International Journal of Analysis of Basic and Applied Science **ISSN: 2457-0451**

Vol. No.6, Issue I, Jan-Mar, 2022 http://bharatpublication.com/current-issue.php?jID=30/IJABAS

Characterization of Brain Frequency Using EEG Signals

***Sailesh Kumar T, **Dr Kakasaheb Chandrakant Mohite**

**Research Scholar, **Research Supervisor*
Department of Physics,
Himalayan University,
Itanagar, Arunachal Pradesh

ABSTRACT

Billions of neurons hold an electrical charge in the brain. Membrane transport proteins to neuron by pumping the ions across their membrane, this results that they are charged or polarized. Resting potential is maintained due to constant exchange of ions with the extracellular environment by brain neurons and also to propagate action potentials. In wave propagation, many ions are liberated from many neurons simultaneously since ions of similar charge repel each other and at the same time, neighbours ions are pushed and this process go on in a wave form.

INTRODUCTION

Collection of interconnected neurons and their firing activity represent behavior of the human. The output of interconnected neurons is acquired using electrodes for EEG. The acquired signal is commonly characterized on frequency bands, 0.1 Hz – 100 Hz. Frequency band (0.1-3Hz) is called delta wave, Frequency band (4-8Hz) is called theta wave, frequency band (8-13 Hz) is called alpha wave, frequency band of (14-30 Hz) is called beta wave, Frequency band of (40Hz +) is called gamma wave. These frequency band are used to diagnosis the trauma level.

Delta Wave (0.1 – 3 Hz): It is slowest wave and observed during sleep. This frequency band represents the grey matter of brain. It shows abnormal for awaked adult whereas normal in infant.

Theta Wave (4 – 8 Hz): Theta wave ranges from 4 – 8 Hz. These are presented due to subconscious activity and can be observed in deep relaxation and meditation. Similarly to delta wave, it is normal to children up to 13 years whereas abnormal in awake adults.

Alpha Wave (8 – 13): Alpha waves can be typically found in back side of head. Its signal frequency lies between 8 -13 Hz. It has higher amplitude and dominates in normal relaxed adults. It is recorded from occipital and parietal area of the brain. Conscious and subconscious states of mind are linked to it.

Beta Wave (14 – 30 Hz): Beta frequency band are connected to the front part of the head. Its signal frequency range 14 – 30 Hz is considered to behaviour and actions. It is related to senses such as fear, smell, taste, a touch. These activities are present around cortical activity and represent ability to think and access. Fig. 1 shows the frequency bands of rhythmic activity.

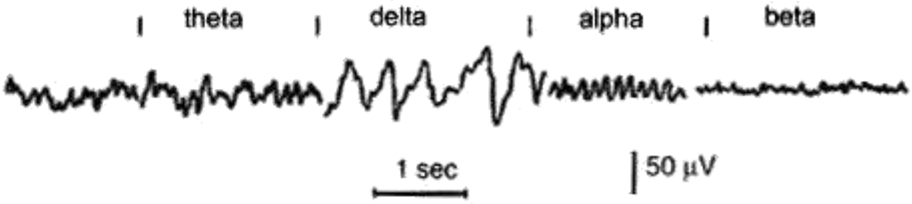

Fig. 1: EEG frequency signal wave

INFORMATION PROCESSING IN BRAIN

The ability to process information is a critical brain function. Physical sensory signals, including those for touch, sound, light, etc., are generated and processed in response to external activities. The brain's algorithms repeatedly perform this bottom-up and top-down processing on this data. In contrast to top-down processing, which makes use of judgements made at various steps, the bottom-up approach to object recognition is based on information received from the object itself. Bottom-up processing compiles very basic details like colour and orientation in order to look at an item, while changes in the object's borders determine whether or not the object is actually seen.

Upon pre-processing the signals up to a degree, a decision is taken by an attention filter about the significance the signal and its cognitive processes functions. In a noise room a student can identify his name during the roll call /attendance by the class teacher. Here, attendance process results are modulated by attention repeatedly, called multi stages of processing.

