EEG analysis of human perception based on Video-Audio Stimuli

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Abstract - **Emotions plays a potential role in human computer interaction which are having an obligatory models of cognitive measures. The emotions are dominated by the human physiological communication channels. Those emotions could affects several human activities like learning, decision makiing, communication, perception, cognitive and so on. Also, some of the emotions are quite difficult to measure and interpret and having difficulty in incorporating them into a technology and design. On the other hand, state of the technologies has enabled us to capture the emotions and integrate them for the use of human computer interaction contexts. This paper delivers an attempt to model the emotions using electroencephalograpghy (EEG). The video stimuli for the two representative are based on a few negative, positive and neutral contents were shown to volunteers and EEG data was obtained. Further, EEG analysis were experimented and collected about their emotional states with subject's self reports. This study determines that the human emotions could be modelled for affect assessment module or for the usage in human computer interaction and affect based intelligent interactions.**

Keywords – EEG, Human Computer Interaction, Emotion Patterns, Emotions in Affective Computing.

I. Introduction

The human body tends reacts psychological stimuli and express variety of different physical changes. These adaptions exhibits brain signals, skin conductance, heartbeat, facial expressions, body temperature, pulse rate and so on. The evolvement of biomedical sector has given us the chances to predict even micro change in the parameters of physiological. For example, the enormous amount of releasing the fear will release certain amount of sweat compared to normal happiness and conditions that makes our body warm. There are quite a number of physical changes reported in the surveys which proliferates the generation of affective computing. Since, last two decades the affective computing domain has been impeccably factorized through a broad attention of researchers towards the view of emotion in human computer interaction and the surface of technology. The evolvement of the computer has seen a number of developments and came a long way from calculator to super computers. But still the evolvement strives to proliferates in the emotional intelligence domain which could examines the terms of response of person's frustration, anger, happiness and etc. Affective computing is an one step forward motive on filling this strive gap. This domain has grasped a broad attention from all sectors of science and technology around the global notions. Assessment of emotions was successfully done in various research community by the measures of biomedical tools like electrocardiogram (ECG), electroencephalography (EEG), heart rate variability (HRV) and galvanic skin response (GSR). These technologies may benefits several applications like interactive human computer interface, affective computer, human robot / machine interaction and learning in autism, etc.

A. EEG and Emotions

Electroencephalography (EEG) is a form of non-invasive teachnique for measuring the temporal resolution in milliseconds. It could delivers the adapted neuron activity from a certain part of a brain, that kind of activities are recorded with an electrode as an oscillating signal which could reflects the form of electric potential in a cluster of neurons fixed in a nearest proximity to the electrode. The innovation of EEG has given a meaning to the oscillating recorded signal from various parts of the brain. This activity has resulted in the capability of detecting a broad range of various physiological and psychological factors. Also, this recording has found suitable for detecting enormous differences in the pattern such as epileptic seizures. More recording equipments are available for précised recording terms which gives the possibility on detecting more subtle modifications in the recorded electric potential data. These subtle modifications are recognized to integrate for affective processes of brain such as working memory, different types of behaviour, mental calculations and attentions. These possibilities made to look forward on the usage of detecting emotions through EEG. Based on the functions of brain EEG is segemented into eight frequency bands such as delta, theta, low alpha, high alpha, low beta, high beta , low gama and high gama. Each frequency has it's own a terminologies that examine different activites .

Frequency bands	Signal range
Delta	1 – 3 Hz
Theta	4 – 7 Hz
Low alpha	8 – 9 Hz
High alpha	10 – 12 Hz
Low beta	13 – 17 Hz
High beta	18 – 30 Hz
Low gamma	31 – 40 Hz
High gamma	41 – 50 Hz

Table 1. Frequency bands and signal range

The delta and theta bands are commonly examined during calm state of the brain or in sleeping state. Alpha is mainly occurs during the low mental activity and whereas in high cognitive functions on the brain examines the beta and gamma bands. In case of the alterations in the features and these bands could be assessed to determine the various emotional states. The arousal shows that the negative correlations in beta, theta and gamma band. It shows that the proliferation of arousal leads to the minimization of beta, theta and gamma powers. For valence term, it examines the negative correlation in gamma band and positive correlation in the beta band. It determines the leveragement of valence leads to an maximization of beta power and minimization of gamma power. Arousal shows robust minimization in alpha frequency band.

