ISSN: 0975-8585

Research Journal of Pharmaceutical, Biological and Chemical Sciences

Literature review of Human Stress analysis using EEG Signal.

Prashant S Lahane[1]*, and Mythili Thirugnanam[2]

[1]Research Scholar, School of Computer Science and Engineering, VIT University, Vellore, Tamil Nadu, India
[2]Associate Professor, School of Computer Science and Engineering, VIT University, Vellore, Tamil Nadu, India

ABSTRACT

At present Brain Computer Interface (BCI) technology plays an important role in the field of biomedical. BCI can be used to identify human stress based on various emotion states – happy, sad, disgust, fear. Various techniques such as Neural networks (ANN) , statistical methods, autoregressive model (AM), mixture of densities approach, independent component analysis (ICA), time-frequency analysis (TFA), bayes quadratic, hidden markov model (HMM) and linear discriminate analysis (LDA) have been used for EEG signal analysis. There are some issues which are being focused on while extracting features are –handling irrelevant and redundant features require more computation for decomposition of EEG signals. And the paper is considering following issues while carrying out classification - inability in processing complicated set of data, low performance when training data set is huge .This paper focuses on addressing above mentioned issues and appropriately analyzes various EEG signals which would in turn help us to improve the process of feature extraction and improve the accuracy in classification. In addition to acknowledging above problems, this paper proposes a framework which would be helpful in identifying human stress level and as a result, differentiate a normal or stressed person/subject.

Keywords: Electroencephalogram (EEG), Brain-computer interface (BCI), Emotion recognition, Stress.

Corresponding author

INTRODUCTION

In the field of psychology, stress is a type of emotion which consists of strain and pressure. At times stress is beneficial and even healthy. Positive stress enhances better work performance at workplace. Excessive amount of stress may lead to increased risk of strokes, heart attacks, ulcers and mental disorders such as depression. There are different types of stress like cognitive, emotional, physical or behavioral. The brain is the central organ of human body. Brain consists of billions of interconnected neurons which relate the brain activity to the physiological events. These brain activities are measured by Electroencephalogram. EEG has been used in cognitive neuroscience to investigate the regulation and processing of emotion for the past decades. Numerous studies have focused on ways to make Brain-computer interaction more intelligent and natural. This helps us to monitor brain activity for stress evaluation. Norizam Sulaimanetal. Have suggested the combination of electroencephalogram

(EEG) power spectrum ratio and Spectral Centroids techniques to extract unique features for evaluation of human stress. Realization of Stress Detection using physiological Signals for Improvement of Human-Computer Interactions has been carried out by Jing Zhai et al. [1], Shahzabeen et al. [2] have described an affective computation model for emotion classification based on subjects emotionally induced with audio and video emotion stimuli using the international affective pictures and system (IAPS). Kernel density estimation (KDE) and multi-layer perceptron (MLP) were used to classify four basic emotions like sad, fear, happy and calm. Many EEG-based emotion recognition algorithms were suggested by researchers.

Rest of the paper is organized as follows: The second section gives a brief introduction about stress, emotions, brain and BCI. The third section talks about different types of bioelectric signal of brain and 10-20 EEG electrode placement method used in signal analysis. The fourth section discusses the survey of exiting methodology used for emotion/stress recognition of a subject as well as the classification of EEG signals. Finally, fifth section concludes the paper and suggested some improvements for future.

BRAIN COMPUTER INTERFACE, BRAIN, EMOTIONS AND STRESS

Brain Computer Interface (BCI) - BCI is a technology which allows us to interact with computers, peripherals or other electronic devices with our thoughts. It does so by sending physiological signals generated in the brain to a computer or a device connected to a computer.BCI uses various sensors for measuring required physiological signals. Sensors used in emotion recognition are Blood volume pulse (BVP also called as photoplethysmography), Electrocardiography(ECG), Temperature(T), Electromyography(EMG), Skin Conductance (SC), Respiration (RSP), Electroencephalography (EEG). In past decade, the development of brain computer/machine interface (BCI/BMI) was started in the field of neuroscience, electronic technologies and several research groups around the world. It gives direct communication and control from brain to external devices.

