Classification of EEG Signals on Emotion Using Artificial Neural Network

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Abstract- *The recent advances have analyzed that is possible to decoding the multivarious aspects of visually presented stimuli from the signals of scalp EEG measurements. such multivariate methods have been commonly used to decode visual-spatial features such as location, orientation, or spatial frequency. In this project it is explained that it is possible to recognize emotions through visual videos using Feed Forward Neural Network on patterns of EEG activity. Building on other recent demonstrations, we show that emotion stimuli: reflects sensory qualities (as opposed to, for example, verbal labelling) with a prominent contribution from posterior electrodes contralateral to the stimulus, conforms to a parametric coding space, is possible in multi-item displays, and is comparable in frequency bandwidth to the recognizing of visual stimulus orientation. While exercising our data we provide an estimation of the approximate trails and participants through decoding. Finally, we cleared that while visual recognition can be sensitive to some differences in luminance, our emotion recognition results are primarily driven by measured frequency differences between stimuli. Brain decoding opens a relevant new dimension in which to track visual processing using scalp EEG measurements, while bypassing potential hertz as associated with decoding approaches that focus on spatial features. This project proposes a 2-step approach. In the first step, electroencephalographic (EEG) signals are acquired from the electrodes placed over the entire scalp using the EEG device.*

I. INTRODUCTION

Emotions are biological states related to the nervous systems, which are usually reflection of changes in neuro-physiological condition. Being an indispensable part of human life, if emotions could be anticipated by machines precisely, it would accelerate the progress of artificial intelligence or the brain–computer interface field. Presently there is no scientific agreement on a definition of emotions.

One of the definitions, as given by William James, claims that "the bodily changes follow directly the perception of the exciting fact, and that our feelings of the changes as they occur are emotion". As an evolving field of research with vital importance and vast implementation, emotion classification has drawn interest from different disciplines like neuroscience, neural engineering, psychology, computer science, mathematics, biology, physics and has always remained in the spotlight. Various experiments are being done to accomplish higher instinctive human–computer interaction and ultimate goal is to devise advanced gadgets, which would distinguish various human emotions, in real-time. With the absence of the capability to quantify emotions, computers and robots cannot naturally connect with humans. Therefore, human emotion recognition is the key technology for human–machine interaction. Additionally, several researches have proved the reliability of EEG for application in the BCI, electronic gadgets as well as in medicine to closely inspect various brain disorders. Some EEG-based research indicate that EEG builds enhanced databases in comparison with other available emotion databases like the non-physiological datasets. Thus, because EEG is meticulously tied in with brain activities and also because it is immediate and comparatively reliable than electrodermal activity (EDA; sometimes known as galvanic skin response, or GSR), electrocardiogram (ECG), photoplethysmography (PPG), electromyography (EMG), etc., is highly recommended over any other physiological signals.

II. BACKGROUND HISTROY

The Brain Computer Interface (BCI) is sometimes called as Neural Control Interface (NCI). It is a computer-based system that acquires brain signals, analyses them and translates them into commands that are relayed to an output device to carry out a desired action. In 1970, research on BCI started at the university of California. Hans Berger's innovation in the field of human brain research and its electrical activity has a close connection with the discovery of brain computer interfaces and development of Electroencephalography (EEG). Richard Canton's 1857's discovery of electrical signals in animal brain was an inspiration for Berger. Monkeys and rats are used to operate BCI and produce movement in several laboratories. In 1970 the researchers found that monkeys could quickly learn to voluntarily control the firing rates of individual and multiple neurons and generated appropriate patterns of neural activity with them. In 2020, Elon Musk's neural link was successfully implanted in a pig and he successfully enabled a monkey to play video games using neural link's device. There are two conventional rules to follow when categorizing human emotions, namely, the discrete basic emotion description and the dimension approaches. According to the discrete basic emotion description approach, emotions can be classified into six basic emotions: sadness, joy, surprise, anger, disgust, and fear. For the dimension approach, the emotions can be classified into two (valence and arousal) or three dimensions (valence, arousal, and dominance). Among these dimensions, valence describes the level of positivity or negativity of one person, and arousal describes the level of excitement or apathy of emotion. The scale of dominance ranges from submissive (without control) to dominance (empowered). The emotion recognition is usually based on the dimension approach because of its simplicity compared to the discrete basic emotion description. Different kinds of methods have been devised to recognize the underlying emotion of a person. Notably, emotion recognition (ER) from facial expression, voice intonation, gesture, and signal from Autonomous Nervous System (ANS) like heart rate and Galvanic Skin Response (GSR) had been being carrying out. ER from Electroencephalography (EEG) signals is relatively new in the field of affective computing. ER from EEG signals overcome some of the drawback that arises while using the technique of ER from facial expression, GSR, heart rate, like facial expression can be easily faked, for example a person might be really feeling pain inside but he might show the expression of happy. Signal from ANS is more susceptible to noise, for example, GSR signals might not only originate from emotional influence but may also from physical influence. On the contrary, signal from central nervous system like EEG is captured form the origin of emotional experience. Moreover, EEG signals which have fine resolution are easy to record with affordable cost. Different techniques and step are needed to classify the emotion from EEG Signals. These steps include the recording of Signals, pre-processing of recorded raw signals to remove the artifacts from it, extracting the most suitable feature from processed signals, formatting the dataset and evaluating it with the use of machine learning tool.

