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Affective modelling of users in HCI using EEG

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Abstract

Emotions have potential to play a role in HCI which is primarily dominated by cognitive measures. Human physiological communication channels are dominated by emotions. Emotion affects several human activities like communication, learning, decision making, cognition, perception etc. Further, as emotions are difficult to interpret and hard to measure, technologists and designers have been struggling to incorporate them in design and technology. On the other hand, advancement of technology has both necessitated and enabled us to understand emotions and put them to use in contexts like human computer interaction. This study reports an attempt to model emotions by means of electroencephalography (EEG). Video stimuli of four representative basic emotions based on *Navarasa* theory of Ancient Indian treatise called Natya Shastra were shown to participants and EEG data was collected. Power spectrum analysis of EEG signals associated with emotions was done. Further, the EEG analysis findings were compared with the subject's self-reports about their emotional states during the experiment. EEG results have shown significantly consistent frequency patterns across the brain lobes for a given emotion. This study suggests that human emotions can be modeled for use in HCI either as an affect assessment tool or for affect based intelligent interactions.

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Keywords:HCI;EEG;Emotion: Affective computing

1. Introduction

Human body responds physiologically to physical and psychological stimuli and exhibits different physical changes. These changes comprise of facial expressions, skin conductance, heartbeat, brain signals, body temperature, pulse rate, etc. Advancement in biomedical technology has given us access to identify even smaller change in physiological parameters. For example fear release excessive amount of sweat compare to normal condition and happiness makes our body warm[1]. There are number of such physical changes reported in literature

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which bolster the era of Affective Computing. Since, last two decades human computer interaction has come over the surface of technology and captivated a wide attention of researchers towards the role of emotion in HCI[2, 3].

Since the birth of computer it has seen number of developments. It has come a long way from calculator to computer and finally took shape of smart computer. But still it lacks of emotional intelligence, response of person's anger, frustration, happiness etc. Affective computing is a forward step in the direction of filling this gap. Since last one decade, this title has grabbed a wide attention from all area of science and technology around the globe. Emotion assessment was successfully done in by different research community by means of different biomedical tools like, electroencephalography (EEG), electrocardiogram (ECG), galvanic skin response (GSR), heart rate variability (HRV) [4, 5, 6]. Various steps like data acquisition, preprocessing, feature extraction and classification have been followed in this process. The outcome of this area may benefit applications like Human Robot/Machine interaction, Interactive human computer interface, learning in autism, Affective computer etc.

1.1. EEG and Emotion:

EEG is a noninvasive measurement technique with temporal resolution in milliseconds. It shows the synchronized neuronal activity from a region of a brain, recorded by an electrode as an oscillating signal reflecting the electric potential from the group of neurons situated in close proximity to the electrode[7]. Ever since the invention of EEG, Constant attempts have been made to give meaning to the oscillating signal recorded from different parts of brain. This has resulted in the ability to detect a wide range of different psychological and physiological phenomenon. This recording was in the early days only suitable for detecting large differences in the pattern, such as epileptic seizures[8].

More precise recording equipment, empirical studies of EEG, and the availability of sufficient computational software tools, gives rise the possibility to detect even more subtle changes in the electric potential recorded. These subtle changes have been recognized to encode for cognitive and affective processes of brain such as attention, working memory, mental calculations, as well as different types of behavior [9, 10, 11]. These possibilities motivated to look forward for detecting emotion through EEG. Based on the brain functions EEG is categorized into five frequency bands, including delta (δ: 1–3 Hz), theta (θ: 4–7 Hz), alpha (α: 8–13 Hz), beta (β: 14–30 Hz), and gamma (γ: 31–50 Hz) [12]. Delta and theta bands are commonly found during sleep or clam state of brain. Alpha is evident mainly during the low mental activity whereas beta and gamma are produced when brain is involved in higher cognitive functions[13]. Alteration in these bands and their features are often assessed to examine the emotional states. YisiLui reports that arousal shows negative correlations in theta, beta, and gamma band. It means increase of arousal leads to a decrease of theta, beta, and gamma powers. It is found that beta band of electrodes FC2 has a negative correlation with arousal. For valence, we get a positive correlation in beta band and a negative correlation in gamma band. It means that an increase of valence leads to an increase of beta power and a decrease of gamma power[14]. Sander Koelstra states in DEAP database that central alpha power decreases with arousal. All frequency bands shows positive correlation with valance in occipital lobe but central beta power decreases with valance[15]. He further reports that valance shows negative correlation in right posterior alpha power whereas left central increases and right frontal decreases in beta power. Arousal shows robust decrease in right posterior in alpha power.

