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Prediction of Musical Perception using EEG and Functional Connectivity in the Brain

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***Abstract*—Music has various effects on the brain and body. Multiple studies have suggested a marked difference in information processing between musicians and non-musicians when listening to music. However, the occurrence of these changes within the brain is yet to be instantiated. The amount of data obtained to study information processing in the brain is huge and surplus features obtained may be redundant and there is thus an increased need to reduce amount of data. In this study information processing in the brain is determined by obtaining optimum features using data reduction processes. Features obtained are compared with brain activation in an attempt to predict behavioral data. Twenty healthy subjects were considered of which 10 were musicians and 10 were non-musicians. All subjects were made to listen to a music stimulus that was played. Electroencephalography was used to record responses and behavioral data too was obtained. The Major predictors for musicians were frontal and temporal lobe electrodes and this was absent in non-musicians. Although some electrodes have high node strengths, they were not indicated as predictors. The enhanced inter and intra hemispheric functional connectivity was seen for the musicians which was due to familiarity and music learning.**

Keywords—Information processing; data reduction; prediction; brain activation; familiarity

I. Introduction

Music listening has a great impact on the brain and the sequence of events leads to a positive effect on the hormone system. It has the ability to change the mood of a person and depending on the category of music; the change induced may be either positive or negative [1], [2]. Owing to its ability to enhance mood and relieve stress and tension [2], music has been used in therapy. Its capability of influencing numerous neurobiological processes [4] indicates a potentially important role for music in psychological treatment [1]. It has also been known to affect cognition. Yet how it is instantiated within the brain is yet to be fully characterized [3].

Most studies make use of FMRI (functional magnetic resonance imaging) and EEG (electroencephalography) to obtain information on the brain. Several aspects of EEG make it useful for investigating neural correlates of cognitive functions [5]. Music works on energy centers of the body thus facilitating neural and other physiological responses.

On recording brain activity using EEG, the amount of data obtained is exceedingly large, as EEG being a non-stationary signal changes every second. Thus, feature extraction is necessary and all features cannot be used to get required information. A need for data reduction arises to reduce complexity and simplify assumptions [6]. Different methods of data reduction may be used. Popular methods include Principal Component Analysis (PCA) and Multiple Regression (MR). The current study used multiple regression as a method of data reduction. Multiple linear regression makes use of generation of a best fit or optimum equation between predictors and dependent [7] and is generally preferred due to its ease of use as no parameters have to be tuned [8]. Connectivity of predictors is further evaluated using functional connectivity brain maps. Functional connectivity using EEG is a relatively new approach [9] and is an accurate visualization method to study connectivity between lobes of the brain during information processing. In this study, it was observed that major activation and connectivity existed between temporal and frontal lobes of musicians and these regions were also generated as predictors. These regions of the brain correspond to functions of memory and emotional regulation respectively. Correlation of predictors with other electrodes too was considered using correlograms. The high connectivity of frontal and temporal lobes existed only in musicians and not in non-musicians due to a familiarity of music in musicians. This study thus attempts at using objective responses to music and brain activation to try predicting behavioral data obtained as subjective feelings from the participants.

II. Methods and Materials

A. Subjects Summary

Twenty participants with a mean age of 20 were recruited for the study. The Goldsmith Musical Sophistication Index (Gold-MSI) was used to classify the participants as musicians and non-musicians (Daniel Mullensiefen et al., 2014). All participants were exposed to the music stimulus for the first time. The experiment was conducted in a soundproof environment where the participants were provided with comfortable seating arrangements. The entire procedure was performed in accordance with the guidelines of the Institutional Ethics Committee for human volunteer research. Participants were informed that they could stop the procedure anytime they felt uncomfortable or insecure. The experiment was conducted after receiving an informed consent from each of the participants.

B. Stimulus Selection

The stimulus chosen for the study was pleasant and had evenly distributed frequencies for the selected epoch. The maximum frequency was 2000 Hz. Although it wasn't an upbeat stimulus participants indicated that the music was a pleasant and liked one. The instrumental music played on the violin was in a lower pitch.

The stimulus chosen was a Carnatic piece in the ragam "Mohanam". A pentatonic scale, the aarohanam (ascending scale) and avarohanam (descending scale) are as follows:

Aarohanam- S R2 G3 P D2 S
Avarohanam- S D2 P G3 R2 S

The graph of the signal and its corresponding signal for the 1st minute are shown in Fig. 1 and 2.

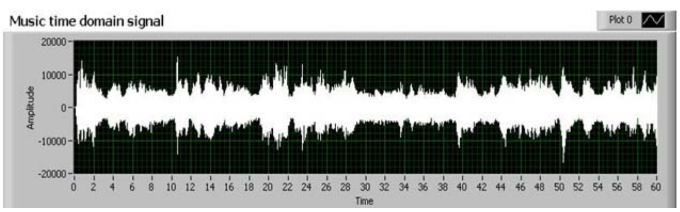

Fig. 1. Music time domain signal.