B. Emotional Computing Models

The term affective computing was coined bt R. Piccard, it grasped the every research community attention on comprising neuropsychology, physics, engineering and psychology. The physiological measures can be mapped through the emotions and it is obligatory to measure the possibility of different emotional aspects. There are two methods which are used in computing the emotional models. In the first method, the emotional models can be represented on multidimensional space and another method is mapping the every individual emotions. Those emotions could be classified into eight different classes namely fear, sadness, anger, surprise, anticipation, joy, acceptance and disgust. Lot of survey shows the emotion variations with facial expressions while studying and it computes different emotions such as disgust, fear, happiness, anger, surprise and sadness. Later those computed emotions are compliment with different emotional aspects such as contempt, embrassament, guilt, excitement, pride in achieving, contempt, relief, shame, sensory, satisfaction and amusement. Among various perspectives of the dimensional spaces, one of the most widely used computing method is bipolar-model and valence- arousal dimensions. The arousal denotes the numerical weights f activation level ranges from not arousal to arousal. The valence denotes the efficiency of an emotion which ranges from pleasent to unpleasant. Later these dimensional models Arousal-Pleasure-Dominance (APD) was developed by mehrabin and Russell. In this model, dominance dimensional is added as additional space.

II. EXPERIMENTAL DESIGN

A. Stimuli Selection

Till now, there are only a few affective computing EEG databases has been published. Some of the databases are DEAP database, eNTERFACE and etc. These database has reported with different set of stimuli entities such as audio, images and musical video that were used for eliciting the emotions. Among the video stimuli and audio stimuli, the video stimuli holds the impeccable factor on choosing the most affective terms in emotions. In this research work, the core aim is to compute emotional models based on psychological factors using EEG. Most of the previous research works has shown the impact on using the video stimuli, but in this study a clip of 3 minutes video-audio stimuli was used as a testing stimuli. The selected video-audio stimuli consist of visual contect and semantic context for emitting the requisite emotions. The selection process for the stimuli based on a few set of randomly selected video which holds the positive, neutral and negative contexts from different sources. Each video stimuli has each it's unique emotion elicitation. In this research work, 2 participants emotional elicitations has been recorded based on the selected stimuli with the EEG device. Though, each participants elicitates different emotional aspects on each video and after that the EEG signals were observed and subjected to different frequency bands. This method of selection was undertaken to measure the emotion and it is necessary to ensure a proper time gap for avoiding the emotions decipted by the previously seen video-audio stimuli. Those time gaps are used for the filtering process on the EEG signals to avoid the past viewed clips and also it is would be useful to develop a prior mood of other video stimuli leads to the current video stimuli.

Video Stimuli	Emotions	Ranking	Start (Secs)	End (Secs)
Video_01	Negative	ID1	0	0.8
	Neutral	ID1	0.9	1.2
Video_02	Negative	ID2	0.5	1
	Neutral	ID2	0	0.4
Video_03	Neutral	ID3	0.7	0.9
	Negative	ID3	0	0.6
Video_04	Negative	ID4	0.4	0.8
	Positive	ID4	0	0.3
Video_05	Negative	ID5	0	0.4

	Neutral	ID5	0.5	0.8
Video_06	Negative	ID6	0.6	1.0
	Neutral	ID6	0	0.5
Video_07	Negative	ID7	0	0.6
		ID7	0.7	0.9

Table 2. Video-audio stimuli data

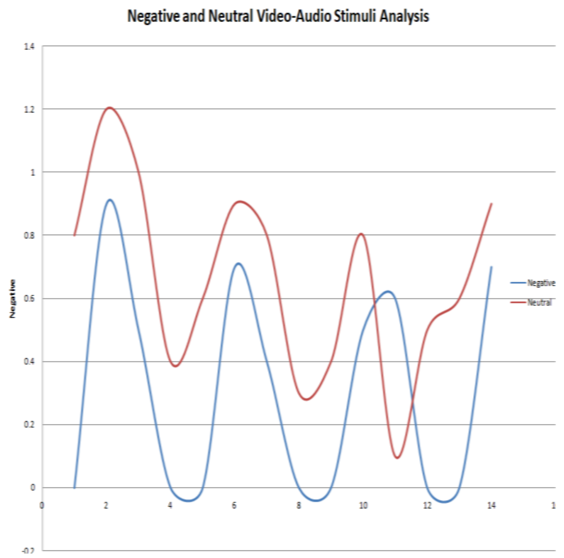


Figure 1. Neutral and Negative video-audio stimuli analysis

Video-Audio Stimuli ID	Stimulated Emotions	Observation		
		Avg	Max	Min
Video_01	Anger	0.4	0.8	0
Video_02	Disgust	0.3	0.5	0.1
Video_03	Embrassament	0.8	0.7	0.9
Video_04	Anger	0.6	0.4	0.8
Video_05	Disgust	0.2	0	0.4
Video_06	Anger	0.8	0.6	1.0
Video_07	Fear	0.8	0.7	0.9