III. METHODOLOGY

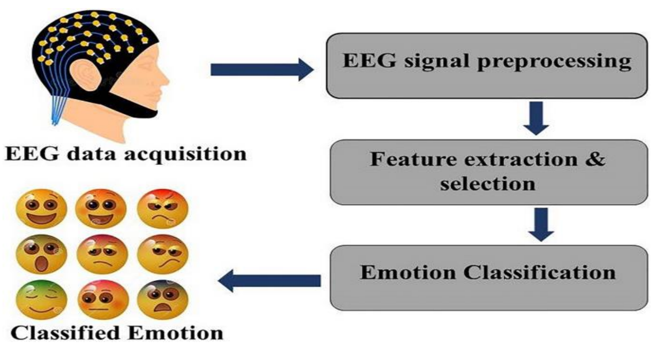


Figure. 1.0.BCI Stages

The methodology consists of various modules. Where they describe how the recognition has been handled out. The dataset from the various persons has been taken by using EEG device which uses the 5 electrodes from which the signals are driven. The signals are driven using MATLAB and the values are identified for pre-processing. The pre-processing state has various frequency to find the time, mean and variance. From which the frequency band Gama, Alpha, Beta, Theta and Delta are derived in graphical units. The Fast Fourier Transformation (FFT) has been used to drive these frequency wavelengths and to be extracted. The feature extraction has followed Entropy method to extract. Whereas, Energy entropy as a Wavelet Dynamics entropy is used to drive frequency band width and power spectral density along with power spectral entropy has been used to extract. The extracted values are classified using the traditional Artificial Neural Network with the advance technology like Feed Forward Neural Network. The FFNN technology use Back Propagation Algorithm to classify the extracted values. The values which are classified has been used for high accuracy.

A. Dataset

The database used for this work is from EEG Resources of Sri Ramakrishna Institute of Technology, which is free access and provided sessions from 60 patients, whose 40 are normal stimuli patients. For this study were randomly chosen, ten patients such as seen in Table I. The EEG recordings have a resolution of 16 bits and sampling frequency of 60Hz. Besides, for electrodes placement, the international 4-5 systems were used, with 5 channels and a G-Nautilus device with Electroencephalography. The EEG recordings have been acquired with different patients.

Patient watching video

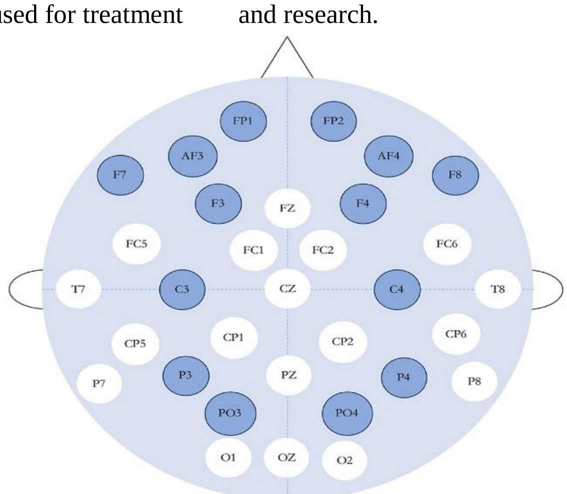
B. Signal Acquisition

High-density EEG data were recorded using a 5-channel EEG Geodesic Hydrocele system (Electrical Geodesics, Eugene, Oregon) with a sampling rate of less than