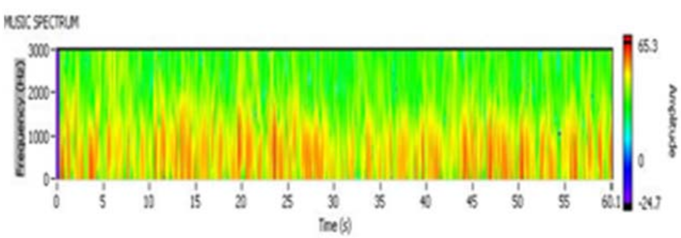

Fig. 2. Music spectrum.

C. Experiment Protocol

The protocol was for 7 minutes. Participants were exposed to an initial 2 minute baseline, which was followed by the 3 minute stimulus and then 2 minutes of rest (control, without stimulus). Epoch analysis of 180 seconds and 120 seconds were considered. Participants' mood was assessed using the Positive And Negative Affect Schedule (PANAS) mood test prior to recording their EEG and after listening to the stimulus. Subjective feeling ratings were also obtained using the Self-Assessment Manikin test (see Fig. 3).

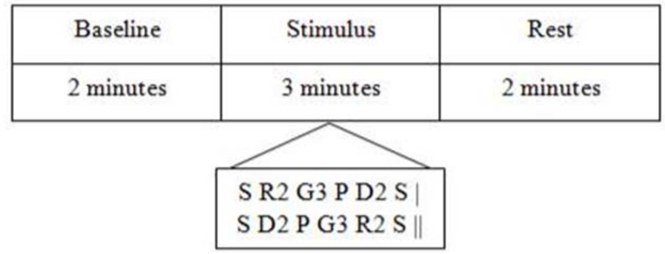

Fig. 3. Experiment protocol.

D. Behavioral Data

Objective data to gauge participants' mood and emotions to the musical pieces was obtained using PANAS and SAMS scale respectively.

The Positive And Negative Affect Schedule (PANAS) test, a self-report 20-item test to measure positive and negative affect (Watson et al., 1988) was used to procure information regarding effective mood of participants before and after the stimulus was played. It consists of a 5 point scale indicating and classifying overall mood of listener as either positive or negative affect. Whereas, the Self-Assessment Manikin Scale (SAMS) was employed to obtain information regarding emotion felt by listeners to a musical piece [10]. The scale is a non-verbal, graphical representation of a figure ranging from a happy face to a frowning face indicating pleasure, an excited, wide eyed face to droopy eyed face indicating excitement and a small sized figure to a larger sized one indicating power or control [10]. Classified as valence, arousal and dominance respectively, the 5 point scale indicates pleasantness of music, excitement and involvement of listener when listening to the music which helps to assess emotional perception of participants to the stimulus played.

E. Electrode Placement

Electroencephalographic waves were recorded using the 10-20 electrode placement system. A total of 21 electrodes were placed along the Frontal, Parietal, Central and Occipital lobes [11]. Nineteen electrodes placed to acquire the EEG signals were Fz, Cz, Pz, Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5 and T6. The reference electrodes, A1 and A2 were placed on the ear lobe. Ag/AgCl electrodes were used to prevent shifts due to electrode polarization [2], [9]. Impedance was kept low (5 -10 Kilo Ohms) to enable proper conduction of the signals and sampling frequency was set at 256 Hz/channel.

The power line interference of 50 Hz due to electrical interference was eliminated using a notch filter of 50Hz and muscle artifacts were eliminated using an EMG (electromyography) filter [2], [9], [12]. Both filters were applied directly using the Acquire software during data acquisition. The experimental set up is as shown in Fig. 4.

Fig. 4. Experimental setup.

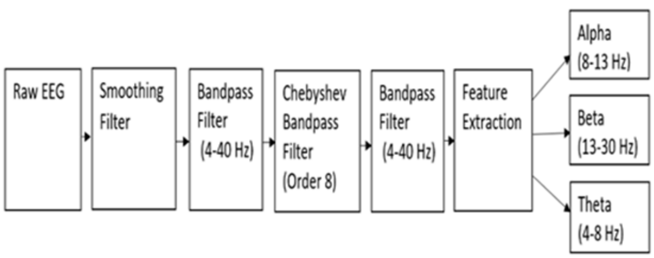

Fig. 5. Signal processing flowchart.

F. Signal Processing

The raw EEG obtained during acquisition using the acquire software was preprocessed and necessary features were extracted using the NI-LabVIEW software.

