RESEARCHERID
THOMSON REUTERS

[ICRTCET-2018]

ISSN 2348 – 8034
Impact Factor- 5.070

GLOBAL JOURNAL OF ENGINEERING SCIENCE AND RESEARCHES

CLASSIFICATION OF EEG SIGNALS TO STUDY THE EFFECT OF DIFFERENT MUSIC GENRE ON EMOTIONAL STRESS RELIEF

Nikhita Raghunath[1], Nirmal Patil[2], Karthika Kamath[3], Savi Kankani[4] , Pradnya Patil[5] , R D Daruwala[6] & Rahul Ingle[7]

[1,2,3,4,5,6,7] Electrical Department, Veermata Jijabai Technological Institute, Mumbai, India.

ABSTRACT

Stress is recognized as a mental state in which an individual human is expected to perform too much under sheer pressure. According to the research in neuroscience, the perceptions of the human brain determine whether a situation is menacing and stressful, hence the human brain is the main target of stress [4]. Electrical activities of human brain can be measured using Electroencephalogram (EEG). Hence biomedical researchers uses EEG signals for research purpose. EEG is used as the inimitable signal. For the selection of proper EEG channels we used the subjective model of the human brain under induced stress [14]. Studies and research reveal that music therapy can be used to soothe stress levels. It has the sole link to our emotions, so it can be an intensely efficient stress management tool.

Examination of EEG signals to study the degree of relief that a be done by negative valence and positive arousal [15]. Stress affects the brain activity and these events can be monitored by the Electroencephalography (EEG) [11]. It is preferred because it is noninvasive, with the electrodes of ENOBIO device placed on the scalp. The EEG waves consists of frequencies of various bands.

Emotional “intensity” comes with stress and Emotional “intensity” is correlated with alpha waves (8-13 Hz). In stressed condition frontal alpha asymmetry differences have been reported [15]. Theories state that music is considered to be one of the best ways for reducing stress [8]. particular music genre does is researched in this paper. EEG data of 10 subjects was acquired. The four music genres used were Indian classical, western classical, jazz and metallic. The acquired EEG data was then pre-processed using EEGLAB library. Statistical features like standard deviation and Kurtosis [9] were obtained from the discrete wavelet transform coefficients of alpha band (8-13 Hz) after segmenting the data into idle, stress inducing and hearing music conditions [10]. These features were given to a SVM classifier to classify into stress and non-stress classes and to estimate the degree of belongingness of a particular music in the non-stressed class..

Keywords: *Electroencephalogram (EEG), Music, Discrete Wavelet Transform (DWT), Feature extraction, SVM, Classification.*

I. INTRODUCTION

Emotional stress is a physiological response to a trigger from the environment and our perception of that situation. Due to modernization in the way of our living, it is experienced by many people especially over the last decade. Stress or anxiety affects at physiological, neurobiological and psychological levels. It affects major aspects of our living resulting in degrading of quality of life. Hence measures to minimize the effects of stress has gained much importance in the last decade either for individual health or for the society welfare [15]. Stress can be positive stress or negative stress [14]. Positive stress ensures a healthy competition and aims for better outcomes and results. Negative stress adversely affects the mental state and is not desirable. Characterization of stress can be done by negative valence and positive arousal [15]. Stress affects the brain activity and these events can be monitored by the Electroencephalography (EEG) [11]. It is preferred because it is noninvasive, with the electrodes of ENOBIO device placed on the scalp. The EEG waves consists of frequencies of various bands.

ISSN 2348 – 8034
Impact Factor- 5.070

Emotional “intensity” comes with stress and Emotional “intensity” is correlated with alpha waves (8-13 Hz). In stressed condition frontal alpha asymmetry differences have been reported [15]. Theories state that music is considered to be one of the best ways for reducing stress [8].

Table I. types of brain waves

Serial No.	Waves	Originate	Frequency Range (in Hz)
1	Alpha	Occipital lobe and back side of the head	7.5-12
2	Beta	Central area of the brain and front side of head	13-30
3	Theta	Central, temporal and parietal parts of head	3.5-7.5
4	Gamma	All parts	>30

Music is fundamentally a right brain activity and language a left brain activity. Metallic, Jazz, Indian classical and Western classical were the four genres of music used in this research.