Table 1. Simulation of specific emotions

B . Experiment Setup and Procedure

An experiemental environment was measured and maintained with no unwanted stimuli and no external sound or scenarios that would not disturb the participants. All of the video-audio stimuli of certain durations were played in the order of queue with a gap of certain seconds. This interval seconds could maintain the baseline for the prioritize the recorded signal to the experimental module. After every stimuli, the signals can be generated with the report of each participants self assessment with the emotions they undergone through.

III. Observation and Analysis

A. Data Preprocessing

Although the data collection has been measured in a proper care but the raw EEG signals are quite generally measured by the external noise. Apart from the external noise, the muscular movements and various artifacts are present in the raw signals. In order to remove the noise and unwanted elements from data the filtering processing was initiated such as signal pre-processing. The interval gap differentiated between the post and prior stimuli was fixed upto 10 seconds were removed for obtaining the effective dataset. A broad number of features can be seen in frequency term rather than the time domain. So, after the pre-processing task, Fourier Transform (FT) was applied for converting the frequency into time domain. Though the presence of electrical noises from the raw signals was removed using the Butterworth notch filter (1 -40Hz). An another analysis term was also applied in this pre-processing task namely Independent component analysis (ICA) was performed to measure and identify the independent components and local sources.

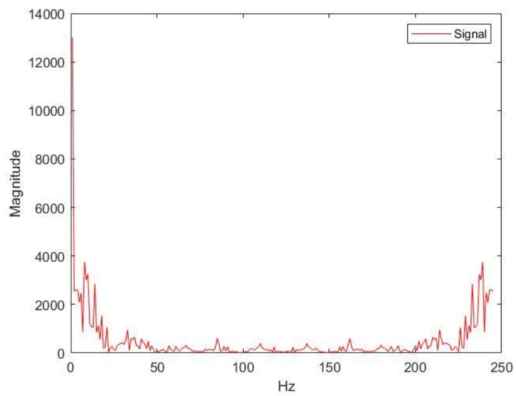


Figure 2, Frequency signal A with noise

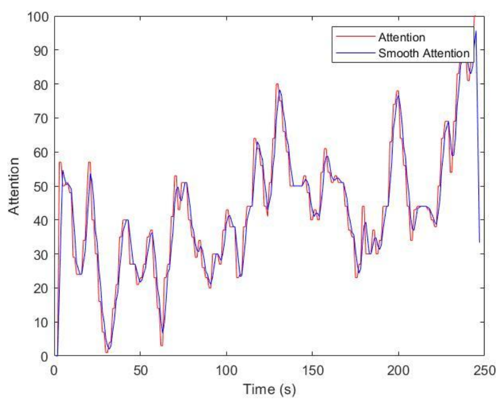


Figure 3, Frequency signal A with attention

The Independent component analysis algorithm is a kind of technique for seperating event generated data and artefactual data. The EEG data could contains various different artifact signals like ECG, Eye blinks, EOG,EMG, etc. The independent component analysis was used to separate neutrally generated data from these various aspects of artifacts. In order to restrain the orginal data, then the recorded data should be represented with a matrix of time course in voltage with differences between the one or more reference data and projections of the source data to an another data. After the component analysis, each row is analyzed with a data activation matrix for filtering the time course of an activity from the channel data with an one component . These artifacts reported with three major features such as the grasped signal data shows a rigid far-frontal projection of various artifacts. There is a smooth minimization EEG spectrum is a typical of an eye artifact.