The signal processing flowchart is depicted in Fig. 5. The raw waveform obtained was smoothened using a moving average triangular filter and band limited from 4 to 40 Hz using an IIR Chebyshev band pass filter of order 3 [2], [9]. The smoothing filter was used to remove sudden signal changes by decreasing high frequencies, and delta waves were removed to avoid effect of electronic drift and eye movements [2], [9], [12].

Each of the other waves was separated and obtained using a Chebyshev filter or order 8 and filter specifications included a pass band ripple of 1db and an attenuation of 20dB. Alpha, Beta and Theta waves were thus extracted.

Total power of each of these waves was obtained and relative power was calculated from Total power and absolute powers of each frequency band [9].

$$\textit{Relative Power} = \textit{Absolute Power}/\textit{Total Power} \qquad (1)$$

G. Statistical Analysis

The data obtained for different frequency bands and conditions were not normally distributed. Hence, non-parametric tests were performed using IBM SPSS Statistics 24. An independent sample design was considered where musicians and non-musicians were the independent variables while relative powers of frequency bands calculated across all nineteen electrodes were the related samples. Multiple statistic tests were carried out on the variables to check for the presence of a significant difference. Threshold for significant difference was set to p=0.05 implying that values lower than 0.05 were indicative of statistical significance.

A Friedman test was performed on the entire distribution to check for a significant difference among all data samples. The test was performed for all conditions (baseline, stimulus and rest) for both musicians and non-musicians. The test was carried out for 171 variables and works by assigning ranks to each value and then considering the value of ranks by columns. Since a significant difference was obtained, further statistical tests such as the Wilcoxon Signed Ranked test were carried out.

Wilcoxon Signed Rank test, a non-parametric test was carried out between related samples to check for significant differences. The test assesses the difference between the population mean of two related scores from the same source. Here, the significant difference obtained from the Friedman test is further investigated individually. Data obtained during conditions of rest and stimuli were considered to be related samples. In this case, the comparison was done for each of the 19 electrodes before the stimulus (baseline) and after listening to the stimulus. Along with the significant difference value (p) a Z-value which determines the difference between the values obtained and the population mean was considered.

The Mann-Whitney test was performed on independent data samples. Here, two independent samples from the same population were compared based on their ranks. This was used to compare the data obtained for the stimulus for both musicians and non-musicians to check for a significant difference.

Functional connectivity determines the strength of connections between elements or nodes of the brain. Connectivity in the brain can be visualized using techniques of graph theory called brain connectomes [13]. These functional connectivity maps were generated using MATLAB BrainNet Viewer. Each electrode is considered a node and edges describe strength of the connection between nodes [9], [14]. The strength of a node is indicated by the size of the circle representing the node while the strength of edges are represented using a color bar [13]. Node strength was obtained from t-value. Thus, a ball and stick model of the brain is obtained for the ease of view of connectivity.

Intra-hemispherical and inter-hemispherical connections between the lobes of the brain were further visualized using correlation. The correlation between the 19 electrodes was determined using the Spearman's Correlation test used to evaluate the strength of connectivity between nodes across all electrode locations. The computed correlation coefficients for each electrode location with every other electrode were then employed in the generation of a correlation matrix and visualized using MATLAB's BrainNet Viewer. High values of correlation corresponded to higher statistical significances or lower p-values.

The factors that influenced information processing in the brain were analyzed using multiple regression in an attempt to obtain a relationship between the dependent criterion and its potential predictor variables. The dependent variables were parameters of behavioral data (Valence, Arousal and Dominance) while independent variables were the different electrode locations at either stimulus or rest for a particular EEG band. The regression coefficient R value represents a correlation between actual value of dependent and predicted value of dependent. High correlation of predicted and actual values of dependent is indicated by high values of R indicating a perfect fit on the linear curve. The B coefficients are the unstandardized coefficients that represent the degree by which a particular predictor variable must be varied in order to reflect a unit change in the value of the dependent variable. A multiple regression chart was plotted and an equation stating the relationship between dependent and predictor variables was also written.

The complete methodology followed is as depicted in Fig. 6.

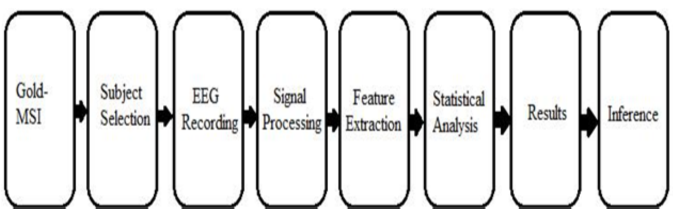

Fig. 6. Flowchart depicting methodology followed.

III. Results

A. Behavioral Data

On the SAMS scale, higher value of valence, arousal and dominance was obtained for musicians in response to the stimulus than in non-musicians. Both musicians and non-musicians however, rated the stimulus as a pleasant one with correspondingly high scores for valence. Further, parameters of arousal and dominance in musicians were observed to be significantly higher (p=0.005) than in non-musicians as shown in Fig 7.

