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Machine Intelligence Based Detection and Classification of Human Physiology and Emotions

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Abstract: Automated analysis of the physiological signals like ECG (electrocardiogram) and EEG (electroencephalogram) has become more extensive during the last three decades and is recognized as an effective medical analysis tool in the physiological field. While human computer interface, Human components are both a science and a field of designing. It is concerned with human proficiencies, impediments, and execution, and with the outline of frameworks that are proficient, safe, agreeable, and even pleasant for the humans who use them. EEG-based emotion recognition has performed using EEG signals gather red from kaggle website and using benchmark DEAP dataset. The music-videos are used as stimuli for emotion recognition in DEAP dataset. A novel feature extraction method is proposed for four emotion (Happy, Angry, Sad, and Relax) analysis using Gray level co-occurrence matrix (GLCM) features. GLCM features such as contrast, correlation, energy, and homogeneity are used as texture features. The Theta, Alpha and Beta band asymmetry is used as frequency domain feature. The results showed that asymmetry of band power was effectively discriminating the emotions. EEG-based analysis might lead to an assessment of the emotional states in natural way which is useful in Human-Machine Interface (HMI).This research outcome is helpful for developers in order to help them guide how to test and their inventions and gather data related to the feedback for their applications.

Keywords: Electroencephalography, Meditation, Emotion, Cognitive load, Power Spectral Density, Higher Order Crossing, functional connectivity

I. Introduction

Emotions play an important role in everyday human life. Managing and control of emotions is of paramount importance for the personal and professional development of an individual. Students at the Under Graduate (UG) level, particularly do face a lot of turmoil in emotional life associated with their age, pressures to perform in academic parameters, uncertainty regarding the future prospect, etc. The application of ancient meditation practices bring in stability and emotional balance to an individual. Students can be immensely benefited in their day to day life with the adoption of meditative practices. It has been observed that the mental training enhances personal happiness and wellbeing [1, 2]. There has been increasing curiosity among western researchers and neuroscientists for evaluating and validating the outcome of the mental training. The purpose of this research work is to carry out a step forward in this direction.

The human brain is the supreme controller of the body. The brain is the central part of the nervous system which governs the functions of various organs in the body. The brain consists of billions of neurons that are very closely interconnected via axons and dendrites [3]. Neurons are the basic data processing units of the brain. Each neuron receives electrical inputs from other neurons. Impulses arriving simultaneously are added together and, if sufficiently strong, lead to the generation of an electrical discharge, known as an action potential (a nerve impulse"). The action potential then forms the input to the next neuron in the network. Anatomically the brain can be divided into three major parts; cerebrum, cerebellum and brainstem [3] as illustrated in Figure 1. The three parts of the brain are discussed below.

(1) Cerebrum: The cerebrum is the largest and most important part of the human brain and is generally associated with brain functions related to cognition, movements, emotions and motor functions. The cerebral cortex is the outermost layer of the cerebrum. The cerebrum consists of two hemispheres, such as right and left hemispheres which are separated by a deep fissure and connected by the corpus callosum [3].

The hemispheres are divided into the following lobes: frontal, temporal, parietal and occipital. The Frontal lobe is responsible for emotions, cognitive tasks, executive functions, parts of speech and movement. The Parietal lobe is responsible for recognition, sensation, orientation and movement. The Occipital lobe is responsible for visual processing. The Temporal lobe is responsible for auditory, long-term memory, speech.

(2) Cerebellum: The cerebellum is the second largest structure of the brain and located at the lower back of the head. The cerebellum is responsible for muscle movements, balance regulation and control, sensory perception and coordination.

(3) Brainstem: The brainstem is located at the bottom of the brain and connects the cerebrum to the spinal cord. The brainstem is main control panel of the body like receive message of sensation (heat, pain), breathing, movements, hunger, and heartbeat.