1.2 .Computational models of emotion

"The Emotions are all those feelings that so change men as to affect their judgments, and that are also attended by pain or pleasure. Such are anger, pity, fear and the like, with their opposites." (Aristotle, 1378b, English translation by W. Rhys Roberts) [15]

Since the term affective computing was coined by R. Piccard, It grabbed attention of many research community comprising Psychology, neuroscience, neuropsychology, physics, and engineering. To map emotions through physiological measures, it is very important to identify possible types of emotions. Two approaches can be found in literature to model emotions. One is mapping of individual emotions and another is representation of emotion on multidimensional space[16]. In first category, Plutchik proposed eight basic emotion states: anger, fear, sadness, disgust, surprise, anticipation, acceptance, and joy[17]. Ekman used model of six emotions while studying of relation associated with facial expressions: anger, disgust, fear, happiness, sadness and surprise. Later Ekman expanded the basic emotions by adding amusement, contempt, contentment, embarrassment, excitement, guilt, and pride in achievement, relief, satisfaction, sensory pleasure, and shame[18]. From the dimensional perspective, the most widely used classification is the bipolar model - valence and arousal dimensions advocated by Russell[19]. Valence represents the quality of an emotion, ranging from unpleasant to pleasant. Arousal denotes the quantitative activation level, from not aroused to aroused. Later a three dimensional Pleasure-Arousal-Dominance (PAD) model was proposed by Mehrabian and Russell[20, 21]. In this model, besides the arousal and valence dimensions, an additional dimension called dominance is added.

Ancient Indian dance and dramatics literature has described the process of elicitation of emotions and has identified nine emotions in called as Navaras[22]. The treatise describes emotions or ‘rasa’ as the developed relishable state of a permanent mood, which is called sthayIbhava. The process of elicitation of emotion has been described as a result of the interplay of attendant emotional conditions called Vibhavas, anubhavas and sanchari/ vyabhicharIbhavas[23, 24]. Vibhava mean cause of an emotion. Anubhava is the phase of development of emotion evoked in vibhava. Vibhavas are argued to be caused by Alambana and uddipana. Alambana is caused by the person due to one’s personal dispositions towards stimuli. Uddipana is the external cause of evocation of emotion. Vyabichari/sanchari bhavas is the phase where the emotions decline. This theory of rasa has been fundamental to many forms of traditional Indian arts including dance, music, musical theatre, cinema and literature and has been operationalized in performances.

This paper has taken its understanding of emotions form the ‘rasa’ theory and the ‘Navaras model’. The nine emotions described in ‘navarasa model’ are Shringara (love), Hasya (laughter), karuna (compassion), Rudra (anger), Veera (courage), Bhayanaka (terror), Bheebhastya (disgust), Adbhuta (surprise), and Shanta (peace). Out of these nine emotions, Shringara (love), Raudra (anger), Veera (courage) and Bheebhatsya (disgust) are considered as four primary emotions[25]. This paper has selected the four emotions described as primary emotions in ‘navarasa model’, as focus of EEG study and subsequently suitable stimuli (uddipana) were identified. Further, based on the rasa theory, it was tried that the further development of emotion into spontaneous myriad shades called anubhava phase in development of emotions in rasa theory, by keeping the stimuli of short duration and a controlled experiment environment.