The results of the questionnaire PANAS indicated that musicians were in a positive mood before the test and the mean positive score and the mean negative score obtained before presenting the stimulus were 33.1± 2.2967 and 18.2±2.8823, respectively. The mean positive and negative score after the stimulus were 35.7±3.58 and 13.3±1.8641 respectively. Positivity remained constant before and after the stimulus was played. Negative score before and after stimulus too remained constant. The results for non-musicians too, indicated a positive mood prior to test and mean positive score and the mean negative score before the stimulus were found to be 32.8±3.5387 and 17.9±3.3572, respectively. The mean positive score and negative score after the stimulus were recorded as 27.9±3.5144 and 12.9±1.62611, respectively. After listening to stimulus however, a significant decrease was noted in negative (p=0.005) and positive (p=0.011) affect scores of non-musicians as shown in Fig. 8 and 9, respectively.

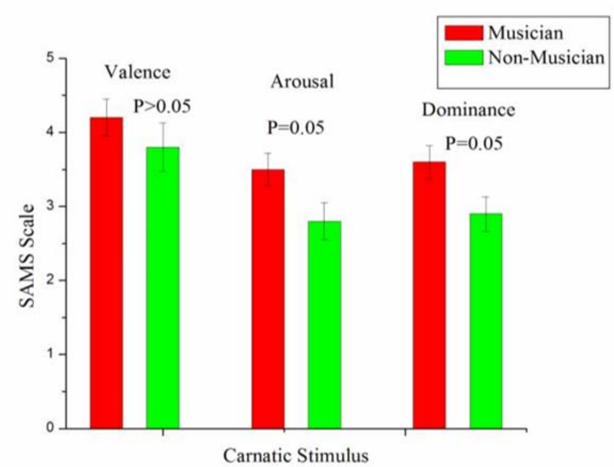

Fig. 7. Comparison of SAM scale responses of musicians and non-musicians in response to stimulus.

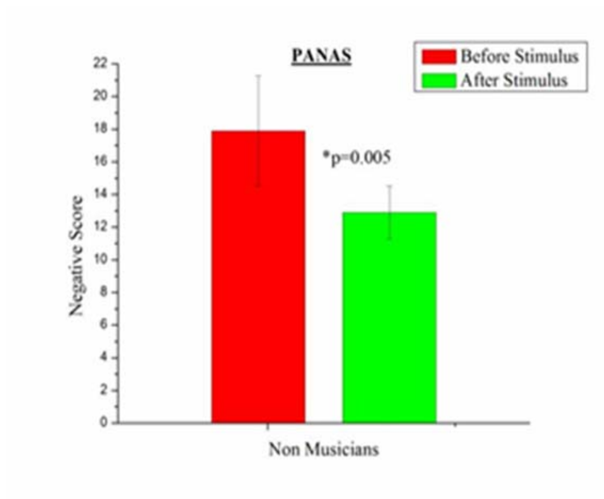

Fig. 8. Plot of negative affect before and after stimulus in non-musicians.

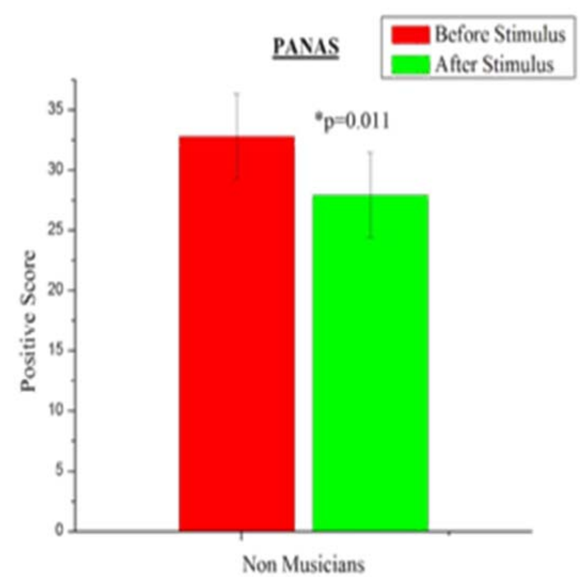

Fig. 9. Plot of positive affect before and after stimulus in non-musicians.