II. METHODOLOGY

a. Data Acquisition

EEG data was acquired using the device ENOBIO. 8 electrodes were used for the purpose and placed at positions T7, F7, P3, CZ, FPZ, F8, T8 and P4 in accordance with the 10-20 International standards. The experiment was performed on 10 subjects, 6 male and 4 females of age group 19-24.

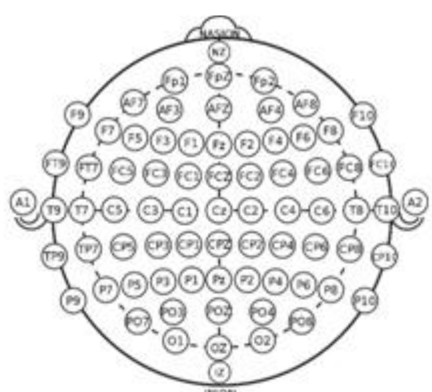

Fig 1. 10-20 International standard

ISSN 2348 – 8034
Impact Factor- 5.070

The Kahenman +2/+3/+4 methods were used for inducing stress in a subject [Thinking, Fast and Slow by Daniel Kahenman]. The subject had to perform mathematical operations within a specific duration of time. In Kahenman +3 method, 3 should be added to every digit of a number ignoring the overflow bit.

Then out of the four music genres, one was randomly selected and the subject was made to listen to it. This process was repeated for all the remaining genres. The acquired EEG was sampled at 500Hz by the ENOBIO device. The ear was considered to be the reference throughout the experiment.

Fig 2. Device used for recording EEG signals of the subjects

b. Preprocessing

The collected multichannel signal was cleaned by removing artifacts and keeping just what is necessary to analyze. EEGLAB library was used to filter out signal from 1-49 Hz using basic FIR filter, so that the 50 Hz line noise and low frequency components such as those caused by movement and breathing are eliminated [13]. After which eye blink artifacts seen as sudden spikes were removed manually by visualizing the EEG signals [12] as seen in Fig. 3.

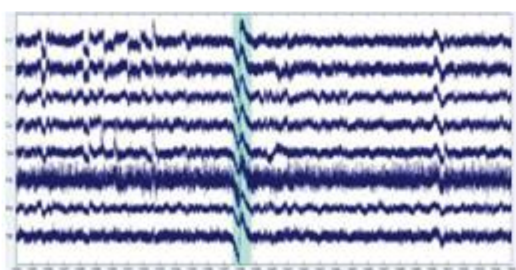

Fig 3. Eye blink artifacts seen as a sudden spike across all channels.

It was re-referenced to Cz so that reference is a point on the scalp and then down sampled to 256 Hz in order to save memory and disk storage, keeping Nyquist criteria in mind so that frequency reconstruction doesn't result in much loss of data