Like microprocessor based system, the brain must first store the information in order to process it and then it needs to be encoded. Each type of sensory stimuli has specific types of encoding. Structural encoded is carried out for the verbal input. It gives the shape of word looks like and sound semantically and also referring to word means. Hypothesizing the long term memory information is being maintained through structure of certain types of proteins. The management of knowledge and information processing in the brain can be studied through various models. Neurophysiology model, computer based model, human subjects retrieve model are some of the models used for brain activity.

The nodes are linked based on their states of being related and states are nodes representing concepts, form the semantic network model. Pattern of neuronal activation is represented by a piece of knowledge which forms the connectionist model. Each model has advantages and disadvantages, though there is no universal model brain activity. Retrieval of memories storage is required on storing of information in it. Recollecting past events from brain memory is not like reading semiconductor memory; here it is a process of reconstructing the event from the stored brain information and its recall. The performance of getting back of information from memory depends upon the firing of recall. The chance of recalling the memory is higher if the retrieval cue is better. It may be possible that retrieval cue makes reconstruct memory information improperly. There are various ways which can produce the memory distortion such as asking about the incident / event which has not occurred i.e. changing the wording of a question.

About forty different neuron types have been mapped across the cortex, but they can all be broken down into only two major categories: projection neurons and local inter-neurons. An excitatory cell type, projection neurons (or primary neurons) are often found in cortical layers III, V, and VI. Although inter-neurons are present in all cortical layers, they only account for 20–25% of neurons and typically exhibit inhibitory properties. The cortical processing of information is a multi-step process, with information being transferred between stages through the axons of projection neurons, which can span long distances. As long as they are in the same level of information processing, inter-neurons can receive the same input as primary neurons and simply relay it to local cells.

MODELLING OF THE EEG SIGNAL

Modelling is the mathematical representation of EEG signal by differential equations to study the dynamic response of traumaor. There is various model of EEG signal, such as Hidden Markov model, Hodkin – Huxley model, parametric model, and Jansen model. In the present work, Jansen model is used since it is based on the psychological EEG record and describes an interaction of excitatory and inhibitory neurons populations. Main population is represented by cell body. Fig. 2 shows the cortical mode of cell.

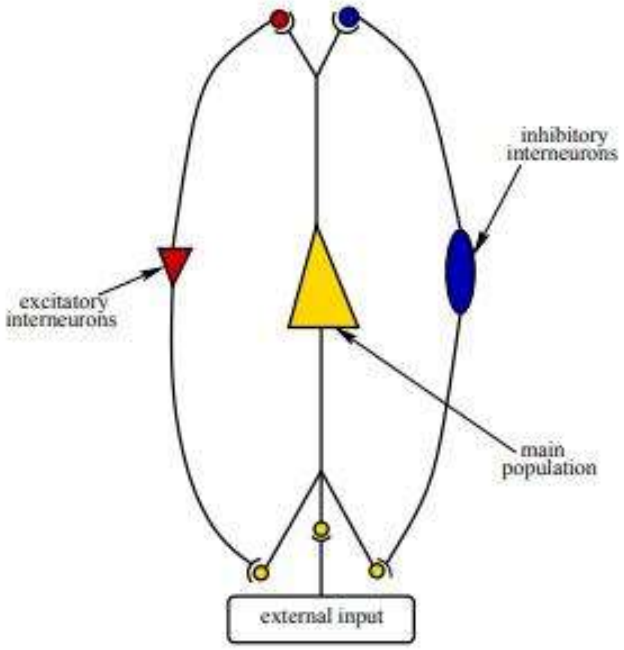

Fig. 2: Model of cortical

Jansen's Single-Column Model

Cortical column model developed by Jansen draws inspiration from studies by Lopes Da Silva et al. and Van Rotterdam et al. In order to model the spontaneous electrical activities of neuronal assemblies as captured by EEG, with a focus on alpha activity, they created a mathematical framework influenced by biology. Using excitation and inhibition between neuronal populations, they postulated that alpha activity could be generated. After some testing, Jansen and Rit found that the model could also reproduce evoked potentials, or the changes in EEG activity that occur following sensory input (by a flash of light, a sound, etc.). Recent work by Wendling et al. uses this model to simulate behaviours seen in people with epilepsy. The Sigmoidal boxes are a neuronal cell body model because they convert the membrane potential of a population into an output firing rate. These changes are not linear.