B. Predictive Analysis Using Regression

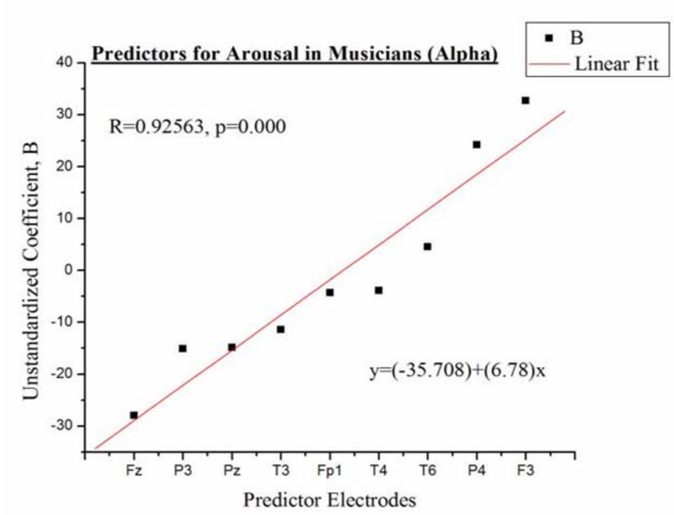

Fig. 10. Multiple regression chart showing predictors for arousal in Musicians.

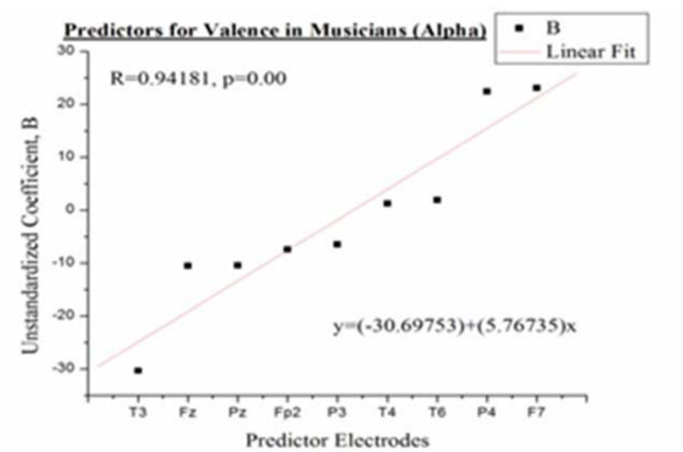

Fig. 11. Multiple regression chart showing predictors for valence in musicians.

For Arousal in musicians, electrode locations for alpha band during stimulus condition were considered as predictors (R= 0.95263, p=0.000). This is depicted in Fig. 10.

The prediction equation for arousal as predictor can thus be written as

$$Arousal = 9.382 – (27.94)\ (Fz) – (14.880)\ (Pz) – (4.316)\ (FP1) + (32.655)\ (F3) – (15.146)\ (P3) + (24.181)\ (P4) – (11.471)\ (T3) – (3.904)\ (T4) + (4.564)\ (T6) \qquad (2)$$

For Valence in musicians, electrode locations for alpha band during stimulus condition were considered as predictors (R= 0.94181, p=0.000). This is depicted in Fig. 11.

The prediction equation for valence as predictor can thus be written as

$$Valence = 9.064 – (10.541)\ (Fz) – (10.487)\ (Pz) – (7.470)\ (FP2) + (23.07)\ (F7) – (6.492)\ (P3) + (22.438)\ (P4) – (30.355)(T3)+(1.220)(T4)+(1.870)(T6) \qquad (3)$$

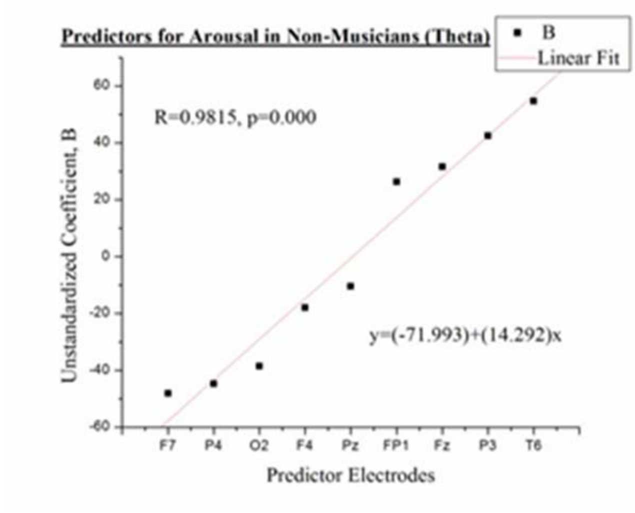

Fig. 12. Multiple regression chart showing predictors for arousal in non-musicians.

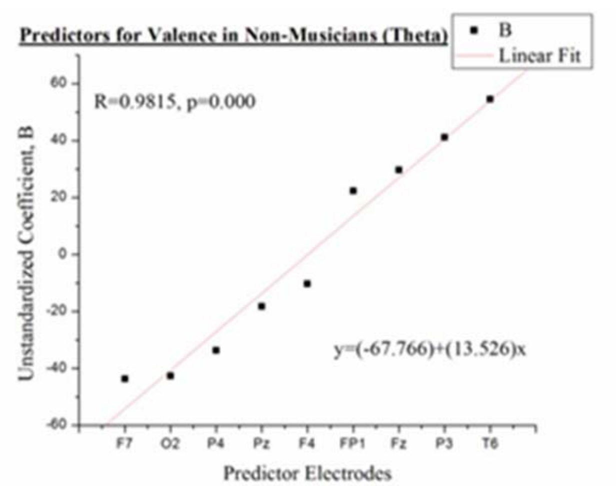

Fig. 13. Multiple regression chart showing predictors for valence in non-musicians.