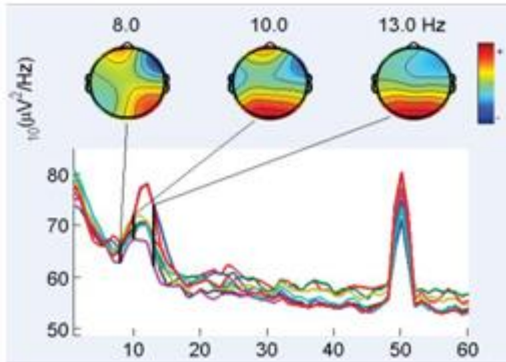

Fig 4. Plot of log power spectral density vs frequency before pre processing

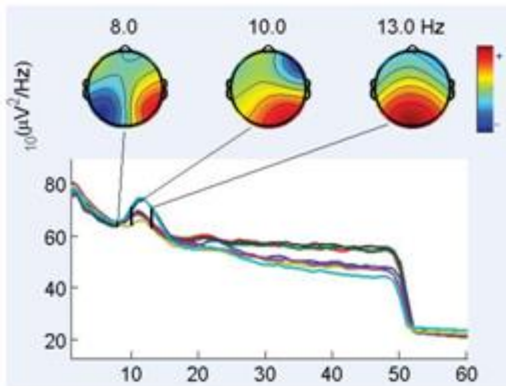

Fig 5. Plot of log power spectral density vs frequency after pre processing

c. Feature Extraction

In this work feature extraction is done by wavelet transform. A function is decomposed into an infinite series of wavelet in wavelet transform. The concept concealed wavelet analysis is a signal can be expressed as a linear combination of specific functions like WT. This combination is acquired by moving and dilating a mother wavelet across signal. Wavelet coefficients are obtained by decomposition of the signal. Features related to the signal which are not possibly founded by the Fourier transform which appears due to transient nature can be determined due to wavelet transform. . So time-scale regions are defined [5].

Ψp/q(t) is a mother wavelet function.

$$\psi_{p/q}(t) = \frac{1}{\sqrt{p}}\psi\left(\frac{t-q}{p}\right)$$

Where p, q R where the wavelet space is given by R and p

The scaling factor is given by ‘p’ and shifting factor is given by ‘q’. > 0. The scaling factor is given by ‘p’ and shifting factor is given by ‘q’.

$$C_{\psi} = \int_{-\infty}^{\infty} \frac{|\psi(w)|^2}{w} dw < \infty$$

Whereas the Fourier transform of Ψp/q(t) is Ψ(ω).

Frequency domain of signal is divided in half repeatedly by filtering the signal with a combination of filters until desired frequency range is obtained. Hence after filtering, the signal is divided into two coefficient sets. First coefficient set is approximation coefficients (cA) and the second coefficient set is detailed coefficients (cD) obtained by discrete wavelet transform. The above mentioned process is performed again on approximation coefficients. A table of detail coefficients and approximation coefficients at different scales are generated by repeating this process. [7].

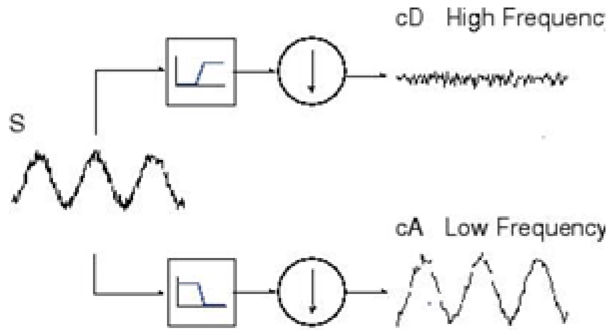

Fig 6. Detailed coefficients (CA) and approximation coefficients (CD) representation

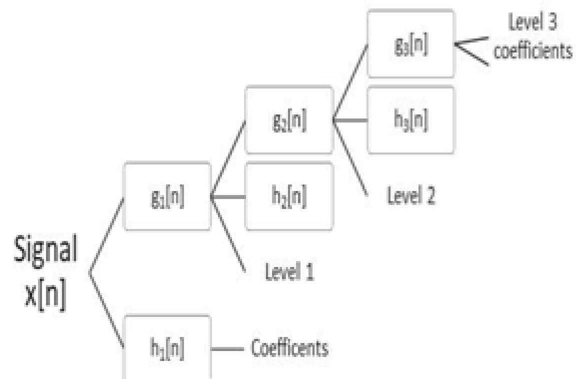

Fig 7. Third level filter bank block diagram representation of wavelet transformation

In this work, Daubechies 4 (db4) wavelet is used as a mother wavelet as it is the most suitable to process biomedical signals. The input signal has a frequency band of 1-49 Hz and the signal was decomposed upto level 5 to fully separate frequency band into lowest frequency, delta, but since the relevant information lies in the alpha rhythm (8-13 Hz), the coefficients of D3 were considered for features extraction. The EEG signal of three stages were calculated separately in MATLAB. The wavelet coefficient of the decomposed signal was still too large and not suitable to be used directly for pattern recognition in neural network. Therefore, feature extraction is done for simplifying the larger data set.

Table II. EEG signals decomposed into distinct frequency bands and sampled at 256 hz.

