Classification and Determination of Human Emotional States using EEG

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Abstract

Emotion plays an important role in everybody's life and in this paper I show how the brain waves tells us which emotion is being experienced by a person. This research studies the brain waves in happy, sad and disgust emotion and determines how the brain waves pertaining to the emotions are distinguishable from each other and how the brain waves of a single emotion is consistent (or inconsistent) from person to person. In doing this research EEG machine is used and video clips are used to instigate the different emotions.

Keywords - *Happy emotion, sad emotion, disgust emotion, alpha waves*

I. INTRODUCTION

This Electroencephalography (EEG) is an electrophysiological monitoring method to record electrical activity of the brain. It is typically non-invasive, with the electrodes placed along the scalp.EEG measures voltage fluctuations resulting from ionic current within the neurons of the brain. In clinical contexts, EEG refers to the recording of the brains spontaneous electrical activity over a period of time, as recorded from multiple electrodes placed on the scalp. Diagnostic applications generally focus on event-related-potentials or on the spectral content of EEG. The former investigates potential fluctuations time locked to an event like stimulus onset. The latter analyses the type of neural oscillations that can be observed in the EEG in the frequency domain.

Our brain consists of 5 different types of brain waves; Delta, Theta, Alpha, Beta and Gamma brain waves. Each of these waves has its own normal frequency range in which they operate.

Gamma waves: 41 Hz to 100Hz
Beta waves: 13 Hz to 40 Hz
Alpha waves: 8 Hz to 12
Theta waves: 4 Hz to 7 Hz
Delta waves: 1 Hz to 3 Hz

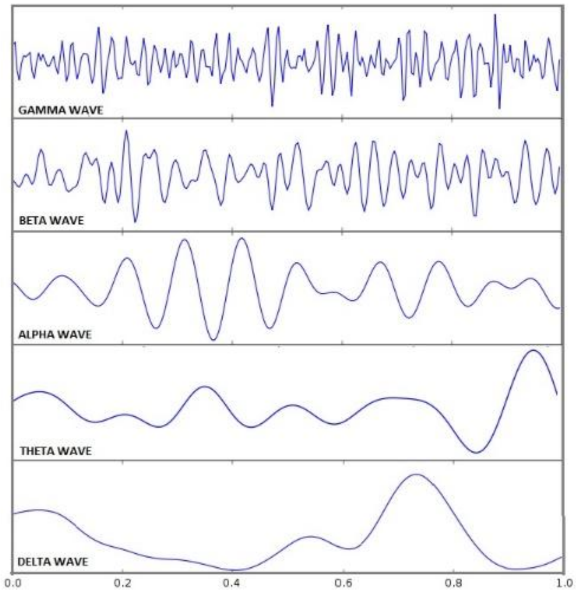

Fig 1.

Emotion is any conscious experience characterized by intense mental activity and a high degree of pleasure or displeasure. Emotion is often intertwined with mood, temperament, personality, disposition and motivation. Those acting primarily on the emotions they are feeling may seem as if they are not thinking, but mental processes are still essential, particularly in the interpretation of events.

EEG has primarily been used in clinical purposes for identifying epilepsies and seizures. In foreign research centres, EEG is being used in neural and non-neural rehabilitation. EEG, with the help of an Artificial Neural Network based embedded system, has proved revolutionary in the area of rehabilitation of patients suffering from paralysis, amputation, loss of organs due to accidents, etc. Using EEG for emotional determination is a lesser explored area of this major field.Previous studies has shown primarily the comparison of a general positive emotion and general negative emotion, without the specificity of the actual emotion being experienced by the person. Previous works include papers published on "Emotion-enable EEG-based interactions", Real-time EEG-based happiness detection system, EEG-based emotion estimation using Bayesian Weighted-log-posterior function and perception convergence algorithm, EEG based emotion recognition using frequency domain features.

Although this a very upcoming topic in the research centres around the globe, this has not been explored that much in India and this paper aims to take an initiative in exploring that area. Papers published in India include "Emotion Recognition System based on Autoregressive Model and Sequential Forward Feature Selection of Electroencephalogram Signals", "Classifying Different Emotional States by Means of EEG-based Functional Connectivity Patterns", etc.

In this paper we have tried to solve this ambiguity by showing that even if a negative emotion is being experienced by a person, the specific emotion also dictates the characteristics of the EEG readings. We have concentrated our study specifically to the behavior of the temporal lobe of the brain to get the waves due to emotional excitation. This has been done to complement the fact that majority of emotional activity takes place in the temporal lobe and to reduce artefact contamination due to blinking, head movement and other external contributing factors.