60 Hz. The recording reference was at Cz (vertex of the head), and the impedances were kept below 30kΩ. All the analyses were performed using MATLAB version 2018b. EEG data was automatically pre-processed using the current version (2.4.3). Auto magic is an open-source MATLAB toolbox that acts as a wrapper to run currently available EEG pre-processing methods and offers objective standardized quality assessment for large studies. Our pre-processing pipeline consisted of the following steps. First, except the 5 electrodes in the outermost circumference (chin and neck) were excluded from further processing as they capture little brain activity and mainly record muscular activity.

C. Electroencephalography (EEG)

Electroencephalography (EEG) is a reliable and effective technology used to measure brain signal activity. Detecting emotion using EEG signals involves multiple steps and being performed in an sequence to satisfy the requirements based on brain–computer interface (BCI). Usually, these steps include removing artifacts from the EEG signals, extracting temporal or spectral features from the EEG signal's frequency or time domain, respectively, and designing a multi-class classification strategy. Feature extraction dramatically increases the accuracy of the emotion classification strategy. EEG, and the related study of ERPs are used extensively in neuroscience, cognitive science, cognitive psychology, neurolinguistics and psychophysiological research, but also to study human functions such as using Many EEG techniques used in research are not standardised due to sufficient clinical use, and many studies fail to report all of the necessary processing steps used in data collection and reduction and also limiting the reproducibility and replicability of many studies. But research based on mental disabilities, such as auditory processing disorder (APD), ADHD, or ADD, is becoming more widely known and EEGs are used for treatment and research.



Signal points using EEG from brain scalp

D. G-Nautilus Device

The G-Nautilus RESEARCH device is intended to be used in research and scientific investigations for the amplification of low voltage electro-physiological signals that can be measured in humans and animals. The devices must not be used for medical applications nor for treatment or diagnosis in medical environments. The device must not be used for finding the human brain death. The term g-Nautilus RESEARCH refers to two types, g-Nautilus RESEARCH wet and other g-Nautilus RESEARCH dry systems. G-technology uses special thin, lightweight and highly flexible cables for active electrodes from the brain to provide high comfort and easy cap mounting, especially for multi-channel recording. These cables are very sensitive and need to be treated with one-to-one special care.

G-Nautilus Device

Preprocessing

Our pre-processing pipeline consisted of the following steps. First, expect 5 electrodes in the outermost circumference (chin and neck) were excluded from further processing as they capture little brain activity and mainly record muscular activity. Additionally, 5 EEG electrodes were used for blink an eye movement detection (and subsequent rejection) during ICA. The EEG electrodes were removed from the data after the pre-processing, yielding a total number of 5 EEG electrodes. Subsequently, bad channels were detected by the algorithms implemented in the EEGLAB, which removes flatline, low-frequency, and noisy channels.

Frequency

The most common classification algorithms uses EEG signal waveform frequency band under which EEG signals can be degraded within 5 different frequency bands.

Hence, the five different frequency bands along with their mental state has been associated with them are briefly described as below.

A. Delta

Delta waves has found in between the frequency range of 0-4 Hz which are detected during the deep sleep or coma. Such waves have are measured in<100 micro volts and has higher amplitude.

B. Theta

Theta waves are under the frequency range of 4-8 Hz. Theta rhythms are observed mainly during creative thinking and in state of focusing. Such waves are observed during short term memory task.

C. Alpha

Alpha waves are present in between the frequency range of 8-13 Hz. These waves are originated from the occipital lobe of brain region during the state of relaxation and calm mindset. It has also founded that the activity of Alpha rhythm has the vision functioning of human being.