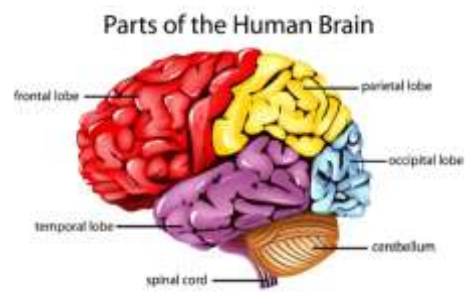


Figure 1: Parts of the Human brain [3]

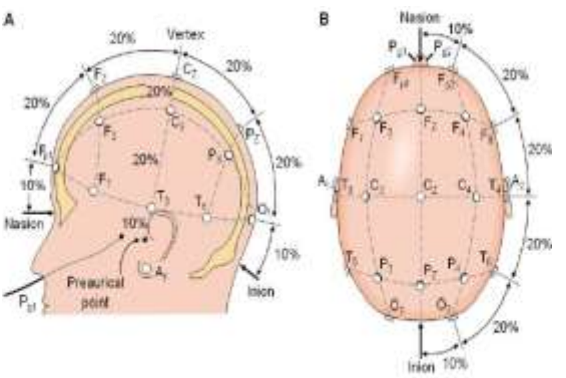
This research focusing on analyzing the human brain wave and emotions analyzing, objective and its contribution. Section 2 provides the detail description of various research activities contributed towards the EEG signel emotions detection. Similarly, section 3 provides the proposed system and its solution. Then, research methodology is considered here to analyse the operation of standards under section IV. Finally, feature and conclusion is carried out in under section V.

II. LITERATURE REVIEW

The Emotion is any mindful skill characterized by powerful psychological action and a high degree of happiness or irritation. EEG recording device or electrodes used assumes a most important role due to the time needed to set up, the comfort of the user and amount of features to process [4]. For these reasons, the number of electrodes should be reduced. A measurement of EEG with more number of electrodes is known as multichannel EEG. EEG is usually recorded with electrodes on the scalp, although it may be recorded from electrodes placed directly on the brain itself. The recording of brain signal is accomplished by various non-invasive methods such as functional Magnetic Resonance Imaging (fMRI), Magneto Encephalography (MEG), Near Infrared Spectroscopy (NIRS) and EEG [7]. The advantage of EEG methodology is its very good temporal resolution, noninvasive, simple to handle and reasonable cost. EEG activity can be divided into three methods based on measurement techniques such as spontaneous, evoked potential and single neuron. Spontaneous activity is measured on the scalp or on the brain [14]. The amplitude of EEG is about 1-100 _V when measured on the scalp, and about 1-2 mV when measured on the surface of the brain. Spontaneous activity measures EEG continuously from individual scalp or brain. The time of EEG recording depends upon the protocol of experiment. Evoked potentials are those components of EEG that arise in response to a stimulus (e.g. music, video, be used.

The International 10-20 electrode placement system is usually used for measuring EEG. The 10 and 20 represent actual distances between neighboring electrodes of the total front-back or right-left distance of the skull. The distance is measured using two positions: nasion (between the forehead) and inon (back of the head) as shown in Figure 2. The electrodes are located on the surface of the scalp. Each electrode is provided with a letter that represents the corresponding region of the brain (F = frontal; FP = prefrontal; T = temporal; P = parietal; O = occipital; and Z = midline electrode). The left-sided electrodes are represented by odd numbers and right-sided electrodes by even numbers. The reference electrodes are A1 and A2 usually attached to the earlobes. There are various electrodes used for recording with minimum 2 to 256 EEG channels [12]. The 10-10 system or 10-5 system are also used for more resolution electrodes. In this research work, fourteen electrodes are used and placed electrodes using 10-20 system [5]. The pattern of connection between the electrodes and the recording channels is known as a montage. There are two basic types of EEG montage: Referential and Bipolar. a) Referential:

The potential difference is measured between an active electrode and reference electrode (both earlobes and mastoids). b) Bipolar: The potential difference is measured between two active electrodes [3].



