A Review on Feature Extraction of EEG Signal using Artificial Intelligence

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Abstract **-** Emotion are complex, involving physiological and social components. Emotion plays significant role in our daily life. Emotion classifications aim to develop and improve the intellectual brain computer interface (BCI) applications. In 1924 Hans Berger, a German brain specialist, used normal radio instrumentation to amplify the brain's electrical activity measured on the human scalp. Emotion recognition could be done from text, facial expression or speech. Automatic emotion detection from EEG signals is receiving more attention with the development of new forms of human-computer interaction with digital media. To Identifying the required data some of algorithms are used like relief, Mrmr and ES BASED feature selection algorithms, it Attempts to directly maximize the classification accuracy.

Keywords **-** *Feature Extraction; Electroencephalogram (EEG); Emotion Reorganization; Feature Selection; Artificial Neural Network (ANN); Brain-computer interface(BCI).*

I. INTRODUCTION

Brain is one of the most important organs in our body. So, its structure and functions have become a part of research. Although a lot of work has already been done in this area, but still it's a challenging field. EEG signals are considered not to be deterministic and they have no special characteristics like ECG signals To understanding exactly what emotions are, researchers have also tried to identify and classify the different types of emotions. In 1972, psychologist Paul Eckman suggested that there are six basic emotions that are universal throughout human cultures. An electroencephalogram (EEG) is a test that detects electrical activity in brain using small, flat metal electrodes attached to the scalp. Brain cells communicate via electrical impulses and are active all the time, even when you are asleep. This activity shows up as wavy lines on an EEG recording. EEG is one of the tests used to diagnose epilepsy.

II. RELATED WORK

Robert janke , Martin Buss, Angelika Peer[1] had worked on Different sets of features and electrodes for emotion recognition from EEG. a systematic analysis and first qualitative insights comparing the wide range of available feature extraction methods using machine learning techniques for feature selection. Multivariate feature selection techniques performed slightly better than univariate methods, generally requiring less than 100 features on average.

Min-Ki Kim, Miyoung Kim, Eunmi Oh, and Sung-Phil Kim[3] had worked on the computational methods used for emotional state estimation. They also described the described the classification methods to discriminate a particular emotional state from EEG features. Hence, a computational model that can predict the emotional state with various stimuli may be required for real world applications.

Leontios J. Hadjileontiadis, Stelios K. Hadjidimitriou[4] had worked on a methodological scheme for the EEG based recognition of music preference. Bilateral average activity from *beta* and *gamma* band, when referred to the RP, led to the best discrimination between liking and disliking judgments. This evidence may point to a connection of music preference to emotional arousal phenomena. The performance of the three examined TF techniques was comparable, with a slight preeminence of the HHS that was further revealed through the robustness of this technique to noise corruption.

Sander Koelstra [6] had worked on database for the analysis of spontaneous emotions. The database contains physiological signals of 32 participants (and frontal face video of 22 participants), where each participant watched and rated their emotional response to 40 music videos along the scales of arousal, valence, and dominance as well as their liking of and familiarity with the videos.

Dan Nie, Xiao-Wei Wang, Li-Chen Shi[7] had worked on two classes of emotion, positive and negative were mainly concerned about. First we averaged the EEG data into delta, theta, alpha, beta and gamma bands, and computed the log energy of each sample. Next a LDS based approach was applied to smooth the original features. Last a linear-SVM was used to work on the training and testing set. The average test accuracy with all the features was 87.53%.

III. CORRELATION OF EEG TO HUMAN EMOTION

EEG has become increasingly important as it can record vast amounts of complex neuronal activity from the human brain. Thus, the qualitative information can be overcome with quantitative measurement provided by the EEG. Finding EEG correlates of emotional states should begin with how to define

the emotional state space. The discrete emotional state comprises seven to ten core emotions such as happiness, surprise, sadness, anger, disgust, contempt, and fear and sometimes expands to contain a large number of emotions with the synonyms of these core emotions.[3] EEG was recorded on animal brain in 1875 by Richard Caton. It was first recorded on human brain by Hans Berger in 1929. EEG is the most used signal acquisition method because of the high temporal resolution, safety, and ease of use. 10-20 standard electrodes placement is used in EEG signal acquisition. A pupillary response feature construction and -selection procedure to extract the useful features that perform best under a linear discriminant analysis (LDA) classifier.[11] EEG has low spatial resolution and is non-stationary in nature. EEG signals are susceptible to artifacts caused by eye blinks, eye movements, heartbeat, muscular activities and the power line interferences.[2] An EEG signal consists of several frequency bands, which are called θ, δ, *α and β* bands.