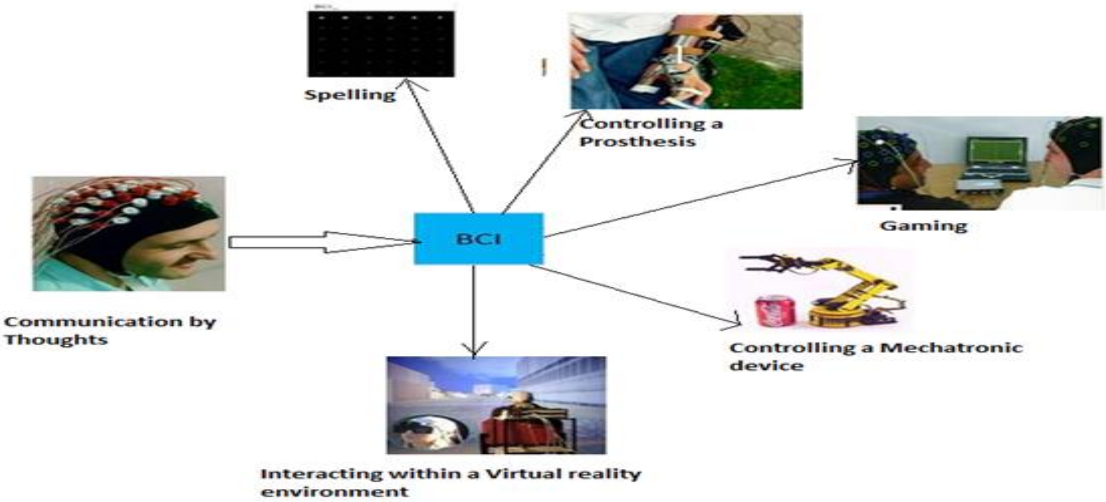


Figure 1-Brain-Computer Interface (BCI) applications (by courtesy of guger technologies OEG)

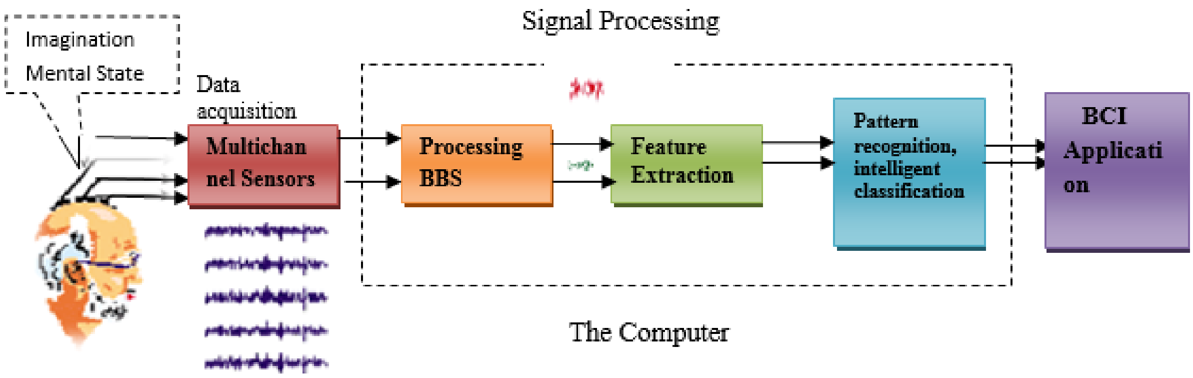
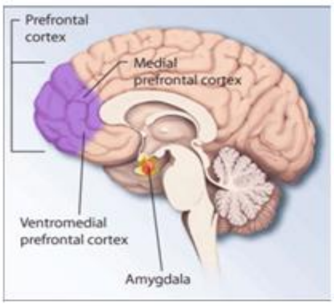


Figure 2-Brain Computer Interface Process (by courtesy of Synesthesia Technology)

Brain is the source of all emotions. The depression and stress could be better understood by looking at the brain signals for various human emotions. Rahnumaa et al. [2] have collected the EEG signals from eight healthy subjects and subject was emotionally induced with audio and video emotion stimuli using the International Affective Pictures and System (IAPS). Using Kernel Density Estimation (KDE) features were extracted and using the Multi-layer Perceptron (MLP) emotions are classified into four basic categories (happy, calm, sad and fear). Experimental results show that, performance accuracy of emotion in homogeneous test provides an improved verification accuracy of 76% compared to Heterogeneous blind test.

Brain-Brain is a center organ of nervous system located in head near sensory organs. Ulrich-Lai et al. [11] have described brain as a controlling center which controls all organs of a human body and it also controls response to the stress. Identifying a stress affected brain region is little difficult and once it is identified, detection of positive and negative stress on the basis of consequences of neural communication becomes easy. Central nervous system (CNS) consists of brain and the spinal cord. Stress can be processed by brain in three main areas: hippocampus, amygdala and prefrontal cortex.

(a)

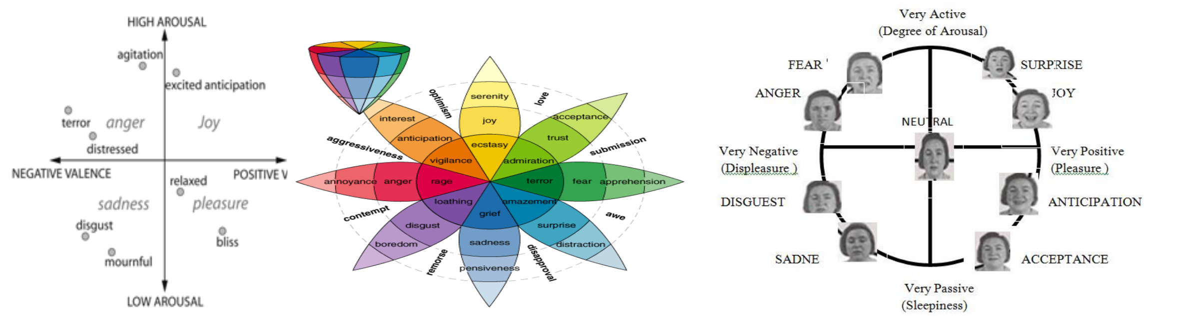


(b)

Figure 3- (a) pictorial view of brain, (b) regions of the brain associated with stress.