2. Experiment design

2.1. Stimuli selection

So far there are only a few affective EEG databases published[14]. Three databases have been reported frequently in literature. The first one is the eNTERFACE database[26], the second one is the DEAP database[27], and the third one is the database established by Yazdani[28]. As reported in these databases, stimuli like images (IAPS), audio (IADS), virtual stroop task and music video were used to elicit emotions[28, 29]. Among the audio, picture and video stimuli, the video stimuli were most effective in electing emotions[30, 31]. In this study, the aim was to model emotion physiologically using EEG. As argued in literature, the video stimuli being the most impactful, in this study video clip of 4-5 minutes were used as experiment stimuli. The video selected were of local semantic context for the participants to be able to elicit requisite emotions. The process for selection of the stimuli is as follows. A large set of randomly selected videos in ratio of 25:1 were collated form different sources. Each video was evaluated for its’ elicitation of each of the four specific navrasa emotions by three researchers who mutually rated the videos. After a mutual consensus, videos were further filtered in 5:1 ratio. Then, 15 users then rated the emotional elicitation for each video and the highest rated video was selected for the EEG experiment for each amotion. Finally 10 altogether different users were subjected to the 4 selected videos related to the 4 emotions while EEG signals were observed. This method of selection of videos was undertaken to ensure that the videos elicited the emotions desired by the videos for EEG recording. Further, as discussed in section 1.2, rasa is the developed relishable state of a permanent mood. So that it is very necessary to take proper time gap to avoid the influence of the emotion depicted by previously seen videos. Time gap of 2-3 days was taken between different stages in the entire filtering process of the videos to avoid bias due to prior mood developed from past viewing of other similar video clips leading to permanent mood (sthayibhav).

Table 1: Video clip details causing stimulation of specific emotions

Video clip name	Stimulated Emotion	Participants feedback on 10 scale		
		Average	Max	Min
Pehlanasha	Love (happy)	8.5	10	5
Best inspirational	Courage	8.3	9.5	6
Nirbhaya BBC doc	Anger	8.1	9	6
Worms eating	Disgust	8.8	10	7

2.2 Participant selection

Total 10 participants (6 male and 4 female) of different age groups (24-51, with a mean of age 29.8) were selected. These participants were among the master's students, research scholars or project staff. Selection of the participants was based on the standard set of questionnaire which ensures that they fit for the experiment. It was ensured that the participants had proper sleep, no drugs consumption and no other health issues prior to the experiment. It was also ensured that they are not going through any mental stress or personally caused emotions (alambana).

2.3 Experiment setup and procedure

An adequate environment was maintained that no external and unwanted stimuli like sound or light can disturb the participants. Each participant was presented with a trial case, followed by a 2 minutes baseline recording without the experimenter, which allowed them to familiarize with the system before the actual recordings. After this, the 4 trials were performed, and included the following steps mentioned in fig 1 (a).
All four videos of 4-5 minutes duration were played in a queue with a gap of 1 minute. Ten seconds of baseline was recorded prior to experiment. After every video participant was asked to report self-assessment feedback for the emotion they have undergone through.

2.4 Apparatus

In all experiments, 14-channel wireless EEG device was used[32]. Positions of electrodes were locating at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 standardized by the American Electroencephalographic Society[33] (plus CMS/DRL as references) . The technical parameters of the device are given as follows:
Bandwidth, 0.2-45Hz, digital notch filters at 50Hz and 60Hz; A/D converter with 16 bits resolution and sampling rate of 128Hz. The data are transferred via wireless receiver. The use of 14 channel wireless EEG device has become popular in the EEG-based research [4] [14].
Stimuli were played on 17 inches LCD screen and good quality of audio speakers was used. Filtering, pre-processing and analysis were done with the help of EEGLAB incorporated with MATLAB software [34].