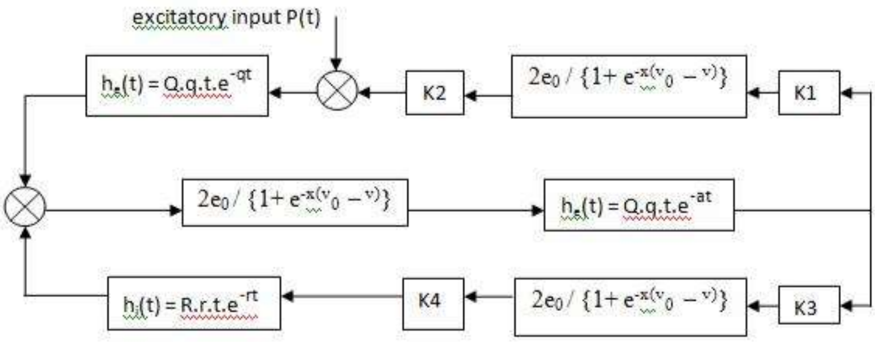

Fig. 3: Jansen's single column model structure

Jansen's double-column model or Coupled Population Model

Jansen's double-column model expands on the earlier work of his single-column model. This example involves a semi-connected pair of single-column models. The resulting system of linear equations, of the second order, is given in the form of eqns. 4.14 – 4.29. Column 1 is described by y=0, y=1, and y=2; column 2 is described by y=3, y=4, and y=5. Jansen's double column model of EEG is depicted in Fig. 4.

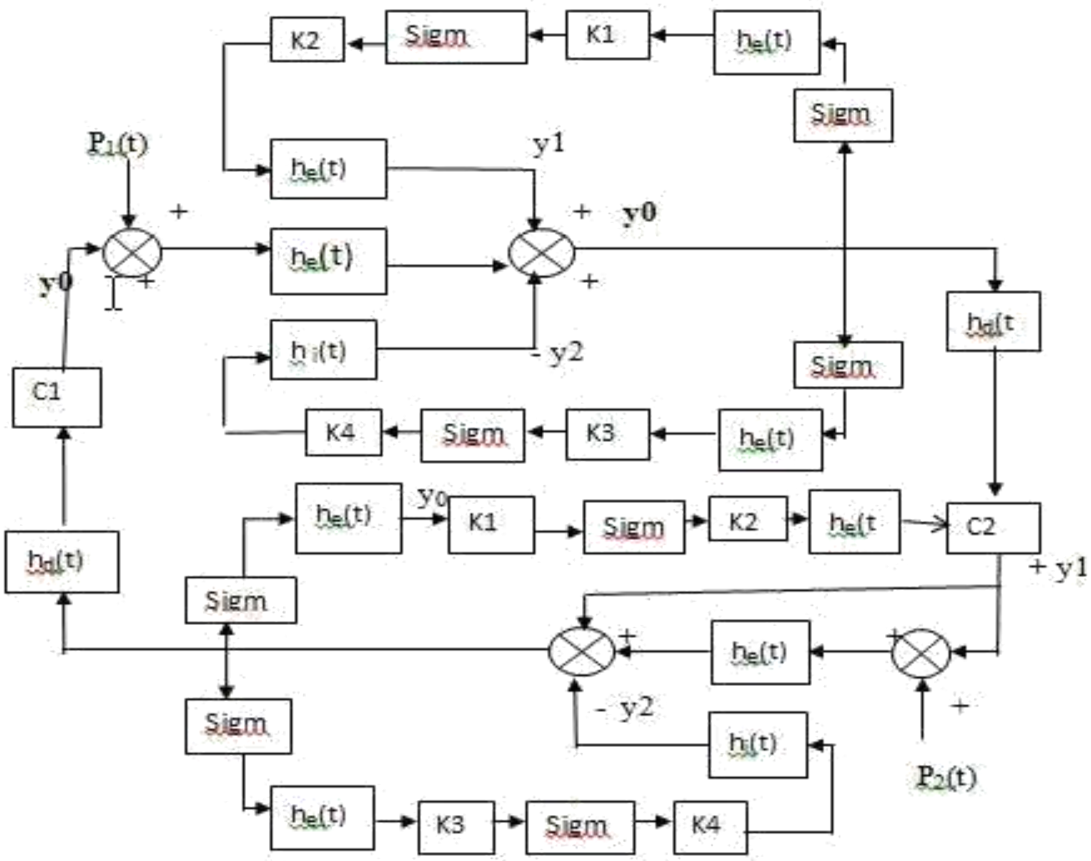

Fig. 4: Jansen's Double column model structure

SIMULATION

The Jansen (single column and double column) mathematical models presented above are based on the EEG activity that should be obtained from these models. The two models are simulated and the results are compared to earlier results. The differential equations are solved using Matlab. Fig. 5 shows the post synaptic response of EEG for single column.