For arousal in non-musicians, the predictors obtained were in the theta band during stimulus condition. R value was 0.9815 and the p-value was 0.000. This is depicted in Fig. 12.

The predictor equation for arousal in non-musicians can be written as:

$$Arousal= 4.473 + (31.534)(Fz) - (10.493)(Pz) + (26.342)(Fp1) - (18.013)(F4) + (42.479)(P3) -(44.747)(P4) - (38.511)(O2) - (48.125)(F7) + (54.718)(T6) \qquad (4)$$

The same predicted electrodes were observed for both arousal and valence in non-musicians in the theta band during stimulus condition. The R value and p-value were the same as obtained with arousal and 0.9815 and 0.000 respectively. This is depicted in Fig. 13.

However the equations for both vary as indicated in the diagram.

$$Valence = 3.142 + (29.605)(Fz) - (18.347)(Pz) + (22.31)(Fp1) - (10.331)(F4) + (41.073)(P3) - (33.724)(P4) - (42.626)(O2) - (43.738)(F7) + (54.546)(T6) \quad (5)$$

C. Functional Connectivity

a) Alpha during stimulus in Musicians

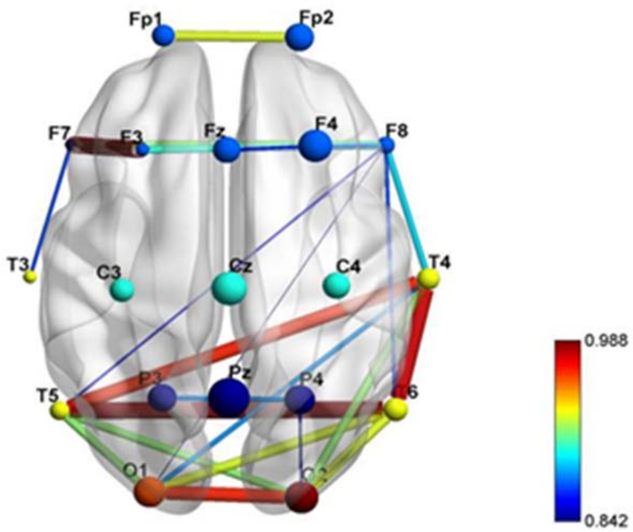

Fig. 14. Functional connectivity in brain – Alpha during stimulus in musicians.

Electrode location PZ had very high node strength and was connected to P3 and P4. Strong intra-hemispherical connectivity was observed between electrode locations F7 and F3. High connection was also observed between electrode locations T4, T5 and T6. Brain regions Fp1 and FP2 were also connected. Connections are as shown in Fig. 14.

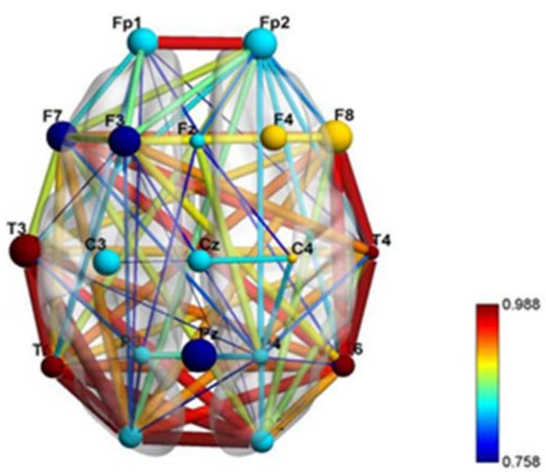

Fig. 15. Functional connectivity in brain – Theta during stimulus in non-musicians.

The node strength was noted to be very high at T3 with strong intra-hemispherical connectivity between T3 and T5. Pz had high node strength and was connected to P3 and P4. Electrode regions F3 and F7 were weakly connected. Frontal regions FP2, F7, F3 and F8 showed high node strength. Connections are as shown in Fig. 15.