Wavelet coefficient	Frequency in Hz
D1	24.5 – 49
D2	12.25 - 24.5
D3	6.125 - 12.25

D4	3.06 - 6.125
D5	1.53 - 3.06

d. Feature Selection

After Feature extraction we got 35 statistical features of the EEG data. These are Kurtosis, Variance, Mean, Skewness

Standard Deviation of all the coefficients of the electrodes T7, F7, P3, FPZ, F8, T8 and P4. We decided significant features to separate our data into 2 classes - Stressed and Non stressed by graphical data analysis using python analytical tools such as Pandas, Matplotlib and Seaborne.

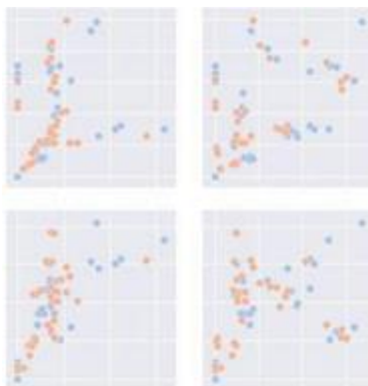

Fig 8. Pair plot of [T8_Variance & p4_Variance] vs [F8_Variance & FPZ_Variance]

Following figures illustrates sub-figures of pair plot of one feature with respect to all Other features. As seen in Fig. 7 Red points represents song data and blue line represents arithmetic calculation data. It is clearly seen that using these features classification into 2 distinct groups cannot be done using any linear hypothesis. Thus features with mixed pairplot same as in Fig. 8 are discarded.

As seen in Fig. 9, the points belonging to Song data (Red points) are clearly separated from points belonging to arithmetic calculation data (Blue points). It is clearly seen that using these features, classification into 2 distinct groups can be done using linear kernel in SVM. Thus features with mixed pairplot same as in Fig. 9 are selected.

Fig 9. Pairplot of [T8_Kurtosis & p4_Kurtosis] vs [F8_Skewness & FPZ_Skewness]

The following table represents the selected features and their values at different stages where state 0 represents arithmetic sum calculation (stressed) data and state 1 represents data belonging to song part (non-stressed).

	STATE	T7_kurt	F7_kurt	P3_kurt	FPZ_kurt	F8_kurt	T8_kurt	P4_kurt	T7_skew	F7_skew	P3_skew	FPZ_skew	F8_skew	T8_skew	P4_skew
SUM	0	0.980058	0.79188	0.226553	0.900038	0.69549	0.570575	0.36254	-0.11263	-0.02033	0.182584	-0.23151	0.050802	0.092205	-0.0093
SUM	0	8.488381	3.416753	0.179526	10.67215	3.787892	1.405073	1.995299	-0.83118	-0.32182	0.045732	-1.11824	-0.32724	0.057498	-0.18146
SUM	0	6.284698	1.928789	0.471826	3.6765	2.596922	0.646203	1.010835	0.295255	-0.02676	0.107159	0.210792	0.209326	0.063548	-0.01024
SUM	0	4.122412	1.696279	1.140661	1.857882	1.451043	6.585979	4.71769	-0.40897	-0.29283	0.023105	0.056419	0.055142	-0.52665	-0.21307
SUM	0	1.659244	0.475512	13.80043	-0.13559	-0.13507	0.068055	4.455205	-0.3348	-0.0841	-1.42921	-0.03543	0.022455	-0.02049	-0.57444
SUM	0	0.207639	4.686937	11.9992	0.612124	0.661883	0.210465	1.381061	-0.11067	0.211565	0.744783	-0.09285	0.071794	-0.07005	0.24857
SUM	0	0.035906	1.195163	14.91669	1.434202	1.250159	0.79115	3.534139	-0.00294	-0.11475	-0.85432	0.060295	0.086142	0.173314	0.081969
SUM	0	0.377142	4.158255	1.653833	0.076342	0.995301	0.498543	-0.04589	-0.10939	0.180716	0.088652	-0.07067	-0.18033	-0.01582	0.136956
SUM	0	0.670948	1.844869	0.600306	1.253759	1.219487	0.713697	1.929562	0.132092	0.200427	0.029201	0.108345	0.038152	0.008698	0.271029
INDIAN	1	38418111	43876551	23165468	21970236	1.10E+08	33563441	25672385	-0.14371	-0.0174	-0.04121	0.06103	0.026119	0.003209	-0.0272
METALLIC	1	26483553	42833402	26309313	19223281	31243405	25964839	19613281	0.088039	0.092976	0.000565	0.068659	0.020637	0.000447	-0.06425
WESTERN	1	24909132	57275099	33246252	18841479	44000512	23381268	24049564	0.173039	-0.02905	-0.15312	-0.01573	0.098916	-0.0253	-0.08193
JAZZ	1	27816523	38814011	22709257	21040551	46570993	30834165	22494518	-0.08557	-0.05451	-0.04804	-0.07291	-0.039	0.025455	0.265869
INDIAN	1	38262169	27255307	2184942	38805383	54173930	36522884	3586817	-0.03504	0.037624	0.290791	0.097659	-0.19178	-0.18716	0.472671
METALLIC	1	54971157	30007674	2393172	41322915	53047101	37556953	3145068	0.028978	-0.1426	-3.47531	-0.09362	-0.08524	-0.25682	-1.61435
WESTERN	1	72887168	28022012	1083483	44133224	49331517	39118570	1527158	-0.01861	0.037229	0.029584	-0.09477	-0.04674	0.014725	0.026171
JAZZ	1	38052317	26906014	2212992	37773860	42367363	31801955	3361904	0.028069	0.095591	2.268634	0.428659	-0.07689	0.039277	1.395095
INDIAN	1	1.85E+08	1.22E+08	19427238	1.02E+08	1.30E+08	92365979	25117386	0.016867	0.018909	0.013354	0.201856	0.012286	-0.02282	-0.02222
METALLIC	1	1.46E+08	1.04E+08	12404900	87547262	1.01E+08	86622214	26014398	0.0174	-0.00428	-0.04966	-0.01253	-0.02207	-0.02855	-0.0294