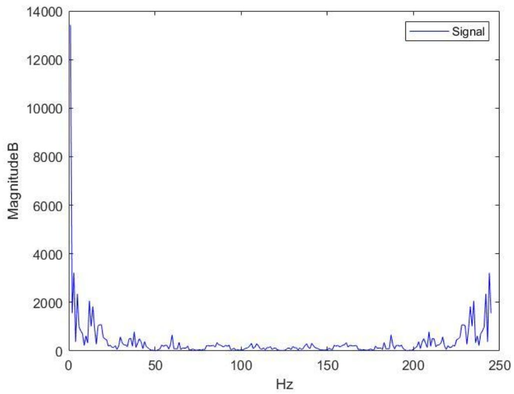


Figure 4, Frequency signal B after component analysis

It is observed that a smooth minimization in EEG pattern has shown in far frontal projection. This projection resultant was integrated into five frequency bands including theta(4-7 Hz), delta (1-3 Hz), beta (14-30 Hz) and (8-13 Hz). The alternation in these characteristics and frequency band which exhibits different types of features set which associates to different emotional states. Based on experimental process, the features were extracted as,

- Different asymmetry of power spectral density
- Correlation with frequency bands.

The frequency signal can calculated with the following formula,

- Total Power in x(t): P = $\int_{-\infty}^{\infty} S_x(f)df = R_x(0)$
- Power in x (time) in range f1 – f2
- P = $\int_{f1}^{f2} Sx(f)df = R_x(0)$

Correlation was calculated in three bands (alpha, beta and theta) for a measuring frontal, parietal, central and occipital. Correlation was calculated by the following formula.

$$r = \frac{N\sum xy - \sum x \sum y}{\sqrt{[N\sum x^2 - (\sum x^2)]\,[N\sum y^2 - (\sum y^2)]}}$$

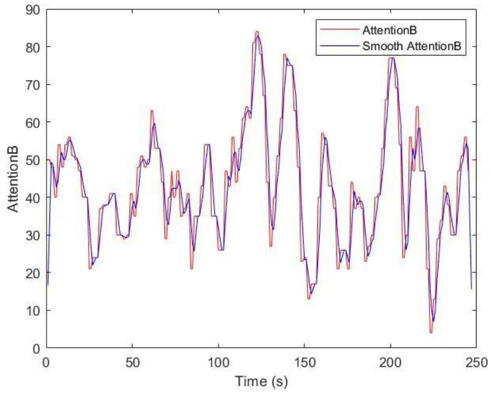


Figure 5, Frquency signal B with smooth attention

IV. Result and Discussion

Once the pre-processing and filtering of raw signal data is done, the power spectra against frequency will be plotted. The frequency range varies from 5 – 50 Hz and it could be plotted on the x-axis and power ranges from -10dB to -20dB and it could be plotted on y-axis. The frequency power varies on the frequency plots as per 2 participants and 5 different emotions and that leads to measure and identify the peak values. The measured peak value ranges in alpha frequency band (10-12Hz) for the first participant and theta frequency band (4-7) for the second participant. Though the analysis is not to separate the sources of frequency but it could merge the spectrum analysis for showing the difference in the frequencies for each emotional phases.

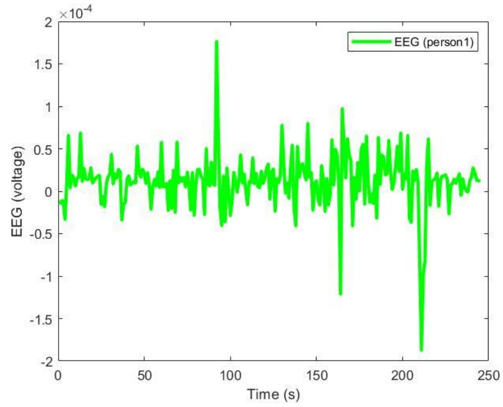
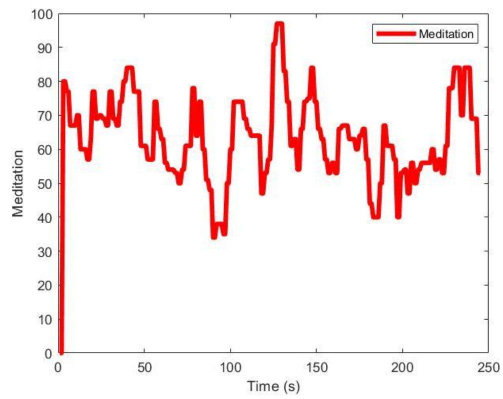
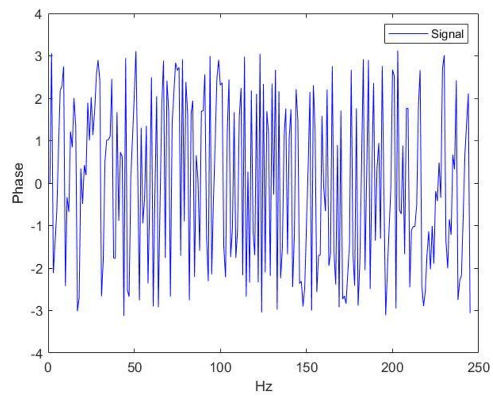