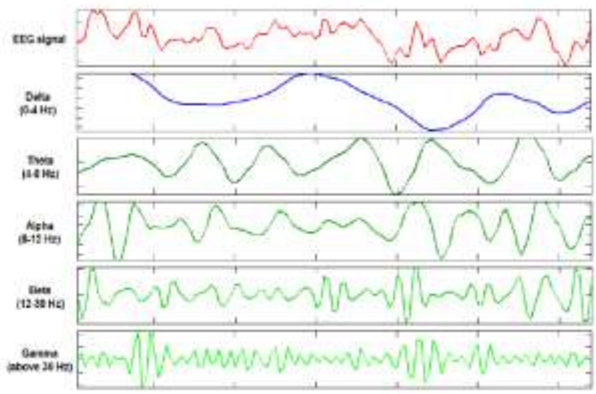


Figure 2: The International 10-20 electrode positioning system, a) left and b) above the head [4] c) EEG frequency bands [5]

EEG rhythms consist of five frequencies such as delta, theta, alpha, beta and gamma bands as shown in Figure 2 c). Delta band is in the range of 0-4 Hz. Delta waves occur in deep sleep. It is the predominant activity in infants, but it is not present a normal component of the EEG in young or middle-aged awake adults. Theta band is in the range of 4 - 7 Hz. It is present during drowsiness [9]. Alpha band present in the range of 8 - 12 Hz. It is present when the person is awake, relaxed and has closed eyes. Beta band represents the active state of the brain in the range 12 - 30 Hz. It is associated with attention, cognitive task, problem solving, panic state. Gamma band is rarely present and is more than 30Hz with low amplitudes.

There are different methods to recognize emotion such as speech [6], facial expressions [7, 8], body language [9] and physiological signals [10].

The physiological signal such as EEG signals are mostly used for emotion study because EEG is noninvasive brain activity measurement method with temporal resolution in milliseconds. There are two models used to classify and represent emotions such as discrete and dimensional. The discrete categorizations of emotions have been proposed by Ekman and Friesen [2]. The emotions are analyzed using EEG and peripheral physiological signals such as Galvanic Skin Response (GSR), respiration rate and pulse rate. An analysis of the effect of GLCM parameters and peripheral physiological signals on four emotions is discussed. The results show that GLCM and physiological features effectively discriminate the emotions. Ekman list six emotions are universal expressions such as anger, fear, sadness, happiness, disgust and surprise shown in Figure 3. Dimensional scales of emotion have been proposed by Plutchik's emotion wheel [11] and the valence-arousal scale by Russell [3].

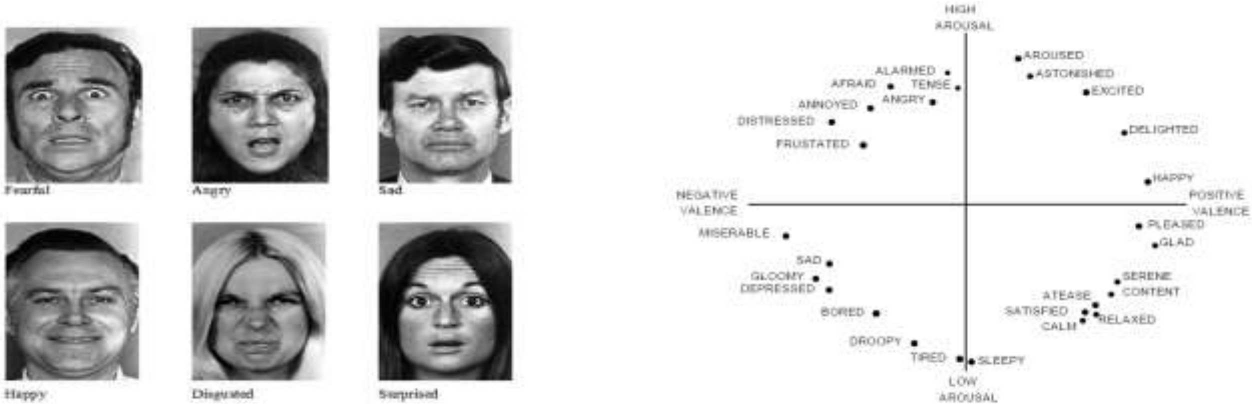


Figure 3: a) Ekman's Six Universal Emotions [2], Russell Valence-Arousal Model [3]

Most literature on emotion recognition uses Russell model of emotions because of its simplicity and universality. Russell model is shown in Figure 1.5. In this work, Russell Valence-Arousal model is used for four emotions (Happy, Angry, Sad and Relax) recognition. From the literature review of emotion and cognitive, it can be concluded that there are different stimuli, protocols and effects observed but what is the effect of meditation on emotion and the cognitive load is not studied yet.