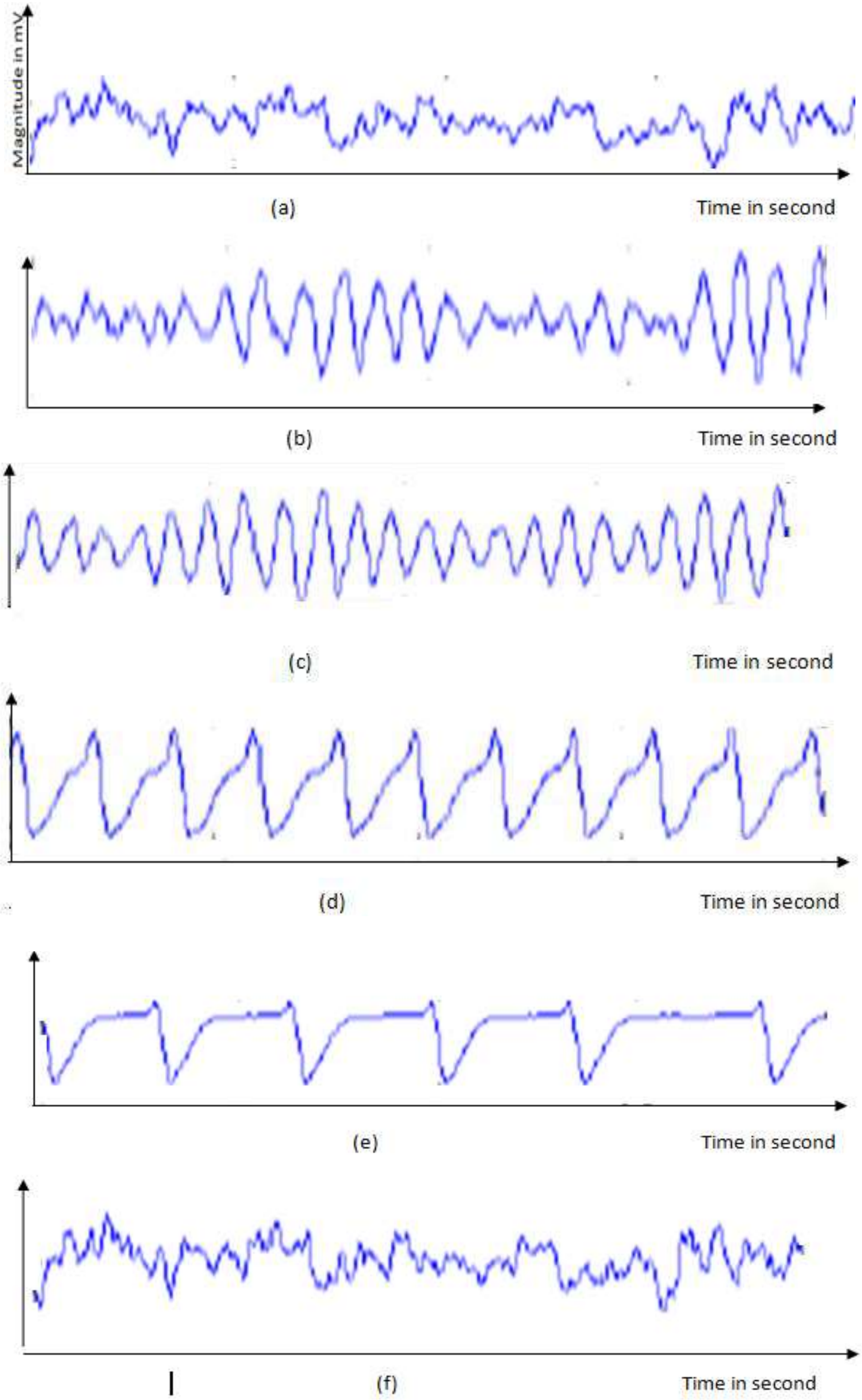

Fig. 6: Simulation response of Single Column

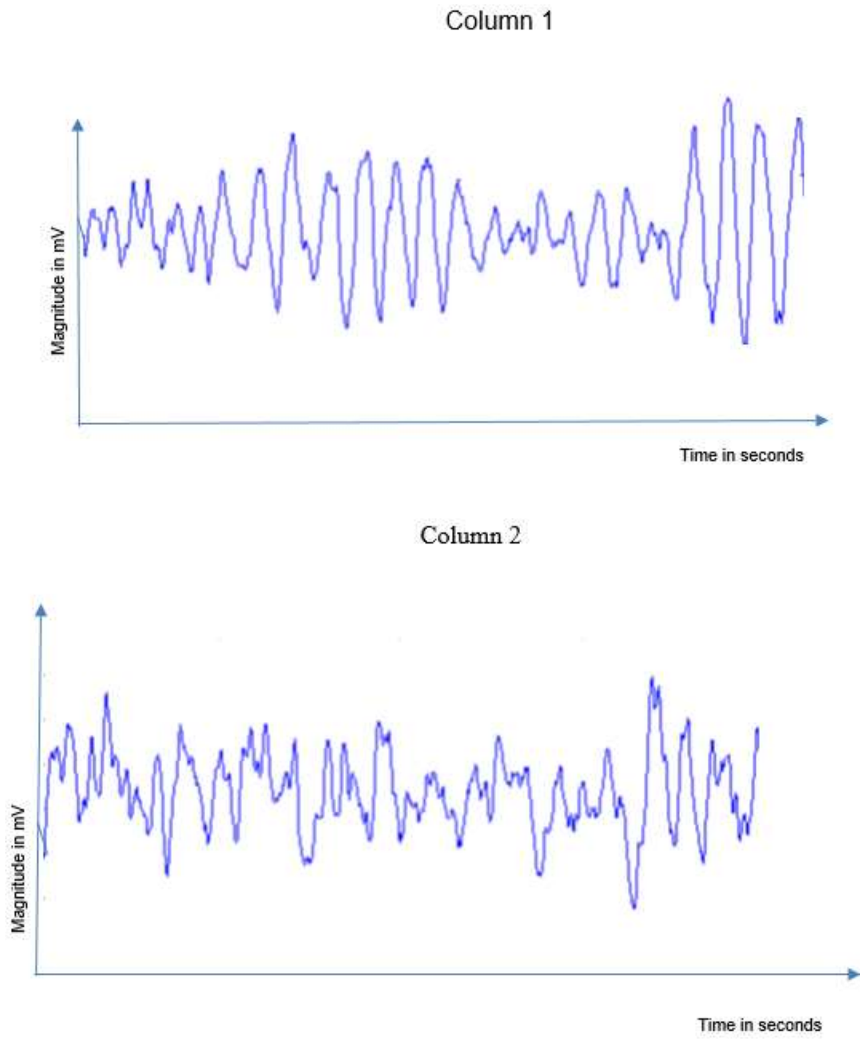

Fig. 7 shows the post synaptic response of EEG for double column.

Jansen's double-column model yielded the second set of findings (model due to the principle of the connection of two cortical columns). Two cortical columns were connected with a delay "ad" and the connectivity constants K1 and K2. Two distinct patterns of EEG activity were initially identified using Jansen's double-column model. The range of connectivity constants was selected based on the relationship between the constants mentioned above to produce alpha activity in column 1 and beta activity in column 2.. The values of K1 and K2 were adjusted to 50 and 500 respectively due to the penetration of these two values corresponded to the area 2 (alpha activity) of column 1 and the area c of column 2 (beta activity) shown in Figure 7.

RESULTS AND DISCUSSIONS

In order to compare the study of Jansen' model of single column and double column we have assumed the parameters as reference. EEG activity from Jansen's single column model apparently changed from beta activity to alpha activity according to a value of the constant K1 (from the top to the bottom K1 equals 68, 128, 135, 270, 675 and 1350 respectively). Alpha activity was acquired for the constant K1 equal to 135 with signal amplitude in the range from 6 to 11mV, beta activity was received for the low values of the constant K1 equal to 68 (signal amplitude from 9 to 12 mV) and 128 (signal amplitude from 5 to 10 mV). Beta activity as the result of Jansen's single-column model was obtained even for the highest value of the constant K1 equal to 1350 but the range of signal amplitude is negative from -14mV to -11mV.