D. Correlation

a) Musicians – Alpha

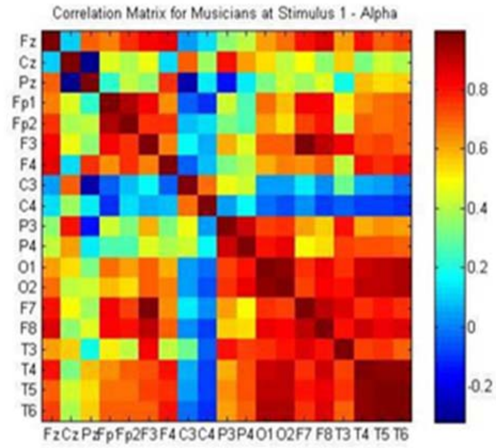

Fig. 16. Block matrix for alpha during stimulus in musicians.

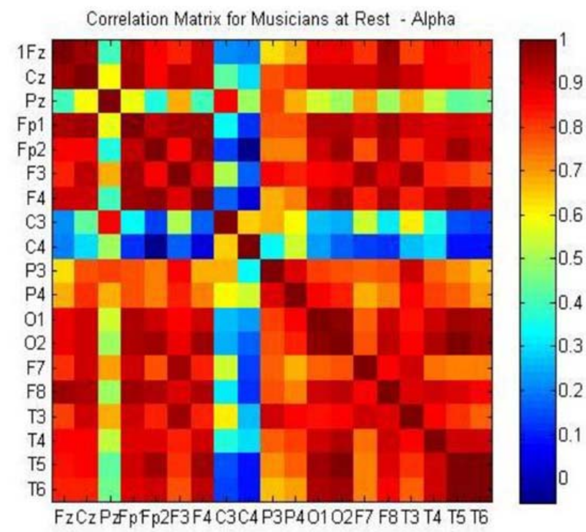

Fig. 17. Block matrix for alpha during rest in musicians.

When comparing the correlation matrices obtained for musicians in the Alpha band in response to stimulus and during rest, it was observed that electrode regions FZ and PZ were highly correlated during rest but not stimulus. Values of correlation at electrode location T3, T4, T5 and T6 were the same for both conditions of stimulus (Fig. 16) and rest (Fig. 17).

A high correlation region was also observed between electrode locations FP1, FP2, F3 and F4 for musicians during rest which was absent during condition of listening to stimulus.

b) Non-Musicians – Theta

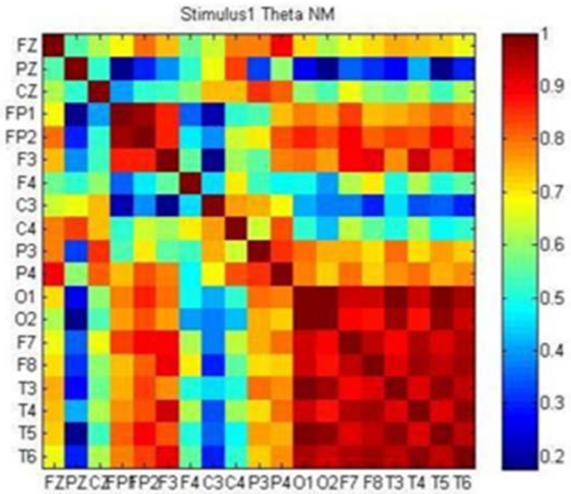

Fig. 18. Block matrix for theta during stimulus in non-musicians.

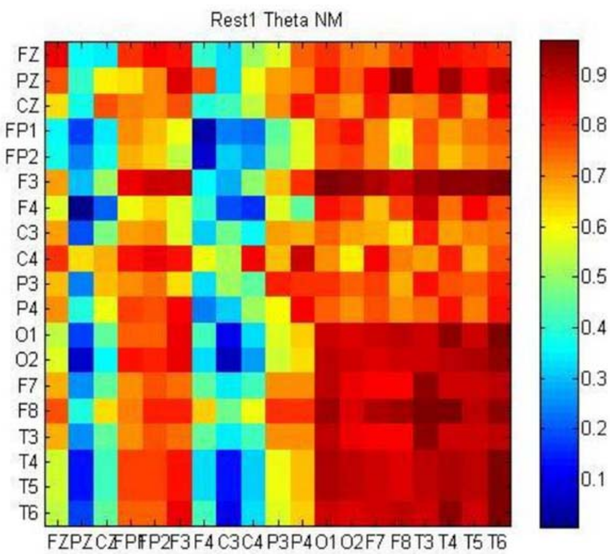

Fig. 19. Block matrix for theta during rest in non-musicians.

When comparing the correlation matrices obtained for non-musicians in the Theta band in response to stimulus (Fig. 18) and during rest (Fig. 19) no difference in correlation values were observed at electrode locations T3, T4, T5 and T6.

Regions Fp1, Fp2, and F3 were highly correlated during the condition of stimulus but not in rest. The FZ region was not engaged during rest.