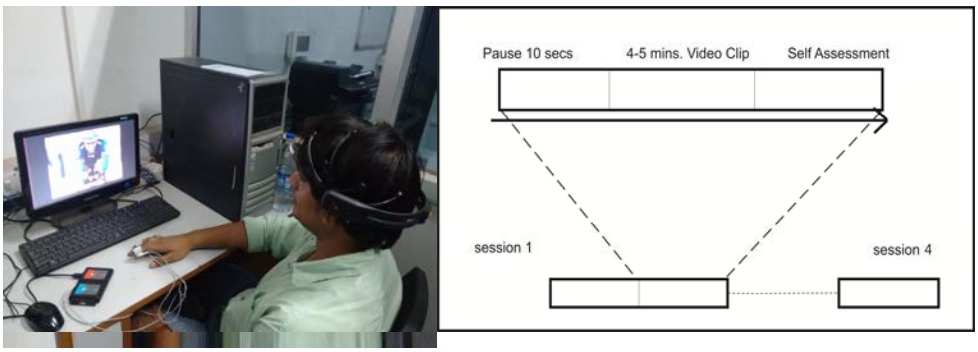

Fig.1. (a) Experimental Setup; (b) The procedure of experiment session

3. Observation and Analysis

3.1 Data preprocessing

Although proper care was taken while the data collection but raw EEG signals are generally found contaminated by external noise. Beside noise various artefacts due to electrostatic devices and muscular movements are present in raw signals [35]. In order to remove all these unwanted elements from the data, signal pre-processing was done. 10 seconds of both post and prior data was also removed in order to get effective data set. An extensive number of features can be seen in frequency domain rather than time domain. So after the process of pre-processing Fast Fourier Transform (FFT) was applied to convert in frequency domain from time domain. Electrical noises were removed from the raw signal by using Butterworth notch filter (01- 40 Hz). Baseline was removed and re-referencing was done with reference channel. Interpolation of electrodes was done to bind the data. Independent component analysis (ICA) was performed to identify the local sources and find the independent components.

ICA algorithms have been proven technique for isolating both artefactual and event generated data. EEG data contains various artefacts signal like EMG, ECG, EOG, Eye blinks etc. ICA separates neurally generated data from these various types of artefacts. In the original scalp channel data, each row of the data recording matrix represents the time course of summed in voltage differences between source projections to one data channel and one or more reference channels. After ICA decomposition, each row of the data activation matrix gives the time course of the activity of one component process spatially filtered from the channel data [34].

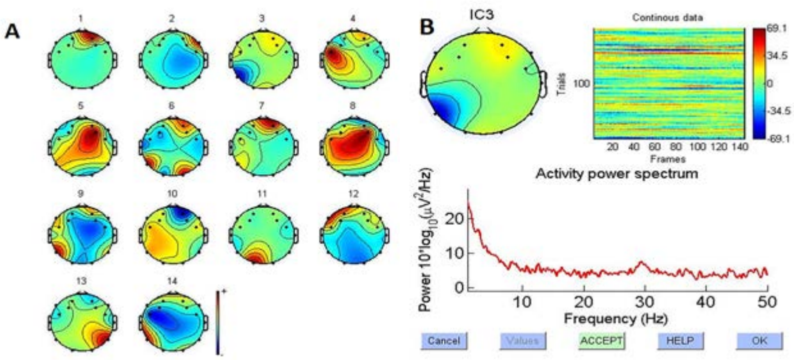

Fig: 2 ICA component map and related independent component properties

For an example, herein we report ICA component spectra and its associated components properties. There are some standard features set reported in literature to identify various types of artefacts such as[35].

- The smoothly decreasing EEG spectrum (bottom panel) is typical of an eye artifact;
- The scalp map shows a strong far-frontal projection typical of eye artifacts; And,
- It is possible to see individual eye movements in the component

As depicted in fig 2 (a), it was observed that a smooth decreasing EEG pattern existed in the far frontal projection in component one. This confirms that first component belonged to eye blink artefacts. Similarly, as evident in component properties spectra fig 2 (b), component 3 showed higher power in high frequency region (25-35 Hz) in far temporal projection and smooth decreasing pattern which indicates muscle artefacts[34]. By analysing component topography and its individual properties such muscle artefacts were removed.