III. SYSTEM METHODOLOGY

To recognize emotion using EEG signals many intermediate steps are to be performed: artifact filtering or pre-processing, feature extraction, and classification. The methodology for Research work is discussed below and shown in Figure .4.

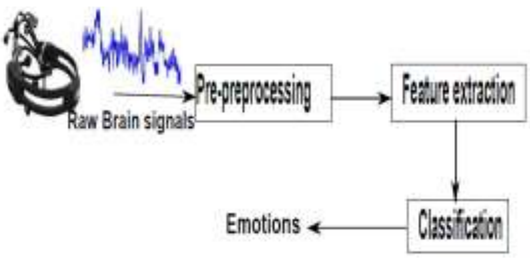


Figure 4: Steps of Emotion Recognition using EEG signals

In this contribution, the effect of peripheral physiological signals on the four emotions with EEG signals is investigated. A benchmark DEAP dataset is used for analysis of four emotions such as happy, angry, sad and relax. These emotions are categorized based on the valence and arousal scale. In the proposed method, pre-processed DEAP EEG dataset is used [14] and is freely available. The DEAP dataset consists of two important datasets 1. EEG data 2. Peripheral Physiological data like EOG, EMG, GSR, Temperature, pulse rate and respiration rate. In this paper, we used GSR, pulse rate and respiration rate as peripheral physiological signals for emotion analysis.The 32 EEG electrodes with 63 seconds sampler present texture for each emotion. In this work, a novel feature extraction method is proposed for emotion analysis using texture features. Gray level co-occurrence matrix (GLCM) features of EEG, such as contrast, correlation, energy, and homogeneity is used as texture features. The emotions are analyzed using EEG and peripheral physiological signals such as Galvanic Skin Response (GSR), respiration rate and pulse rate. An analysis of the effect of GLCM parameters and peripheral physiological signals on four emotions is discussed. The results show that GLCM and physiological features effectively discriminate the emotions. Here, emotion is represented as a texture. EEG-based emotion analysis using texture can be useful for observing spacial and temporal brain lobe variations. It is observed that the classification accuracy is improved using a combination of GLCM and physiological features. This type of analysis does not appear to have been investigated in the literature.

IV. RESULT AND DISCUSSION

4.4.1 Raw brain signals:

In this section, the subjects, experiment device and stimuli or elicitation materials used in this research work is discussed.

a) Subjects or Populations:

EEG signals are recorded from 11 healthy (6 males and 5 females) get the EEG dataset from kaggle websites. Before the experiment, the subjects have given personal profile and also signed a consent that dataset. The experimental work has been approved by the institutional ethics committee. Before the experiment, the subjects have been introduced to EEG and Meditation instruction.

b) Experimental setup/device:

EEG signals are recorded using fourteen electrodes EMOTIV EPOC+ [12] headset with sampling frequency 128 Hz. The fourteen electrodes are AF3, AF4, F3, F4, FC5, FC6, F7, F8, T7, T8, P7, P8, O1, and O2 placed based on the international 10-20 EEG format. EEG signals are recorded on a separate recording laptop and the stimuli are displayed using another laptop. EEG signals are recorded in pre and post-experiment of the same subject.

c) Stimuli or elicitation materials:

In this research work, the two experiments are performed using EMOTIV device such as four emotional response and seven cognitive load levels analysis. The elicitation materials such as four emotion pictures are used for emotion analysis and seven cognitive workload levels are used for cognitive load analysis.

4.4.2 Preprocessing

The removal of artifacts and extraction of epochs are the two steps performed in preprocessing and discussed in this section.

a) Removal of artifacts:

In EMOTIV EPOC+ EEG device, approximately 4200 V DC offset is present [12]. In order to remove the DC offset, especially before performing any kind of analysis it is necessary to remove DC offset by subtracting the mean from the entire data of each electrode as shown in Figure 5.

