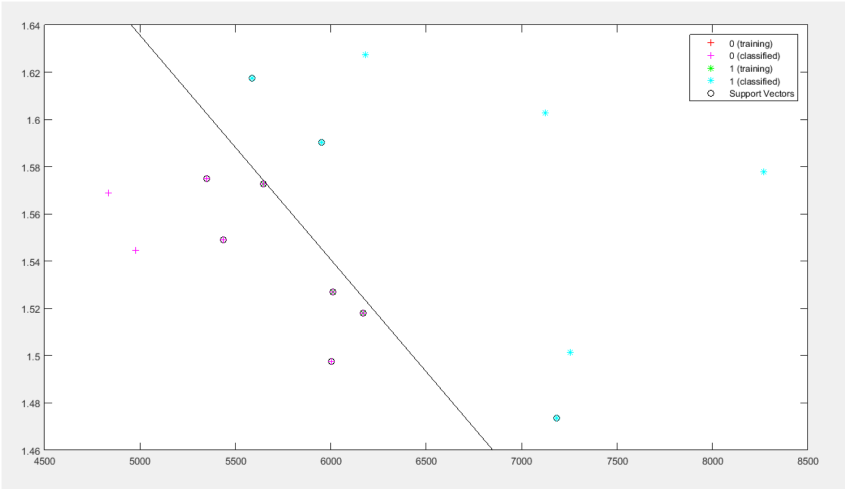


Figure: Hyperplane for 15 signals of 4-level

3.5.8 Conclusion and Future work:

This paper focuses on the classification of EEG signals for right and left first movements based on a specific set of features. Very good results were obtained using SVMs showing that offline discrimination between right and left movement, for executed hand movements, is comparable to leading BCI research. Our methodology is not the best, but is somewhat a simplified efficient one that satisfies the needs for researchers in field of neuroscience.

In the near future, we aim to develop and implement our system in online applications, such as health systems and computer games. In addition, more datasets has to be analyzed for a better knowledge able extraction and more accurate decision rules.

3.5.9. Limitation:

The models are opaque. Although you can explain them with a decision tree, there is a risk of loss or precision. SVMs are very sensitive to the choice of the kernel parameters. The difficulty in choosing the correct kernel parameters may compel you to test many possible values. As a result, the computation time is sometimes lengthy

Chapter 4

Result

4. Results:

In all experiments, 80% samples were randomly selected and used for training and the remaining 20% for testing. This was repeated 10 times, and in each time the datasets were randomly mixed.

For each experiment, the number of hidden nodes for NFC and FL varied from 1 to 20. In SVM, each of the degree and gamma parameters varied from 1 to 10. The mean of the accuracy was calculated for each ten training-testing pairs. It is clear from the testing results that SVM outperforms NFC in most experiments. An SVM topology of degree = 4 and gamma = 4 provides an accuracy of 82.1% if tested with the power, energy and type inputs of the experiment. A NFC of 10 hidden layers can provide an accuracy of 86.5% if all features are used. These results clearly show that the use of advanced feature extraction techniques provides good and clear properties that can be translated using machine learning into machine commands. The next best SVM performance (94.1%)and FL performance is 74% is achieved using the energy and type features. In general, there has been an increase in the classification performance with the use of more discriminative features, such as the total energy, compared to the power and mean inputs.

Chapter 5

Conclusion

5. Conclusion:

Machine learning algorithm have shown that in every section of science we can use them in proper way with different accuracy and time duration. Such as the neuro fuzzy is the best option to analysis those type of EEG data. Because neuro fuzzy have 3 section to analysis the whole data.it can compact the data with mean median and average value. That means the feature extraction of the neuro fuzzy is the best option to make the analysis easier with the same data which is compacted by feature extraction. Then the algorithm shows that the analysis gets its 55% of accuracy rate of result. Though it is much more low accuracy as we use small EEG data. If we could work with big EEG data, then accuracy would be more perfect.

All over the process neuro fuzzy takes a lot of time to analysis accurate result. Therefore, analysis time increased in very much delay.

In the other hand fuzzy logic shows the result with membership function. which is not more accurate than neuro fuzzy analysis. But it solves and analysis the EEG data very fast and accuracy rate higher than SVM. Thus SVM just shows how the result should be in a demanded line. 2 part of data, one is hand’s data and the other part is foot’s data. They show a result with very low accuracy of EEG data analysis. But it takes less time to analysis than the neuro fuzzy function. that’s the advantage of SVM.

Moreover, neuro fuzzy try to analysis the result with higher accuracy rather than fastest time calculation and the SVM and fuzzy logic analysis the result very fast rather than higher accuracy.

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