Bremner, J.D et al.[14], Fuchs, E et al. [12] have provided evidences which demonstrates that chronic psychological stress can change the responsiveness of central peripheral regulatory systems .The altered responses may be less efficient and less adaptive which are unfavorable to health. Friedman, B.H et al. [13], Hughes, J.W et al. [14] have described that, in chronic stress, depression and anxiety have repeatedly been found to be associated with abnormalities in autonomic nervous system (ANS) function. Papousek, I et al. [15] have hypothesized that sustained stress may be related to altered hemisphere asymmetries in the modulation of ANS functions.

Emotions-EEG provides noninvasive measurement of ongoing brain activity. EEG has been used in cognitive neuroscience to investigate the regulation and processing of emotion for the past decades. Hosseini et al. [5] have demonstrated that EEG signals can be used for emotional stress assessment. They have used an approach to classify emotional stress states in two main areas of the valance-arousal space with EEG signals using higher order spectra (HOS). K.H.Kim et al. [6], J.Kim et al. [7], J.Kim et al. [8] have demonstrated that emotional states can be characterized by measuring physiological responses. Signals captured from the brain in central nervous system (CNS) have been proved to get informative characteristics in responses to the emotional states. American psychologist Ekman identified the human emotion problem and suggested the model with six universal emotions: anger, happiness, disgust, surprise, sadness and fear. Kim, J et al. [8] have described multiple dimensions space with continuous scales as another approach of categorizing emotions. Figure 4 (a) shows a persons' impression about elicited emotions with scales. In Plutchik's [20] model there are eight fundamental emotions: joy, trust, fear, surprise, sadness, disgust, anger and anticipation. Figure 4 (b) shows color wheel of different emotions with basic affect and Figure4 (c) shows Plutchik's 2D model of emotions with eight primary emotions.



(a) (b) (c)

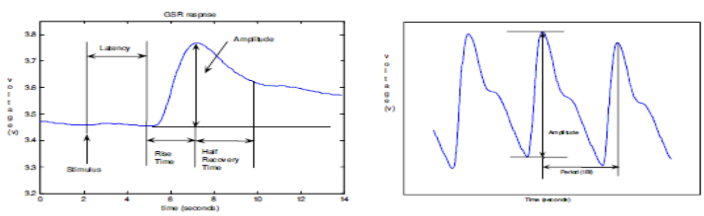
Figure 4- Emotion models (a) Valence and arousal model with two-dimension. (b) Color wheel of emotions by Plutchik's (c) 2D model of emotions with visualization of Plutchik's eight primary emotions.

Stress

Stress is experienced by humans when they believe that the resource for coping with obstacles is not enough. Stress typically describes a condition that can have an impact on person mental and physical health. Examples of excessive and accumulated prolonged stress are anxiety and depression. Various age groups can actually experience stress. Various reasons which can contribute to stress may be jobs, financial crisis, personal problems and many other contributing factors. It is closely related to mental health which means it can cause severe mental health disorders. In detecting human stress, EEG has become an alternative method. This is due to the linked between stresses with human negative emotion and can be measured by brain's electrical activity.

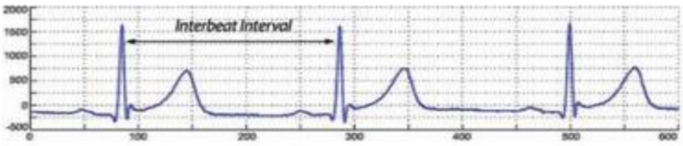
BIOELECTRIC SIGNALS

The eighteen century Galvani explains physiological processes with electrical changes based on association of electricity with medical science. It also tells us about action of living tissues in terms of bioelectric potentials. Living tissues of human body generate electric signal. Potential differences are generated by the electro-chemical changes from the brain. These potential differences can be measured by placing electrodes at specific points on the body. These Potential differences are highly significant for diagnosis and therapy. Typical bioelectric signals are Electrocardiogram (ECG) Figure **5**(c), Electromyogram (EMG) Figure **5**(f), Electroretinogram (ERG), Electrooculogram (EOG), Electronystagmogram, and Electrohysterogram. Various kinds of physiological parameters that affect a person's health and emotions are Cardiac function, Muscle electrical activity, Temperature, Respiration, Skin conductance, Electrical activity of the brain. Typical physiological signals are as follows:

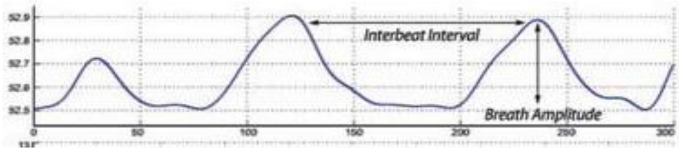


(a) (b)

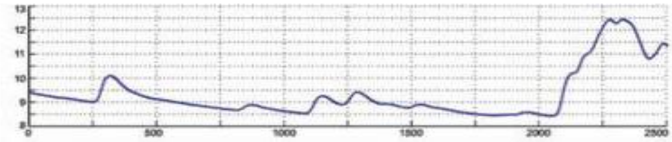
ISSN: 0975-8585



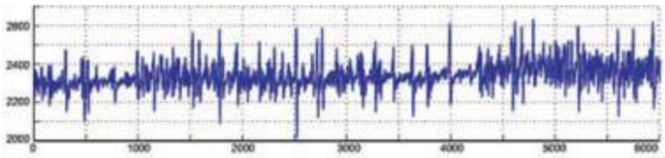
(c)



(d)



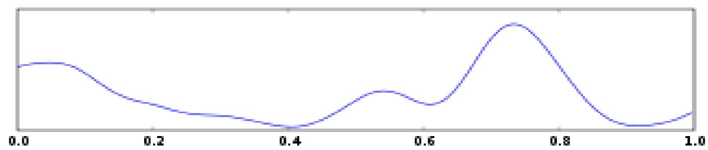
(e)



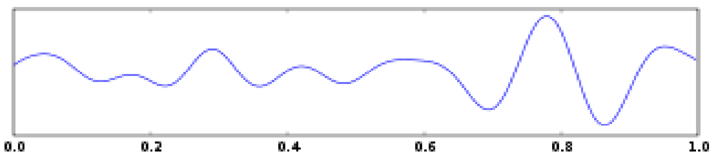
(f)

Figure 5- (a) GSR (b) BVP (c) ECG (d) RSP (e) SP (f) EMG

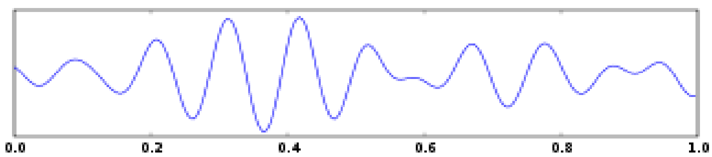
Electroencephalogram (EEG) – EEG acquisition instrument used for recording electrical activity of the brain by suitably placing electrodes on the scalp. Neuronal electrochemical processes form the basis for EEG activity. EEG signals can be picked up from the scalp or directly from the cerebral cortex. The frequency varies greatly with different behavioral states. The normal EEG frequency content ranges from 0.5 to 50 Hz. The nature of wave varies over different parts of scalp. The variations in EEG signals both in terms of amplitude and frequency are of diagnostic value. Basic frequency of EEG range is classified into the five bands for the purpose of EEG analysis: These bands are Delta (δ) 0.5-4 Hz, Theta (θ) 4-8 Hz, Alpha (α) 8-13 Hz, Beta (β) 13-22 Hz and Gamma (γ) 22-30 Hz**.** Brain state of alertness is based on alpha rhythm EEG signal. Alpha activity occurs when person is awake and eyes are closed. It serves as an indicator of the concentration of anesthesia in the operating room. Beta waves begin with eyes open. Delta and Theta waves appear at various stages of drowsiness and sleep. The wave patterns are as shown in figure 5:



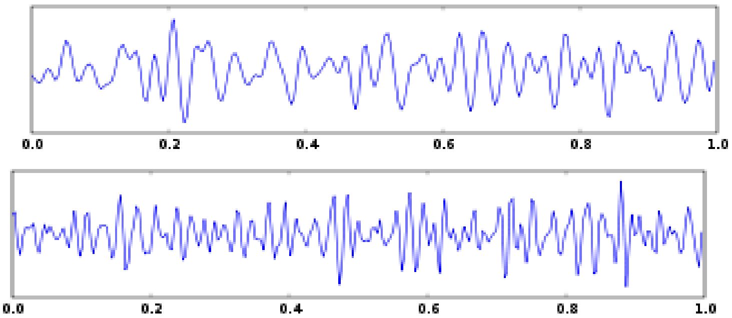
Delta waves



Theta waves



Alpha waves



Beta waves

Gamma waves

Figure 6- EEG wave patterns.