The resultant spectra was isolated into five frequency bands for further investigation, including delta (δ: 1–3 Hz), theta (θ: 4–7 Hz), alpha (α: 8–13 Hz), beta (β: 14–30 Hz), and gamma (γ: 31–50 Hz).As discussed in section 1.1, alteration in these bands and its characteristics lead to different types of features set which relate to different emotional states. Based on finding in literature and experimental studies three main features type were extracted.

- Power spectral density (PSD)
- Differential asymmetry of power spectral density
- Correlation with frequency bands.

First of all individual spectral power from 14 scalp electrodes were used as the feature including AF3, AF4, F3, F4, FC5, FC6, T7, T8, P7, P8, O1 and O2. These 14 features were named as PSD14 (power spectral density of all 14 channels). After that, total 7 asymmetry electrode indexes were derived from 7 symmetry electrode pairs like AF3-AF4, F3-F4, FC5-FC6, T7-T8, P7-P8 and O1-O2. The asymmetry index was calculated by differential power (power of F3- power of F4) and named as 7 DAEP (differential asymmetry of electrode pair). Power spectral density was calculated by following formula.

1. Total Power in x (t): $$P = \int_{-\infty}^{\infty} S_x(f)df = R_x(\mathbf{0}) \quad (1)$$
2. Power in x (t) in range f_1 - f_2: $$P_{12} = \int_{f_1}^{f_2} S_x(f)df = R_x(\mathbf{0}) \quad (2)$$

Correlation was calculated in three bands (theta, alpha and beta) for four different lobes of brain including frontal, central, parietal and occipital. Correlation was calculated by following formula.

$$r = \frac{N\sum xy - \sum x \sum y}{\sqrt{[N\sum x^2 - (\sum x)^2][N\sum y^2 - (\sum y)^2]}} \quad (3)$$

3.2 Results and discussion

After filtering and pre-processing of raw data, power spectra against frequency, for each and every of the 14 channels, were plotted. The frequency range of 5-50 Hz was taken on X-axis and Power varying from -10 dB to +20 dB was taken on Y-axis. For example, in fig 5, power distribution associated with different frequencies for channel 1 has been plotted. In fig 3 (a), one can observe the peak in higher alpha band (11-13 Hz). In similar fashion power versus frequency plots was drawn of all 14 channels for 10*4 (10 participants * 4 emotions) and the peak values were identified. These plots were compared for four different emotions. Though the weakness of this analysis is that it does not separate out the possible sources of the frequency, hence one is blind while analysing as to what could have caused the frequency but this was conducted as still mere power spectrum analysis does show a difference in the frequencies for emotions.

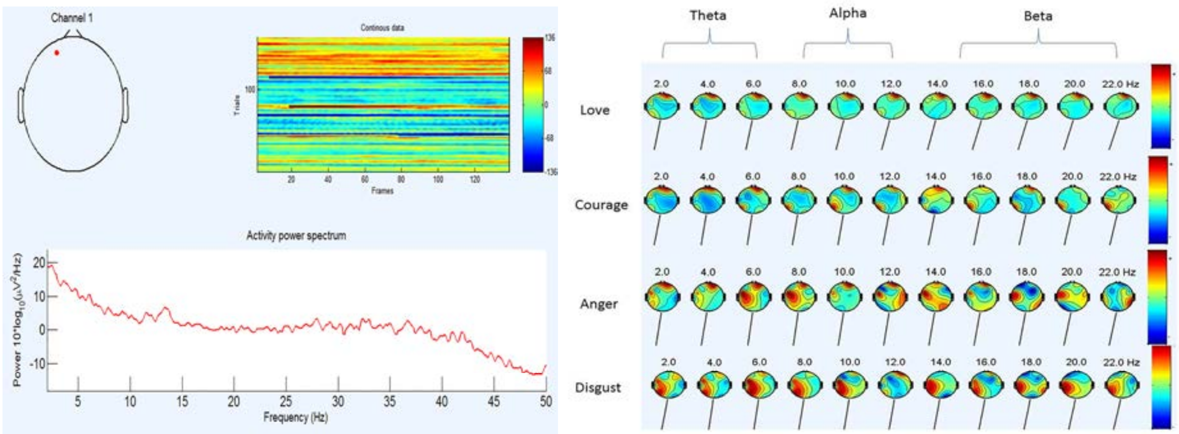

Fig.3. (a) Power spectra of individual channel (b) Power spectral topography of all four emotions with respect to different frequency bands