D. Beta

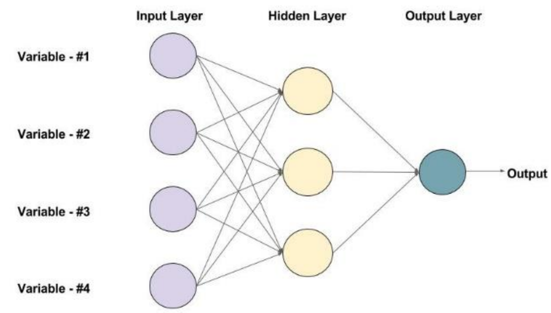
Beta waves are found between the frequency ranges of 13-30 Hz. These waves are associated with anxious thinking of the mindset and active concentration which are originated from the central area of brain region.

E. Gama

Gamma waves has been found in between the frequency ranges of 30-100Hz. Mental state associated with these waves are multi-tasking and conscious waking state.

Feed Forward Neural Network

Feed forward Neural Network is one of the most used ANN in artificial intelligence, which has well-defined layers. The training process and recall patterns are described by connections forward, i.e., each layer is connected with the next layer, but not move backward. In feed-forward neural networks (FFNN), neurons are arranged in multiple layers and the signals are forwarded from the input to the output. When an error occurs, these neurons will return to the previous layer and weights are just adjusted again to reduce the frequency error chances. Also, the backpropagation (BP) method widely employed in training ANN for supervised learning is used in this study. Feedforward Neural Network with BP uses pattern recognition, where the output consists of a vector with 0 and 1 values. The class that we want to be recognized is 1, that is epilepsy, so 0 represents a normal EEG.



IV. PEER REVIEW

[1]Kamitani and Tong, "visual object, semantic objects" and video objects (August 2011)

One goal of brain encoding and decoding applications is to derive a quantitative mapping between the external visual stimulus and the brain response. A variety of previous fMRI studies have shown that brain decoders can be used to reconstruct visual features, such as orientation and motion direction, by learning the quantitative mapping between fMRI-derived brain activity patterns and visual stimulus based on training datasets. Since the previous sections have already discussed neuroimage analysis methods for quantitative measurements of the brain's responses, this section will be devoted to visual stimuli and their quantitative measurements.

[2] Matthew A. Turk and Alex P. Pentland, "Face Recognition using Eigenfaces" – (November 2009)

The detection and identification of human faces which tracks near-real-time face recognition system which tracks a subject's head and then recognizes the per-son by comparing characteristics of the face to those of known individuals. Our approach treats face recognition as a two-dimensional recognition prob-lem, taking advantage of the fact that faces are are normally upright and thus may be described by a small set of 2-D characteristic views. Face images are projected onto a feature space ("face space") that best encodes the variation among known face images. The face space is defined by the "eigen-faces", which are the eigenvectors of the set of faces; they do not necessarily correspond to isolated fea-tures such as eyes, ears, and noses. The framework provides the ability to learn to recognize new faces in an unsupervised manner. The eigen face approach was mainly to face recognition has idea of basing face recognition that has approximate set of known face images. Also it is not an elegant solution to object recognition and does not gives practical solution to face recognition. The eigen method has unsupervised manner and it is noisy or partially clouded face cause recognition performance degrade. The projection occluded by the technique is not clear and clustered.

[3] Mo Chen1, Junwei Han1, Xintao Hu1, Xi Jiang2, Lei Guo1, and Tianming Liu21School of Automation, “Cortical Architecture Imaging and Discovery Lab” - (September 2015)

Extraction of the most relevant fMRI signals from brain scans is the first step to infer meaningful information and to construct brain decoding models. That is, researchers need to determine the structural substrates of functional responses first, based on which fMRI signals can be extracted. Typical, there are two general methodologies used in the literature. The first is to determine ROIs or voxels based on current neuroscience domains knowledge. For instance, neuroscientists can manually draw ROIs in the V1, V2 and V3 areas in the visual cortex (Haxby et al., 2001). The second category of methods is data-driven, which determines the location and size of ROIs from fMRI data itself. For instance, the activation detection results can be used for the determination of relevant brain areas for functional responses modeling (Haxby et al.,2001; Walther et al., 2009). Therefore, most of previous brain encoding/decoding studies can be classified into either voxel-based or ROI-based methods, considering how the fMRI signals were extracted from the volumetric fMRI images. Notably, this classification scheme is borrowed from other fMRI data analysis applications such as fMRI activation detection methods, functional connectivity modeling, and brain network modeling.