EEG electrode and 10-20 electrode placement system - EEG Electrodes transform ionic currents into electrical currents used in EEG preamplifiers. The electrical characteristics are determined primarily by the type of metal used. Silver–silver chloride (Ag-AgCl) is commonly found in electrode discs. Scalp Electrodes, Sphenoidal Electrodes, Nasopharyngeal electrodes, Electrocorticographic electrodes and intracerebral electrodes are the five types of electrodes typically used in EEG systems. The EEG electrode placement gives amplitude, phase and frequency. This placement is based on the frontal, parietal, temporal and occipital cranial areas of the cerebrum. The most popular scheme is the 10-20international EEG electrode placement system established by the international federation. In this setup, the head is mapped by four standard points: the nasion (nose), the inion and the left and right preauricular points (ears).Nineteen electrodes and one for grounding the subject are used. Electrodes are placed using marking points on the shaved head 10, 20, 20, 20, 20 and 10 percent of its length. The vertex, C2 electrode is the midpoint. Figure **7**, shows the complete 10-20 electrode placement system. The letters F, T, C, P, and O stand for Frontal, Temporal, Central, Parietal and Occipital lobe. Even numbers (2, 4, 6, and 8) refer to the right hemisphere and odd numbers (1, 3, 5, and 7) refer to the left hemisphere. The EEG waveforms corresponding to different locations are as follows:

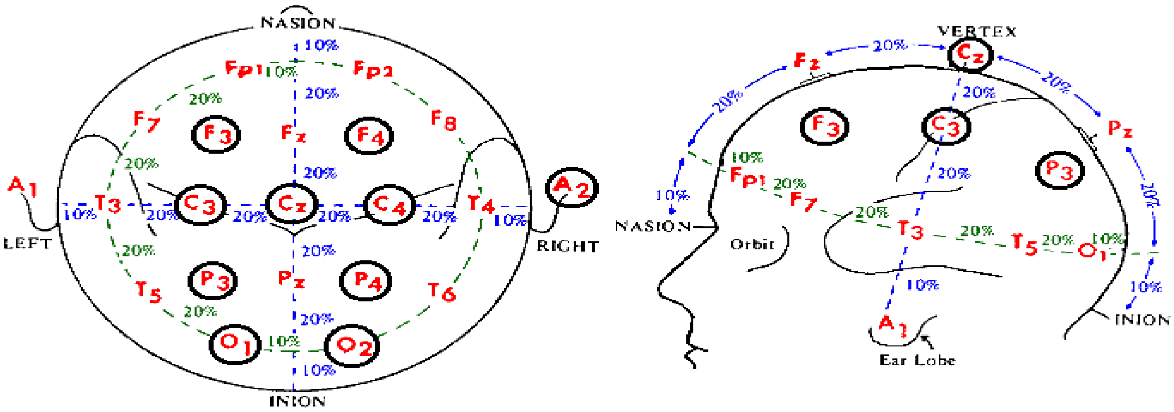


Figure 7- The 10-20 electrode placement system.

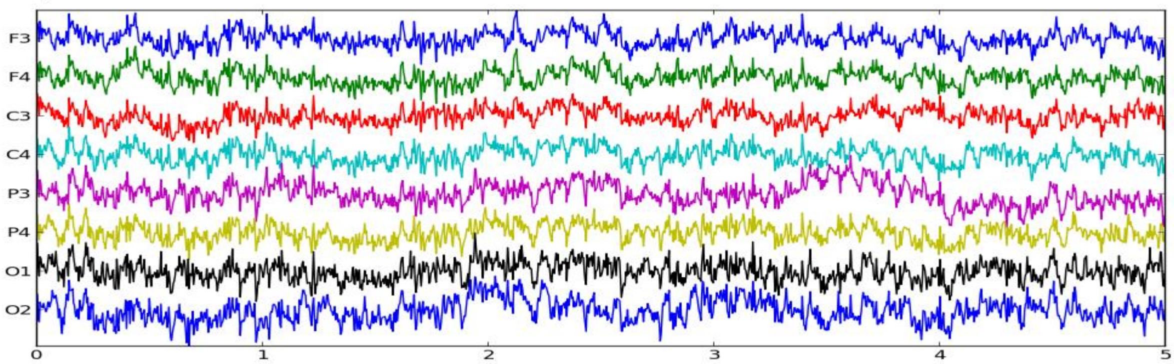


Figure 8- The EEG waveforms corresponding to the electrode locations of 10-20 electrode placement system.

RELATED WORKS

Many researchers have suggested EEG-based emotion recognition algorithms. Lin Y P et al. [11] have used short-time Fourier transform and support vector machine (SVM) for feature extraction and classification respectively. EEG based emotion recognition features are extracted using. Horlings R et al. [8] has concluded SVM accuracy for valence and arousal identification as 32% and 37% respectively. Feature extraction& classification for sadness, happiness, disgust and fear were recognized using wavelet transforms and fuzzy C-means clustering. Li, M et al has classified emotion states in three types: pleasant, neutral and unpleasant. The vector machine applied for happy and relaxed, relaxed and sad, happy and sad with 90% accuracy was obtained. Also, classification of distraction level of a driver was carried out by Mousa Kadhim Wali et al [26] using EEG signals. Khosrowabadi et al. have performed affective computation on EEG emotion recognition system based on affective brain-computer interface (ABCI). The method extracts EEG feature of six emotionally-related musical and vocal stimuli using kernel smoothing density estimation (KSDE) and gaussian mixture model probability estimation (GMM). Sulaiman et al. have introduced stress feature extraction methods. They have considered closed-eyes (CE) and open-eyes (OE) as two cognitive states and extracted the relative energy ratio (RER), Shannon entropy (SE) and spectral centroid (SC) as features. The combination of extracted features (RER and SC) was used to detect and classify stress. And then the classified stress is confirmed by Shannon entropy.