CONCLUSION

In this chapter structure and functions of brain are presented. Also EEG modeling is described for Jansen's single column and double column of EEG signal. Simulation response is presented using MatLab R10. The study can serve as a basis for modeling for complex situations.

REFERENCES

[1]. McMahon, M & Schukat, M (2018), 'A low-cost, open-source, BCI-VR prototype for real-time signal processing of EEG to manipulate 3D VR objects as a form of neurofeedback'. *29th Irish Signals and Systems Conference (ISSC)*, IEEE, pp. 1-6.

[2]. Rahman, M & Joadder, M (2017), 'A review on the components of EEG-based motor imagery classification with quantitative comparison'. *Application and Theory of Computer Technology*, vol. 2, no. 2, pp. 1-15.

[3]. Martín-Clemente, R, Olias J, Thiyam, D, Cichocki, A & Cruces, S (2018), 'Information theoretic approaches for motor-imagery BCI systems: Review and experimental comparison'. *Entropy*, vol. 20, no. 7, pp. 1-29.

[4]. Goel, P, Joshi, R, Sur, M & Murthy, H (2018), 'A common spatial pattern approach for classification of mental counting and motor execution EEG'. *International Conference on Intelligent Human Computer Interaction, Springer*, pp. 26-35.

[5]. Mishuhina, V & Jiang, X (2021), 'Complex common spatial patterns on time-frequency decomposed EEG for brain-computer interface'. *Pattern Recognition*, vol. 115, pp. 107918.

[6]. Al-Saegh, A, Dawwd, S & Abdul-Jabbar, J (2021), 'Deep learning for motor imagery EEG-based classification: A review'. *Biomedical Signal Processing and Control*, vol. 63, p. 102172.

[7]. Padfield, N, Zabalza, J, Zhao, H, Masero, V & Ren, J (2019), 'EEG based brain-computer interfaces using motor-imagery: Techniques and challenges'. *Sensors*, vol. 19, no. 6, p. 1423.

[8]. Bansal, D & Mahajan, R (2019), 'EEG-Based Brain-Computer Interfaces': *Cognitive Analysis and Control Applications*. Academic Press.

[9]. Zahid, S, Aqil, M, Tufail, M & Nazir, M (2020), 'Online Classification of Multiple Motor Imagery Tasks using Filter Bank Based Maximuma-Posteriori Common Spatial Pattern Filters'. *IRBM*, vol. 41, no. 3, pp. 141-150.

[10]. Ang, K, Chin, Z, Zhang, H & Guan, C (2008), 'Filter bank common spatial pattern (FBCSP) in brain-computer interface'. *IEEE International Joint Conference on Neural Networks (IEEE World Congress on Computational Intelligence*, pp. 2390-2397.

[11]. Bhusan, UK, Yadav, M & Bharagava, S, (2015), ‗EEG Analysis for Brainwaves under Closed Eye and Open Eye', *Internat. Journal of Engineer. Research and General Science*, vol.3, no.4, pp 156-160.

[12]. Irrmischer, M, Houtman, SJ, Mansvelder, HD, Tremmel, M, Ott, U & Linkenkaer-Hansen, K, (2018), ‗Controlling the Temporal Structure of Brain Oscillations by Focused Attention Meditation', *Human brain mapping*, vol.39, no.4, pp. 1825-1838.

[13]. Zhuang, N, Zeng, Y, Tong, L, Zhang, C, Zhang, H & Yan, B, (2017), ‗Emotion Recognition from EEG Signals Using Multidimensional Information in EMD Domain', *BioMed research international*, pp. 1-9.

[14]. Ackermann, P, Kohlschein, C, Bitsch, JÁ, Wehrle, K, & Jeschke, S, (2016), ‗EEG-based automatic emotion recognition: Feature extraction, selection and classification methods', *IEEE 18th International Conference on e-Health Networking, Applications and Services (Healthcom)*, pp. 1-6.