[4] Anton G. Maglione, AmbraBrizi Giovanni, Vecchiato, Dario Rossi, Arianna Trettel, EnricaModica and Fabio Babiloni,“A Neuroelectrical Brain ImagingStudy on the Perception of FigurativePaintings against Only their Colour or Shape Contents “- (July 2017)

A group of 16 healthy subjects (7 male and 9 females; average age 38.3 ± 6 y.o.) were involved in this experiment. All the subjects had a specific university education in art at a bachelor level. All subjects participated voluntarily to the study and each one of them gave written informed consent in accordance with the Declaration of Helsinki of 1975, as revised in 2000. The research project related to this study has received the approval of the proper ethical committee of the University of Rome Sapienza. Furthermore, the ethical committee of the IRCCS Fondazione Santa Lucia also approved the same research study. In fact, IRCCS Fondazione Santa Lucia is the institution on which the actual EEG recordings were made.

[5] Dhruvi D. Gosai, Himangini J. Gohil, Prof. Hardik S. Jayswal, “A Review on a Emotion Detection and Recognition from Text using Natural Language Processing” - (November 2018)

Communication and human interaction is carried out to figure Natural Language Processing. Ekman model is included to find emotions like happy, joy, sad, disgust, anger, fear and surprise. Emotion detection from textual source has been used by the concept of Natural Language Processing (NLP). The emotion detection using NLP is classified by Naïve Algorithm. They had researched how to detect emotion from facial and audio information by recognizing emotions from textual data. Sentiment Analysis is the field they used for emotion detection and recognition of text. Sentiment Analysis deals with identifying the positive, negative and neutral state of text. Emotion Analysis also used to find the Ekman emotions and classified as two keyword based detection and learning based detection. This approach classifies the text into emotional content and finds the emotions by facial recognition in face.

[6] K. J. Forseth 1, G. Hickok2, P. S. Rollo 1 & N. Tandon “Language prediction mechanisms in human auditory cortex” - (October 2020)

Thirty-seven patients (20 males, 16 females; mean age 33 ± 9; mean IQ 97 ± 15) undergoing evaluation of intractable epilepsy with intracranial electrodes were enrolled in the study after obtaining informed consent. Study design was approved by the committee for the protection of human subjects at the University of Texas Health Science Centre. A total of 7507 electrodes (6669 depths, 838 grids) were implanted in this cohort. Only electrodes unaffected by epileptic activity, artifacts, or electrical noise were used in subsequent analyses. Hemispheric language dominance was evaluated in all patients with intracarotid sodium amytal injection59 (n = 5), functional magnetic resonance imaging (fMRI) laterality index60 (n = 7), cortical stimulation mapping61 (n = 12), or the Edinburgh Handedness Inventory62 (n = 13). Thirty-two patients were confirmed to be left-hemisphere language-dominant. Two patients were found to be left handed by EHI and did not undergo alternative evaluation; they are assumed to be left-hemisphere dominant, but were excluded from laterality analysis. Three patients were found to be right-hemisphere language-dominant; two by intracarotid sodium amytal injection, and one by fMRI laterality index. For representational purposes, language-dominant supratemporal electrodes in these patients were mirrored onto the same left supratemporal cortical model as left hemisphere language-dominant patient.

[7] Ahmad Tauseef Sohaib & Shahnawaz Qureshi, "An Empirical Study of Machine Learning Techniques for Classifying Emotional States from EEG Data" – (September 2012)

Different methods based on emotional states has been classified on different signal processing techniques. Different methods are used to classify EEG signals and format the dataset for EEG data. This paper aims to find the various emotional states in subjects by looking on to the different pictures and record the EEG signal data. The obtained datas are formatted and then evaluated on various machine learning techniques to find the accurate result and to classify the EEG data accordingly to associated emotional states. Support Vector Machines has been used as a main classifier to evaluate the EEG data signals and Regression Tree as second classifier to EEG data. The specific emotional state has achieved 70% and 60% accuracy. SVM has been better than the RT but RT well deserves by giving high accuracy for EEG data. EPOC device can be also used improve the EEG data acquisition as the advanced technique. Other machine learning techniques can be also used to find the emotional states like Random Forest, ZeroR, Naïve Bayes to seek improvement in classification accuracy.