Table 1- Short survey of technique(s) used for emotion/stress recognition

S.No.	Author(s)	Research Scenario	Physiological Signals	Technique(s)	Observations
1	Norizam S et al.	Experimentation data were categorized into 4 groups from 185 healthy subjects. Subjects with particular state (Closed eyes or Opened eyes) were asked to answer different IQ questions.	Electroence phalogram (EEG)	Feature Extraction Power spectrum Spectral Centroids. Classification- KNN	Detection and classification of human stress was carried out with two cognitive states: Open eye and Closed eye
2	Jing Z et al.	36 data entries were collected from 6 subjects which generated data under two segments: non-stress and stress.	Blood Volume Pulse (BVP), Galvanic Skin Response (GSR) and Pupil Diameter (PD)	Support Vector Machine (SVM)	Automated monitoring of various stress states of computer users.
3	Kazi SR et al.	Experiment on8 healthy subjects in an emotion-induced environment. Subjects were from different cultural and language background.	Electroence phalogram (EEG)	Features extraction - Kernel Density Estimation (KDE), Emotion Classification - Multi-layer Perceptron (MLP).	Analyzed emotions of various subjects which were emotionally induced with audio and video emotion stimuli using the International Affective Pictures and System (IAPS).
4	Shin-ichi I et al.	Experiment on 5 subjects - 4 boys (Avg age: 22.3 years) and 1 girl (Avg age: 23 years).EEG pattern with 4 different conditions - listening to Rock music, Schmaltzy Japanese ballad music, Healing music, and Classical music.	Electroence phalogram (EEG)	Neural Networks(NN) Based on Genetic Algorithms(GA)	Discussed an EEG analysis method which used GA Factor Analysis (FA), and NN. These algorithms specified personal components by GA and estimation of extracted characteristics by NN.
5	V.J Madhuri et	Experiment was carried out on 10 subjects and five	galvanic skin response	Artificial Intelligence, Fuzzy system	Presented a stress-detection system which

	al.	different levels of Stress (Highly tensed, Slightly tensed, Calm, Quietly relaxed, Deeply relaxed) were considered.	(GSR), heart rate (HR),Body temperature(T), Muscle tension, Blood pressure (BP)		uses physiological signals and five different level of stress identified.
6	Shin-ichi I et al.	Experiment on 7 subjects: 5 males (Avg age 22 years) and 2 females (Avg age 23 years).	Electroencephalogram (EEG)	k-nearest neighbor (KNN)	Discussed the relationship between personal feature of EEG signal and Human's Characteristic for BCI based on mental state. EEG pattern were extracted while listening to music.
7	Seyyed AH et al.	Experiment on 15 subjects (20 and 24 years old). All subjects had normal vision and none of them had neurological disorders.	Electroencephalogram (EEG)	Feature Extraction-higher order spectra (HOS). Genetic Algorithm for optimum features selection Classification - SVM	Classified emotional stress states in valance-arousal space by using EEG signals.
8	Uwe G et al.	Experiment on Single subject (male age 23) based on Visual evoked potentials (VEP). Applied a checkerboard stimuli which was inAccordancewith ISCEVstandards(International Society for Clinical Electrophysiology of Vision).	Electroencephalogram (EEG)	Feature extraction-laplacianeigen space.	Presented a new method for spatial harmonic analysis of EEG data using laplacianeigen space.
9	Nabaraj D et al.	Applied visual, tactile, auditory stimuli and different psychomotor vigilance on subjects.	Electroencephalogram (EEG)	Feature extraction – PCA, ICA. Power Spectral Density Analysis and Time Frequency Analysis. Classifier - SVM	Investigated the effect on EEG signal when subjected to stimuli. And developed a cognitive functions model based on stimuli perceived by the brain.
10	Parham G et al.	Recording of EEG signals during a period of one year.	Electroencephalogram (EEG)	Fast Fourier transform (FFT), Continuous Wavelet Transform,	Demonstrated the capabilities of continuous wavelet transform (CWT) by analyzing EEG signals produced through a single-electrode recording device.
11	Postelnicu et al.	Four users were asked to spell below two words "TRAINING_SET" (12 characters) and "TESTING_WORD" (12 characters).	Electrooculography (EOG) and Electroencephalography (EEG)	Classifier - Linear Discriminant Analysis (LDA)	Evaluated physiological hybrid P300-based speller that uses a modified stimulus presentation paradigm-the half checkerboard (HCBP).
12	Chunfeng et al.	Simulations were carried out 200 times on 2048-point signals (corresponding to 4-s length EEG signals in current acquisition	Electroencephalography (EEG)	Transfer Entropy(TE), Akaike's information criterion, Bayesian information criterion,	Analyzed EEG signals recorded with depth electrodes during seizures in patients with drug-resistant epilepsy.