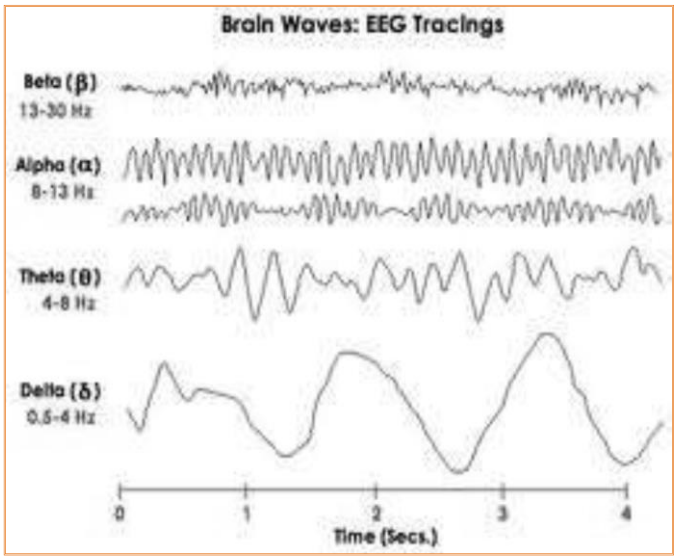

Fig.1: Frequency bands in EEG

Their bandwidths are 0.5–4, 4–8, 8–13, and above 13-30 Hz respectively. The EEG patterns recorded from subjects under relaxation show the characteristics of α waveform, which is the case for most humans.[17] This condition seems to represent a form of synchronization, almost like a natural frequency of brain. The basic approach to signal analysis is to get proper information from the signal by applying the best suitable method. The methods used in this are Fourier and wavelet transforms.[11] Emotions play an important role in human communication and can be expressed either verbally through emotional vocabulary or by expressing nonverbal cues such as intonation of voice, facial expressions, and gestures [6].

IV. OPTIMIZATION USING GENETIC ALGORITHM

Genetic algorithms are motivated by Darwin's hypothesis about development. Answer for an issue explained by genetic algorithms is advanced. Algorithm s begun with a situated of arrangements (spoke to by chromosomes) called population. Arrangements from one populace are taken and used to frame another population.

1. **[Start]** Produce arbitrary population of *n* chromosomes (suitable answers for the issues).

2. **[Fitness]** Assess the fitness *f(x)* of every chromosome *x* in the population.

3. **[New population]** Make another populace by rehashing after ventures until the new populace is finished.

   a) **[Selection]** Select two guardian chromosomes from a populace as indicated by their wellness (the better wellness, the greater opportunity to be chosen).

   b) **[Crossover]** With a hybrid likelihood traverse the folks to shape another posterity (kids). On the off chance that no hybrid was performed, posterity is an accurate duplicate of folks.

   c) **[Mutation]** With a transformation likelihood change new posterity at every locus (position in chromosome).

   d) **[Accepting]** Put new posterity in another populace.

4. **[Replace]** Utilization new produced population for a further run of algorithm.

5. **[Test]** If the end condition is fulfilled, **stop**, and return the best arrangement in current population.

[Loop] Go to step **2.**

V. CONCLUSION

Electroencephalogram (EEG) is a record of the oscillation of brain electric potentials resulting from ionic current flow between brain neurons. EEG signals are acquired by measuring the electrical activities at electrode's positions on the scalp. Automatic emotion recognition is one of the most challenging tasks. To detect emotion from non-stationary EEG signals, a sophisticated learning algorithm that can represent high-level abstraction is required. In this paper, we presented a survey on EEG-based emotion recognition concept and different algorithms are discussed.

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