Fig 10. Segment of the feature table

e. *Classification*

The most well known Machine Learning technique for classifying the EEG signals based on neural activity is Support Vector Machine (SVM). EEG signals are portrayed into high dimensional feature space for analyzing the brain activity. The reason that SVM classifiers are more efficient than the conventional pattern recognition methods is based on the combination of a feature selection procedure and a conventional classifier. Kernel function really plays an important role in Support Vector Machine (SVM). Data points from one feature space to other feature space is mapped by Kernel. SVM gives good performance in many applications, specifically in our case for solving problems with high dimension, nonlinearity and small dataset [1].

So we used SVM to classify the EEG data into two main classes, Stressed and Non-Stressed. With the hypothesis that EEG data acquired during arithmetic mental task is labeled as stressed part and EEG data acquired during music is labeled as non-stressed. For classification Train-Test Ratio was used as [80:20].

The confusion matrix in Fig. 11 shows that only 1 sample from stressed class is classified wrongly into non-stressed.
Accuracy is given by [13]
From the confusion matrix, the accuracy as seen using this formula is of about 94%.

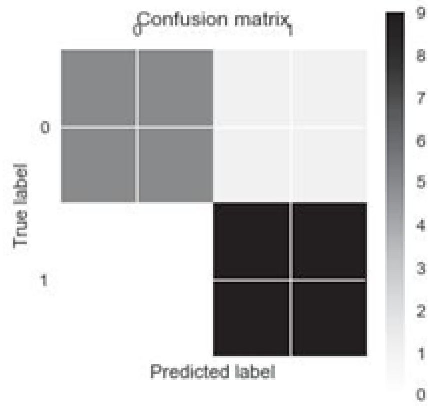

Fig 11. Confusion matrix

III. CONCLUSION

In order to conclude which music out of the four chosen genres serves as the best stress reliever, distance of all the data points from the decision classifier boundary in the class of songs of the SVM model were found and then the average distance for each music was estimated and plotted as in Fig. 12

So, it can be viewed that western classical music has the maximum value of average distance and therefore it is the one which is farthest from the decision boundary or in other words, stress determining boundary. Hence western classical music is the most stress relieving followed by metallic, then Indian classical and finally jazz in the age group of 19-24. Training of the neural network with features extracted with DWT shows that the network is able to achieve classification accuracy at 94%.