The zero mean EEG data of each subject is pre-processed using bandpass filter 4- 30 Hz for removing the artifacts. The bandpass filter is designed using FIR filter with Hamming window. The filter length N is calculated by Kaiser Window method. EEG signals are embedded with various artifacts such as eye blinking or movements, muscle artifacts, and power line source. In this research work, EEG frequency bands such as theta (4-8 Hz), alpha (8-12 Hz) and beta (12-30 Hz) bands are used hence the influence of eye artifacts is dominant below 4 Hz, muscle artifacts above 30 Hz and power line artifacts above 50 Hz are eliminated

b) Extract epochs:

After artifact removing, the four emotions and seven cognitive load levels are extracted as epochs from EEG data. These epochs are used for feature extraction.

4.4.3 Feature extraction:

The preprocessed data is analyzed and relevant features are computed in time domain, frequency and time-frequency domain for each electrode. The various feature extraction methods for EEG-based emotion recognition has been reviewed by Robert Jenke [13]. The time domain statistical, higher order crossing (HOC), Hjorth, Fractal dimension (FD) features have used in this work. Also, Power spectral density (PSD) in the frequency domain and Wavelet features in time-frequency domain are extracted. The detail of feature extraction methods used in the experimental work will be discussed in the respective chapter.

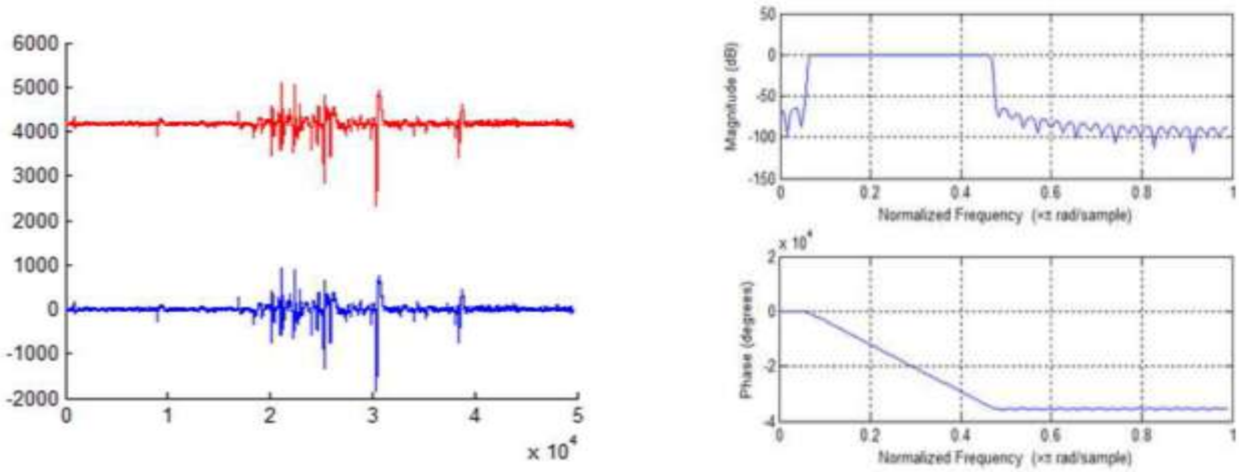


Figure 5: a) DC offset 4200 V removed using zero mean b) Magnitude and Phase response of filter

4.4.4 Classification:

Classification step assigns a class to a set of features (the feature vector) extracted from the signals. This class corresponds to the kind of emotional state identified. K-NN and Support Vector Machine (SVM) classifiers are used for classification of the emotion in this work.

V. CONCLUSION

A novel method for EEG based emotion analysis using GLCM features contrast, correlation, energy, and homogeneity has been proposed in this work. The comparison of GLCM features and peripheral physiological features have been discussed for four emotions in pre and postmeditation. The combination of peripheral physiological and GLCM feature shows the The four emotions (Happy, Angry, Sad and Relax) have been used for emotion recognition experiment. The benchmark DEAP dataset has been used for emotion recognition using the peripheral physiological signals such as GSR, Respiration and Pulse rate with EEG signals. The emotions have been categorized based on valence and arousal scale. The arithmetic addition has been used as a cognitive load for cognitive load analysis research work.

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