In this paper we discuss about the characteristics of EEG readings obtained while a person is experiencing an emotional outburst. Here we study how the EEG readings recorded during the experience of different emotional states are distinguishable from the state where the subject is in a completely relaxed position, how the different emotional states are distinguishable from each other for a given subject, and study the consistency of the EEG reading of the individual emotions throughout the array of subjects.

If this hypothesis is proved right, it could be beneficial for making embedded system that would be able to predict emotions solely based on the EEG. This could be used in clinical cases where a patients likeliness to succumb depression can be identified beforehand. This can also be used in AI to enable them to understand human emotions better, rather than reading them through facial recognition. This can also be used for patients with motor neuron disease, to enable them to express emotions. In short the possibilities are unlimited with this type of research.

This paper is distributed into 5 parts, part 1 is the introduction, part 2 is the proposed methodology. In the methodology section we have discussed the basic working of the research, the procedure followed to perform this research. Part 3 is Results and Discussions where we talking about the findings of the research. Part 4 is Conclusion and Future Scope where we have discussed about the findings and how the findings validate our hypothesis and how the findings can be used in other technology. Part 5 is the Reference section where we have cited the works done by researchers before us.

II. PROPOSED METHODOLOGY

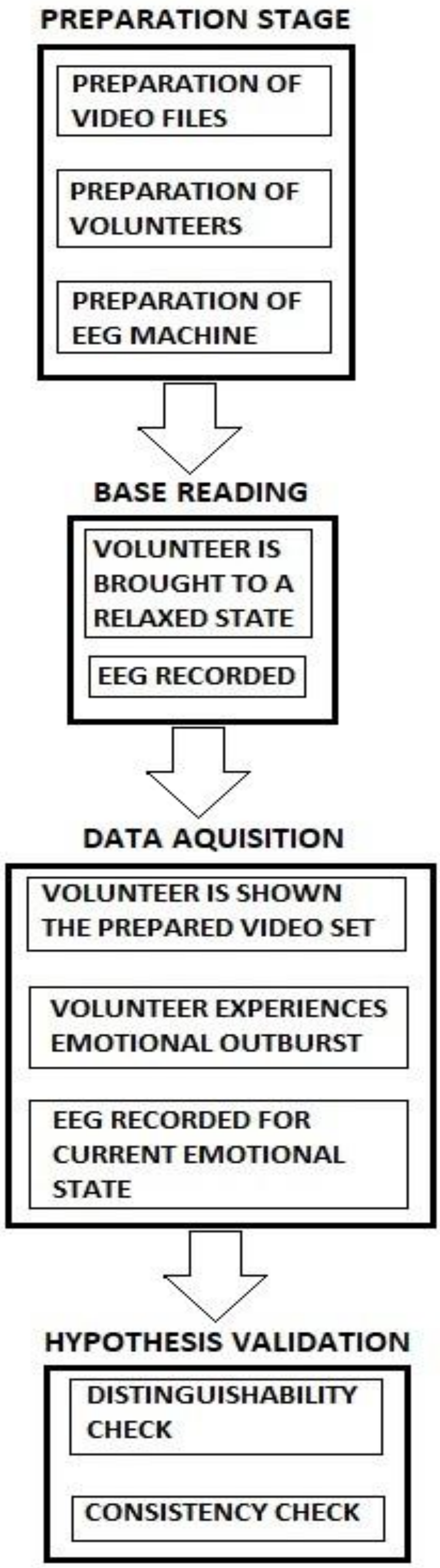

Fig 2.

A. Volunteer Specification
No. of volunteers: 3
Volunteer's age group: 18-24
Volunteer mental health: Stable
Volunteer occupation: Engineering students
Volunteers were asked to shampoo their head to reduce noise due to dirt.
Volunteers consent was taken before taking the EEG readings.
Volunteers were not sedated at any point of the research.
Volunteers did not have any case of medical history.
Volunteers did not show any sign of Seizures during the time the experiment was conducted.
Volunteers did not have epilepsies.
Volunteers remained conscious throughout the process of data acquisition.

B. EEG Specification
EEG machine used: RMS EEG Machine
Electrode placement: 10-20 system
Montage used: Common Reference Montage
Common Reference Electrode: Cz
Electrodes used: Cz, F7, T3, T5, F8, T4, T6
Electrodes O1 and O2 are neglected to remove readings due to head movement
Electrodes Fp1 and Fp2 are neglected to remove readings due to eye movement
SEN: 7.5 microvolt/mm
Notch: 50Hz
Low Pass Filter: 1.0Hz
High Pass Filter: 70Hz
Speed: 30mm/s (N.T. Scale)

C. Video Specification
Total No. of Videos shown: 6
No. of videos shown per emotion: 2
Video length: 3min – 8min per video

D. Data Acquisition
The volunteers were asked to lie down and after the electrodes were attached to the scalp, the volunteers were asked to relax their mind and a preliminary reading was taken. This reading tells us how the waves behave when in a relaxed position.