[8]Jerrin Thomas Panachakel and Angarai Ganesan Ramakrishnan "Decoding Covert Speech From EEG-A Comprehensive Review" – (April 2021)

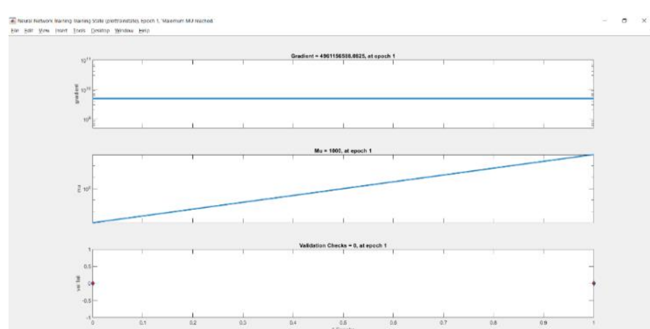
The most common pre-processing step in the literature is temporal filtering. Most of the researchers have band-pass filtered the EEG signal in the range 2 to 50 Hz. it is better to avoid spatial filtering in the pre-processing pipeline. Most of the popular ICA algorithms currently available are not suited for real-time applications and hence other algorithms like those used by Nguyen et al. (2017) should be used. Features and classifiers used: Most of the works that make use of traditional machine learning techniques such as ANN, ELM, and SVM extract features from each channel independently. In the case of works that use deep-learning techniques, features are usually extracted from channel crosscovariance (CCV) matrices. Use of CCV matrices is preferred since they better capture the information transfer between different brain regions. Although researchers in other fields such as speech recognition and computer vision have almost completely moved to deep-learning, researchers working on decoding imagined speech from EEG still make use of conventional machine learning techniques primarily due to the limitation in the amount of data available for training the classifiers.

V. FUTURE WORK

As a future work, we are going to conduct a BCI application that controls a cursor movement on PC by using those signals. This is unlike earlier BCI systems where cursor-controlled movement application is controlled by imagination of foot and hand movement, but no one has controlled it with coloured stimuli before. Such study would be used to simulate an environment where a disabled person would be expected to drive a vehicle in a virtual environment with a possibly uniform background, in which the vehicle will either start and/or stop moving on appearance of green and red lights respectively. In addition, we will test the proposed feature selection algorithm with different EEG signals, which are evoked by another stimulus such as imagery stimulus, to Analyze and understand all the provided review comments thoroughly. Now make the required amendments in your paper. If you are not confident about any review comment, then don't forget to get clarity about that comment. And in some cases there could be chances where your paper receives number of critical remarks. In that cases don't get disheartened and try to improvise the maximum.

VI. RESULTS & DISCUSSIONS

In this classification stage, the area specifies the spectrum features are applied as the input to feed-forward neural network.The feed-forward back-propagation network has been implemented by using the Lavenberg-Marquardt algorithm. The algorithm involves limitation of the error by updating the network and the bias used damped least squares. It implies between the Gauss Newton algorithm and also the method of gradient descent. The total dataset consisting of acquired patterns which has been divided into training and testing the data set of specified patterns respectively. In the present work, the network with four input and one output neurons is implied using the command in MATLAB. The accuracy of the network which is trained is correctly classified by the test patterns into two groups i.e., seizure and healthy.



Epoch Accuracy

#	DATA	SHYAM Elapsed time	TESTING TIME(SECS)	OUTPUT
1	Bt	2.171439	10	0
2	Ht1	2.171439	30	1
3	Ht2	2.119521	15	0
4	Ht3	1.783232	30	1
5	ST1	2.218064	60	1
6	ST2	2.113474	30	0
7	ST3	1.981856	30	1

VII. CONCLUSION

In this research, we proposed a feature selection algorithm for EEG signals by studying the ERPs components. The measurement statistic of our algorithm is based on the residual components itself which is computed using the time-frequency set of the generated peak. In addition, introduced a single trial classification to simulate the online classification and the classification results are compared from all methods within three cases. Our proposed algorithm outperforms the recursive algorithm and it is proved with all the investigated feature extraction methods. This time is much less than the time required by any other stimulus such as hand/foot imagination movement and spelling word. This result proves the main idea behind using emotions in the next generation of BCI systems, which is based on introducing more efficient and speedy systems that are able to give response faster than any other time.

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