		systems) both for linear and physiology-based models.			
13	Patil SS et al.	EEG database collected from Colorado state university.	Electroencephalography (EEG)	Discrete wavelet transform	Identified different mental task by using wavelet de-noising method.
14	Bong et al.	Experiment carried out using Audio, visual stimuli.	Electrocardiogram (ECG)	Elliptic filter and discrete wavelet transform (DWT). nonlinear classifier (K nearest neighbor (KNN))	Heart rate (HR) is used as a statistical feature to distinguish the emotional stress into three different classes namely, negative emotions, positive emotions (surprise and happy) and neutral.
15	Reza K et al.	Experiment on 57 healthy participants were carried out using audio-visual stimuli.	Electroencephalography (EEG)	Feed forward neural network	Investigated discrimination of emotions from EEG based on valence and arousal levels.
16	Hamwira Y et al.	Experiment on 12 children aged between 4 to 6 years.	Electroencephalography (EEG)	Classifier - multi-layer perceptron (MLP).	New technique cerebella model articulation controller (CMAC) is used for feature extraction.

Based on the review, it is clear that various feature extraction and classification techniques have been used for analysis of EEG signals and Artificial Neural networks (ANN), statistical methods], autoregressive model (AM), mixture of densities approach, independent component analysis (ICA), time-frequency analysis (TFA), bayes quadratic, hidden markov model (HMM) and linear discriminate analysis (LDA) are amongst the major EEG classification methods. K.Akrofi et al**. [5, 10]** have described that application of EEG feature extraction technique in combination with other technique is a new trend observed and better results have been obtained in several experiments. Therefore, for the proposed framework, the chosen techniques for analysis of EEG signals are: Kernel Density Estimation (KDE) for feature extraction and Support Vector Machine (SVM) for classification. General issues identified from different EEG analysis techniques are discussed in the below table.

Table 2- General issues in EEG signal analysis techniques

S.No	Author(s)	EEG analysis technique	Observations	Identified issues
1	Vaishnavi L et al.	K-Nearest Neighbor Algorithm	It gives robust result with a recent sample of the baseline data which is training data.	Low runtime performance when training set is huge. Handling irrelevant and redundant features is little difficult. Poor classification results.
2	Lakshmi et al.	Principal Component Analysis (PCA)	Reduced feature dimensions. Classified data using ranking.	Poor performance & low efficiency when large sized data is involved.
3	M R Lakshmi et al.	Independent Component Analysis (ICA)	Efficient and high performance for large size data.	Not applicable for under determined cases. Require more computations for decomposition.
4	M Rajya Lakshmi et al.	Wavelet Transforms	Analyse signal in time and frequency domains. Can extract energy, distance or clusters.	Performance is limited by Heisenberg Uncertainty.
5	Wanprachaet al.	Support vector machine (SVM)	Better performance compared to other linear Classifier.	Computational complexity is high.

It is observed that, EEG signal analysis techniques have general issues such as need multiple electrodes, require sufficient head coverage, handling irrelevant and redundant features is little difficult, require more computation for decomposition of EEG signals in feature extraction and issues observed in classification techniques are unable to process complicated set of data, low performance when training data set is huge, require more computation for decomposition.

Above mentioned issues have motivated us to propose a general framework of BCI which would help us to improve the process of feature extraction and improve the accuracy in classification. A detailed description of the proposed framework is discussed in the following section.

PROPOSED FRAMEWORK

In real time, assessment of human stress is quite difficult and challenging. Physiological signals like Electromyogram (EMG), Electrocardiogram (ECG), Blood Pressure (BP), Galvanic Skin Response (GSR), Skin Temperature (ST), respiration rate (RIP), Blood Volume Pulse (BVP) and Electroencephalogram (EEG) were briefly investigated to identify the stress. Most of the researches have used one or more of these physiological signals and they have analyzed stress by using questionnaire based approach. Due to the issues such as requirement of more computation for decomposition of EEG signals, inability to process complicated set of data, a framework is proposed which consist of five phases.

First phase is to collect standard EEG Datasets, second phase is pre-processing, third phase is feature extraction, fourth phase is classification and final phase is emotion/stress detection. After collecting standard dataset, signals need to be preprocessed. Pre-processing aims to simplify subsequent processing operations, improve signal quality without losing significant information. In this step, the recorded signals are processed to clean and remove noisy artifacts such as eye blinks, heart beat and muscular movements in order to get the relevant information embedded in the signals. The next phase is feature extraction. After getting noise-free signals from the preprocessing phase, important features from the brain activities signals are extracted. Applied various dimensionality reduction algorithms to maintain the important information from loss and at the same time reduce the size of vector dimension to avoid the computational complexity. Representative features obtained from the previous stage are classified using classification approach. Analyzed obtained results and selected a comparatively good classification algorithm which would help us to differentiate a normal and stress person. The schematic view of the proposed framework is shown below:

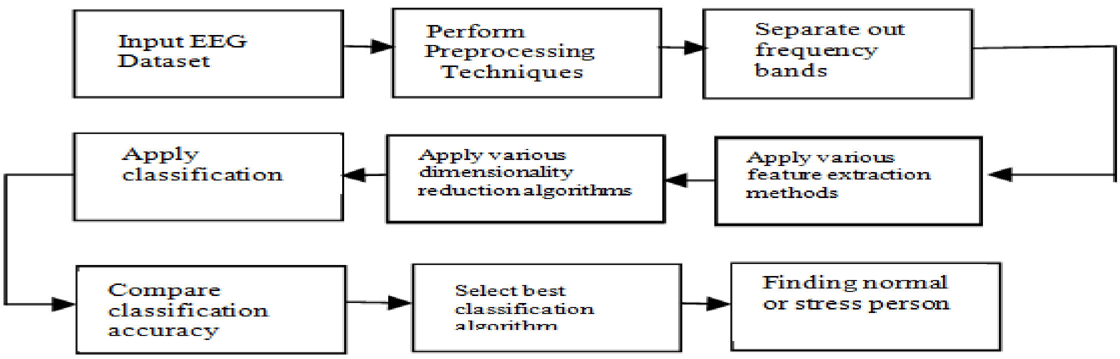


Figure 9- Framework for Human stress analysis based on Brain Computer Interface.

CONCLUSION AND FUTURE WORK

This paper gives a detailed survey of techniques involved in detection and analysis of human stress based on brain computer interface and machine learning algorithms. From the study, EEG signals gives better feature extraction results for emotion recognition compared to other signals. To work on the issues mentioned in table 2, this framework is proposed to analyze human stress using brain computer interface (BCI).The proposed framework will attempt to improve accuracy of feature extraction and classification technique. Further, the proposed framework will be developed in such a way that it may lead to a new mode of medication to relieve a person's/ subjects stress level after appropriately interpreting EEG signals. Also,

ISSN: 0975-8585

subjects would be able to directly control devices such as televisions, wheel chairs, speech synthesizers and computers.

REFERENCES

[1] Jing Zhai, Armando B. Barreto, Craig Chin, Chao Li 2005.
[2] KaziShahzabeenRahnumaa, Abdul Wahaba, Hariyati A Majidb and BjörnCrütsc et 2011
[3] Schneiderman, N.; Ironson, G Siegel, S. D. 2005 1: 607–628.
[4] Herbert, T. B.; Cohen, S. 1993,55 (4): 364–379.
[5] Seyyed Abed Hosseini, Mohammad Ali Khalilzadeh 2010.
[6] K. H. Kim, S. W. Bang, and S. R. Kim, 2004,vol. 42, 3, : 419–427.
[7] J. Kim and E. Andre 2006, 4021: 53–64.
[8] J. Kim and E. Andre 2008,30,12,:2067–2083.
[9] Chanel G., Kronegg J., Grandjean D. , Pun T. 2006:530-537.
[10] Rattanyu K., Ohkura M., Mizukawa M. 2010 :580-583.
[11] Ulrich-Lai, Y. M.; Herman, J. P. 2009, 10 (6): 397–409.
[12] Fuchs, E. &Fluegge, G. 1995, 20: 33-51.
[13] Friedman, B.H. & Thayer, J.F. 1998, 49: 303-323.
[14] Hughes, J.W. & Stoney, C.M. 2000, 62: 796-803.
[15] Papousek, I., Schulter, G., & Premsberger, E. 2002, 52: 257-266.
[16] Lin, Y.P., Wang, C.H., Wu, T.L., Jeng, S.K., Chen, J.H 2009: 489–492.
[17] Bos D.O, 2006.
[18] Murugappan, M., Rizon, M., Nagarajan, R., Yaacob, S., Zunaidi, I., Hazry, D 2008, 2
[19] Li, M., Chai, Q., Kaixiang, T., Wahab, A., Abut, H 2009: 125– 135. Springer US
[20] Reza Khosrowabadi, Abdul Wahab, Kai Keng Ang and Mohammad.H Baniasad 2009, : 14-19.
[21] W. Qiu, K. S. M. Fung, F. H. Y. Chan, F. K. Lam, P. W. F. Poon, and R. P. Hamernik 2002, 49: 225-212.
[22] B. O. Peters, G. Pfurscheller, and H. Flyvjberg 2001, 48 (1): 111-116.
[23] D. Coyle, G. Prasad, and T. M. McGinnity 2005: 461-467.
[24] C. Bigan, M. Ungureanu, R. Strungaru, and V. Lazarescu 2002:604- 605.
[25] T.-P. Jung, S. Makeing, M. Westerfield, J. Townsend, E.Courchesne, T. J. Sejnowski 2001, 14, : 166-185.
[26] MousaKadhimWali, MurugappanMurugappan, Badlishah Ahmad, 2013; 25(9): 1055–1058