Next the volunteer is shown a video which is expected to instigate a desired emotional outburst. The EEG readings are taken while in this state obtained by the video stimulus. After the Reading has been taken the stimulus is removed and the volunteer is allowed to again return to a relaxed position.

This process is repeated for all the emotions and all the volunteers and the real time EEG readings are recorded.

E. Analysis
The EEG readings of all the recorded emotional states are analyzed. The analysis is done in two parts, in the first part the brain waves for the different emotions for the individual volunteers are studied one by one to find out the characteristics of waves so that the waves of the different emotions can be distinguished. The result of the analysis is recorded.

In the second part, the waves pertaining to the individual emotions are analysed one by one for all the tested volunteers. This is done to find out if the characteristics of a single emotion is consistent for all the volunteers. This is done for all the emotions one by one and the observations are recorded.

III. RESULTS AND DISCUSSIONS

A. Relaxed Position
When the volunteer is in a relaxed position, there is visible alpha activity in the brain mainly pertaining to the temporal region. These waves have a characteristic frequency of around 8Hz to 12Hz. State characteristic: significant alpha activity with frequency ranging from 8Hz to 12Hz.

B. Experiencing Happy Emotion
While the volunteer is experiencing a happy emotion, its readings are not very different from its relaxed position, having predominating alpha wave characteristics. This shows that the person is not under stress and is consciously happy and relaxed. These waves have a characteristic frequency of around 8Hz to 12Hz.

State characteristics: Abundance of alpha activity similar to that of the relaxed state. Frequency ranges from 8Hz to 12Hz.

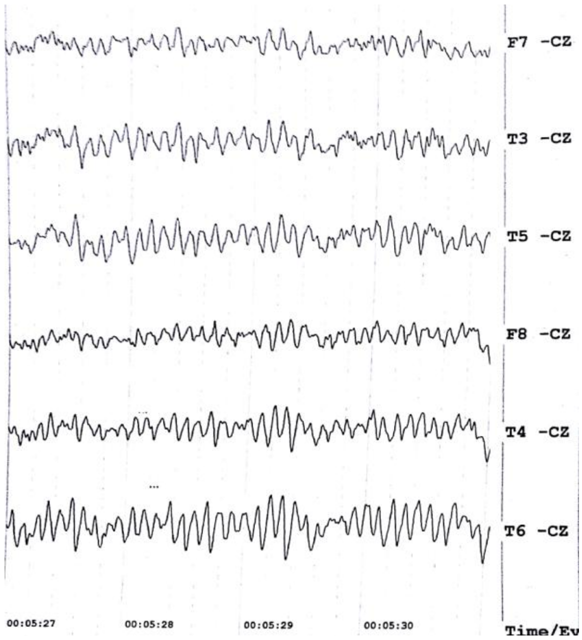

Fig 4.

C. Experiencing Sad Emotion
The volunteer when experiencing a sad emotion, the recorded brain waves showed a significant drop in frequency then in the cases of happy emotion and that of the relaxed state. The

frequency drop points at the absence of alpha waves in the brain activity as evident from the low frequency. Even though there was a frequency drop, the amplitude of the wave remained same as that of the previous two states.
State characteristics: Absence of alpha waves. Significant drop in frequency lower than 8Hz. Amplitude of the wave remained same as in happy and relaxed.