Figure 6, EEG signal of the first participant





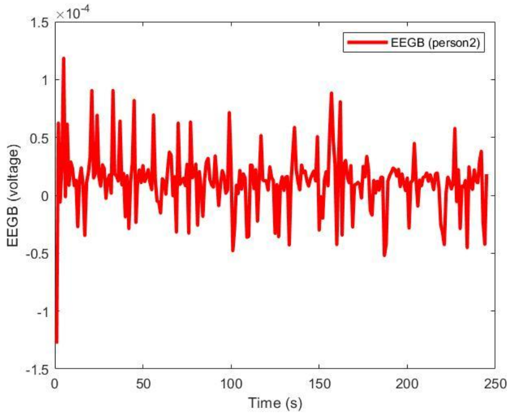


Figure 9, EEG signal of second participant

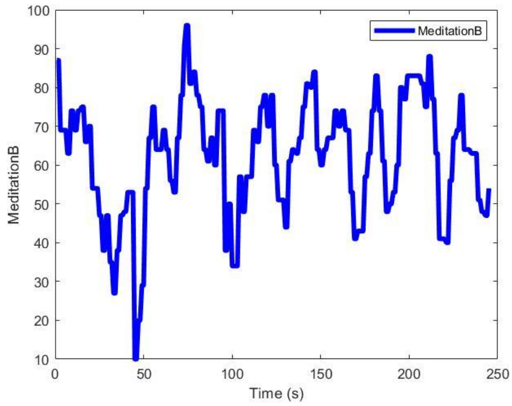


Figure 10, Meditation frequency signal B

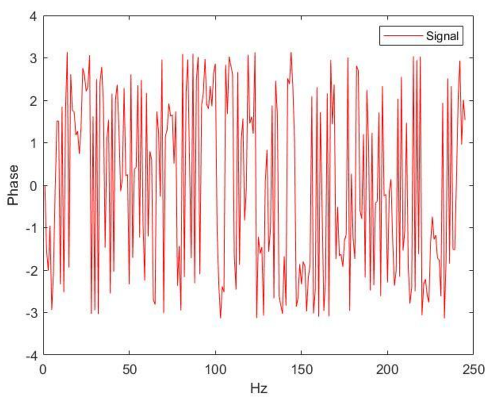


Figure 11, Frequency band (4-7 Hz)

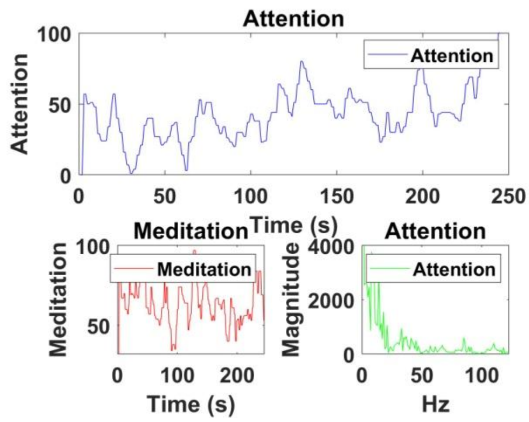


Figure 12, Frequency rate on attention and meditation

The visual stimuli may decipts variety of emotions among the stimuli evoking anger leads to the maximization in theta power. As the increase in theta frequency with anger and relative suppression could be the reason for the low correlation in theta and high correlation in beta frequency and leads to higher brain activity was observed through an increase in overall power of beta frequency.

V. CONCLUSION

This research work has reported EEG correlational features embedded with four different emotions on the selected stimuli. Thie experimental study has showed effective patterns in electroencephalogram signal characteristics of the four emotions anger, embrassament, fear and disgust. This study reports low beta frequency band and high theta frequency bands were found to be best suited in adaptions of these emotional states. Further studies with other emotions would helps to formulate an extensive EEG map of various brain states into several emotional states and also it could be useful for emotion intelligence in advanced human computer interaction.

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