It was observed from the channel power spectrum plots that for a given emotion across participants the peak frequency range was repeating. In order to confirm the observed pattern, power spectrum topography was also plotted. The observations are shows in fig 3 (b). The frequency bands in which peak values were repeating across the participants for a given emotion has been tabulated in table 2.

Table 2: Observation from power spectrum topography

Emotion	Theta		Alpha		Beta		Inferences
	Low	**High**	**Low**	**High**	**Low**	**High**	
Love	FC5 FC6	AF3 AF4 P7		AF3 AF4		AF3 AF4	Increased activity in frontal lobe P7 has negative correlation with frequency
Courage	FC5 FC6 P8	AF3 AF4 F7 P7	FC5 FC6	AF3 AF4 P7		P7 AF3 AF4	Frontal activity decreases with high frequency P7 has positive correlation with high frequency
Anger	T8 P8	AF3 AF4 T7		AF4 T7 P7	AF3 F3 F4 O1	T7 P8	Frontal activity decreases T7 has high positive correlation with frequency O1 has negative correlation
Disgust	AF3 F3	F4 P7 O1	AF3 F3	F4 O1 O2	F3 F7	O1 O2	F3 and AF3 has negative correlation O3 and O4 has positive correlation

As evident from table 2, out of four emotions, the EEG response to visual stimuli depicting emotion of love was found to be correlated with higher frontal lobe activity. The author posits that the emotion love had higher correlation probably because the brain was involved in imagination during the participants watched video stimuli evoking feeling of ‘love’. At the same time, emotion of love showed negative correlation in right temporal and occipital lobe because of less motor imagery activity. For courage, theta and alpha power shows positive correlation in frontal lobe and negative correlation in right occipital lobe as well as central brain. Courage was found to have high positive correlation in left occipital lobe and it was observed that the spectral power increased with increase in frequency of the band. Further, it was observed that the stimuli evoking emotion ‘anger’ lead to increase in theta power theta in frontal lobe while alpha power increased both in frontal and left temporal lobe. Authors posit that since anger is expected to activate motor imagery activity as a human is in fight-flight reaction, one is inclined to have more left temporal lobe activity. As the beta power showed increase in left temporal region with anger, relative suppression might be the reason for the negative correlation observed in the frontal as well as occipital lobe for emotion ‘anger’. Further it was observed that feeling of emotion ‘anger’ led to higher overall brain activity as observed through increase in overall power of beta frequency. Disgust showed very high correlation in theta and alpha power of occipital lob and negative correlation in left frontal. Authors posit that the reason for increase in occipital lobe activity during feeling of disgust might have been due to suppression on further imagination and thinking linked to the stimuli as they were ‘disgusting’ and increase in relative visual processing activity to force out the stimuli from mind without thinking. The suppression of the imagination related to the stimuli might have led to decrease in in beta power of left frontal lobe.

4. Conclusion:

This paper has reported EEG correlational features associated with four different emotions selected from ancient Indian dramatics affective model called ‘navarasa’. The paper has briefly discussed the selection of primary four emotions from the ‘navarasa’ model in ‘rasa’ theory. The experimental study has showed consistent patterns in EEG signal characteristic of the four emotions. This study reports that higher theta, alpha and lower beta frequency bands were found to be most responsive to the change in emotional states. Frontal, left temporal and occipital lobes were observed to exhibit maximum change in activity during the change of emotional states. Further studies with other types of emotions can help towards creating an extensive EEG map of the brain states related to emotional states and be useful in developing emotional intelligence in advanced human computer interaction.

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