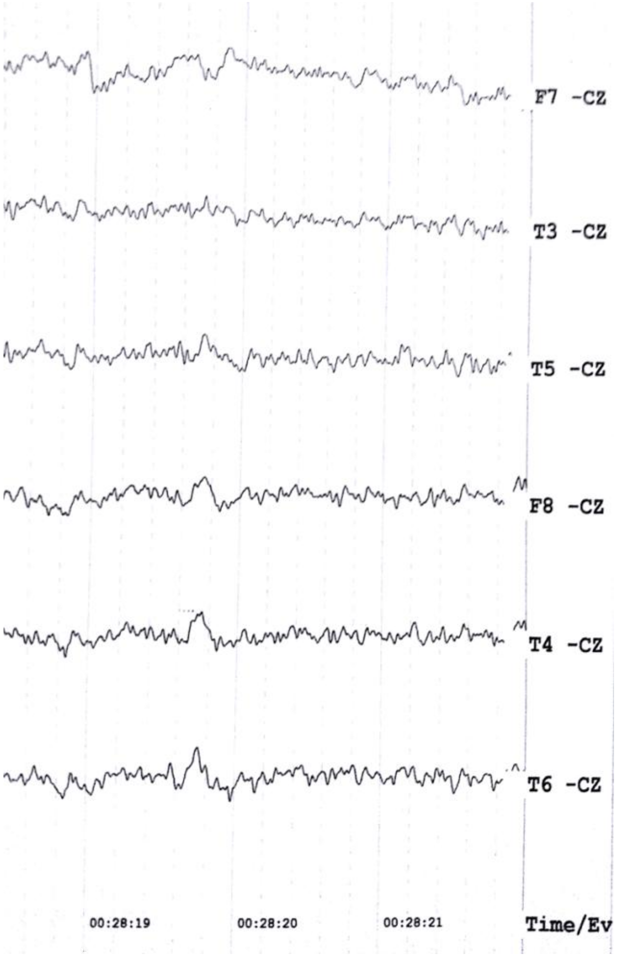

Fig 5.

D. Experiencing Disgust Emotion

When the volunteer was experiencing a disgust emotion, the EEG readings showed that the brainwaves also had lower frequencies than that in the case of happy, and showed the absence of alpha waves. With is absence of alpha waves i.e. the low frequency, the waves also showed a drop in amplitude when compared to the cases of happy, sad and relaxed.

State characteristics: Absence of alpha waves. Drop in frequency than in happy state. Drop in amplitude than in happy, sad and relaxed state.

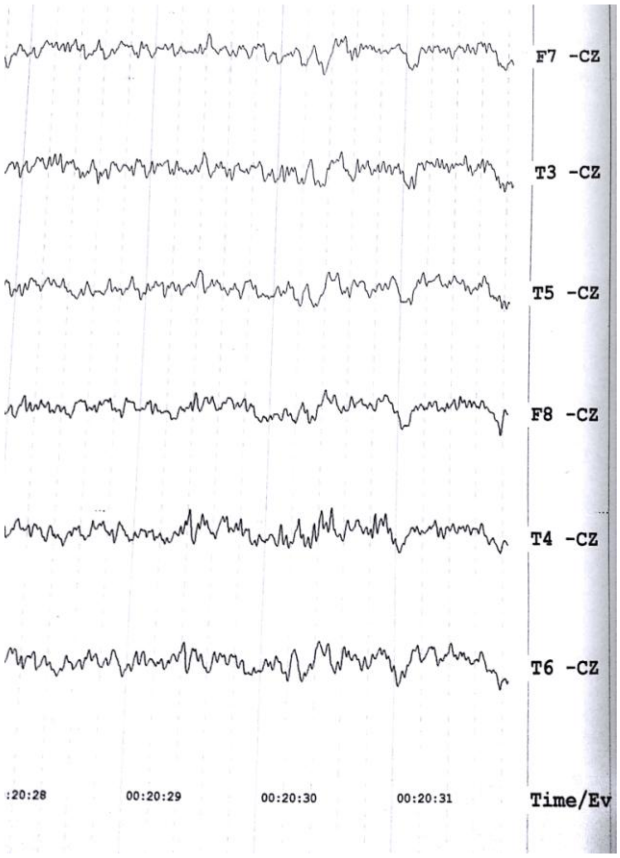

Fig 6.

IV. CONCLUSION AND FUTURE SCOPE

Happy state showed alpha wave activity throughout the time of the emotion being experienced.

Sad state showed an absence of alpha wave as the waves decreased in frequency but the amplitude of the waves were same as that in happy state.

Disgusted state also showed an absence of alpha waves as the waves had decreased frequency but in this case the amplitude of the waves also decreased compared to happy and sad states.

Note that this study shows the visible changes particular to the Temporal lobe thus the readings from the other electrodes have been omitted.
In conclusion, it is evident from the findings of this experiment that for a given volunteer the different emotional states had different wave characteristics with variations in frequency and amplitude and for a given emotion the wave characteristics stayed consistent throughout the array of volunteers pertaining to both frequency and amplitude.

This validation and research findings can be used in creating embedded systems that could read the emotions of a person who is unable to express emotions voluntarily. It can also be used in making A.I. and robots more human like, who are able to determine the emotion of the person in front and able to show emotions as a counter. This can also be used for people with motor neuron diseases, paralysis, etc. This could become very helpful in identifying early stages of depression and could be a very important tool for biomedical rehabilitation.

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