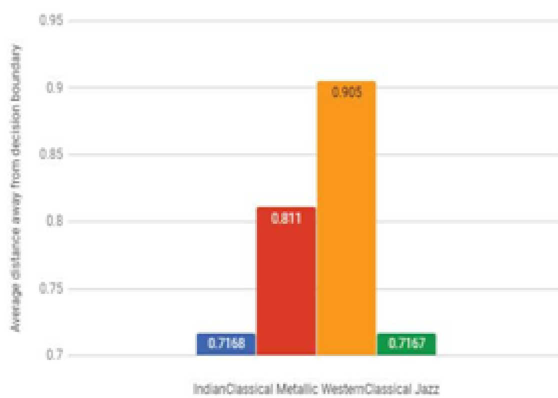

Fig 12. Graph showing average distance from decision boundary vs different music genre

IV. ACKNOWLEDGMENT

This work is promoted by the Head of the Department (HoD) of the Electrical Engineering Department, Dr. R D Daruwala and the faculty of the Biomedical division R. N. Awale and Rahul Ingle, Veermata Jijabai Technological Institute (V.J.T.I.), India. The authors would like to thank everyone who provided their guidance and support during the course of this work.

REFERENCES

1. *Abdi, M.J.; Hosseini, S.M.; Rezghi, M. "A novel weighted support vector machine based on particle swarm optimization for gene selection and tumor classification". Comput. Math. Method 2012, Article ID*
2. *320698.*
3. *Pereira, F., Mitchell, T., and Botvinick, M. (2009). "Machine learning classifiers and fMRI: a tutorial overview". Neuroimage 45, S199–S209. doi: 10.1016/j.neuroimage.2008.11.007*
4. *Han, J., Kamber, M., and Pei, J. (2011). Data Mining: Concepts and Techniques: Concepts and Techniques. Elsevier.*
5. *Ahmad Rauf Subhani, Likun Xia, Aamir Saeed Malik, EEG Signals to Measure Mental Stress, Center for Intelligent Signal and Imaging Research, Department of Electrical and Electronics Engineering, Universiti Teknologi PETRONAS, Perak, Malaysia*
6. *Pari Jahankhani, Vassilis Kodogiannis and Kenneth Revett. "EEG Signal Classification Using Wavelet Feature Extraction and Neural Networks"*
7. *Mohammad H. Alomari1, Emad A. Awada1, Aya Samaha1 & Khaled Alkamha, Wavelet-Based Feature Extraction for the Analysis of EEG*
8. *Signals Associated with Imagined Fists and Feet Movements, Applied Science University, Amman, Jordan*
9. *Chethan, P. and Cox, M. (2002) Frequency characteristics of wavelets. IEEE Transactions on Power Delivery,17(3), 800-804.*
10. *Nyklicek I, Thayer JF, Van Doornen LJP (1997) Cardiorespiratory differentiation of musically induced emotions. J Psychophysiol 11: 304-321.*
11. *Classification of human emotion from EEG using discrete wavelet transform.international Journal of Computer Applications (09758887)Volume 124 No.2, August 2015*
12. *Teplan, M. 2002. Fundamentals of EEG Measurement. Measurement Science Review. 2(2).*
13. *Influence of music on human electroencephalogram.Published in: Applied Electronics (AE), 2011 International Conference*
14. *Parthana Sarma , Prakash Tripathi , Manash Pratim Sarma , Kandarpa Kumar Sarma. "Pre-processing and Feature Extraction Techniques for EEGBCI Applications- A Review of Recent Research" ADBU-Journal of Engineering Technology.*
15. *Lung Chuin Cheong, Rubita Sudirman and Siti Suraya Hussin "feature extraction of eeg signal using wavelet transform for autism classification" VOL. 10, NO 19, OCTOBER, 2015 ISSN 1819-6608 ARPN Journal of Engineering and Applied Sciences.*
16. *"Understanding Stress": Comparing between US, Japanese and Thai management styles Krit Jarinto, Full-time Instructor, Graduate school of commerce, Burapha University, Thailand.*
17. *Giorgos Giannakakis, Dimitris Grigoriadis, Manolis Tsiknakis. "Detection of stress/anxiety state from EEG features during video watching", 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2015.*

.