IV. Discussion

The brain activation while processing music has sequences of data acquired from various signal (EEG) and imaging modalities (fMRI). These data convey the neuronal activity at various brain areas that relate to different functions of the brain. Recording massive brain data reveals vital information which would be helpful to understand the function better [20]. So extracting the useful information will provide the insight to the functional connectivity between lobes. The current study aims to explore the information processing in the brain while listening to the music of choice for musicians and non-musician using EEG. The EEG is a non-stationary signal and it's corrupted with noise, so signal processing becomes important to extract significant features that correspond to various functions of the brain.

The choice of good pre-processing and feature extraction technique has a major impact on the final data reduction [15]. In order to effectively extract the frequency components from EEG recordings, the Chebyshev filter of order 8 was chosen owing to its sharper roll off and stability characteristics over pass band frequencies [9], [16]. It was used to extract Alpha, Beta and Theta bands. After feature extraction the relative power was calculated as spectral analysis can be used to demonstrate the brain activity over the different regions and states [17]. The total power at the electrode locations was determined by taking the mean of the power spectrum [9]. Power spectrums of Alpha, Beta and Theta bands were then extracted using the Blackmann-Harris window by taking Power Spectral Density (PSD) at different electrode sites [9], [17].

Mood refers to relatively long lasting emotions which may have stronger consequences for cognition than for action. Mood can affect the perception of music and a test to record mood prior to and after listening to music was thus necessary. The PANAS scale has been known to have reliability factor of 0.89 for positive affect and 0.85 for negative affect and was thus used due to its ability to provide accurate estimates of mood [18]. The stimulus in the current study recorded a high positive affect for both musicians and non-musicians and a decrease in negative affect post listening in non-musicians thus emphasizing the ability of the stimulus to enhance listener's mood. Arousal refers to degree of physiological activation or to the intensity of an emotional response [19]. Choosing a behavioral measure helps detect a person's internal emotional state to understand listener's preferences [10]. The SAM scale being a relatively simple and highly accurate scale was thus used and music was observed to be a pleasant one.

Noninvasive studies of the human brain generate high amounts of data that need to be simplified during analysis [20]. Data reduction may be useful when these large amounts of data can be approximated by a moderately complex model structure [6]. Redundancy and uninformative data may be removed by techniques of data reduction in the brain in response to the stimulus. The features extracted underwent several data transformation including data reduction using multiple regressions where valence and arousal were the dependent variables and the various EEG bands across nineteen electrode locations for different experiment conditions were independent variables. In the current work the extracted features included 19 electrode locations for conditions of rest and music listening for all 3 EEG bands and together totaled 228 variables. These 228 features were then reduced to 18 variables to describe arousal and valence in musicians and non-musicians.

The role of the predictors obtained was further evaluated by studying the node strength and their connections with other predictors. The nodes of a functional network exhibit connections with multiple other brain areas [21]. Visualization of functional connectivity between electrode locations help assess the different nodes engaged during information processing [22] and was thus deemed important in this study. These connectivity patterns also help deduce information on cognition and action in the brain [21]. Optimal connectivity was noticed between predictors obtained for valence and arousal in both musicians and non-musicians. For arousal in musicians, electrode regions T4 and T6 were observed to be predictors and they have a strong connection with T5. Pz and P3 too were connected. Although electrodes FP2 and F4 have high node strength, they weren't indicated as predictors for arousal in musicians. The predictors for valence and arousal in musicians were observed to be almost the same except for FP2 and F7. Electrode location FP2 showed no intra-hemispherical connections. Even though node strength at F4 is high, no inter-hemispherical or intra-hemispherical connectivity was noticed. This indicates that predictor values are not based on node strength. A strong intra-hemispherical connectivity was also noted between frontal electrode locations F3 and F7. Further, the value of R for electrode location F7 was very high and almost on the linear fit curve. In non-musicians, arousal and valence had similar predictor electrodes. For arousal, node strength was noted to be very high at T3 with strong intra-hemispherical connectivity between T3 and T5. However, despite this neither of these electrodes was obtained as the predictor electrodes. Connections between T5 and T6 were not observed. Activation in the predictor electrodes thus did not depend on node strength and it was observed that Frontal electrodes FP1 and F3 were predictors for arousal in musicians while FP2 and F7 are the predictors for valence in non-musicians.

Functional connectivity of all electrodes can also be carried out using correlation [20]. This approach helps categorize functional architecture of the brain and is a more direct method to realization of processes in the brain [20]. Functional correlation between each electrode was studied using correlogram. Correlograms help understand how all regions of the brain influence each other during information processing as opposed to functional connectivity that only displays brain connections of set thresholds. Correlation of predictors with all other electrode locations was thus analyzed using correlogram to analyze inter-hemispherical and intra-hemispherical connection between the lobes of the brain. The correlograms obtained indicated that even though some regions were not predicted, they had significant correlation and impact on the brain.

V. CONCLUSION

The predictors obtained for musicians and non-musicians were different. For arousal in musicians, the FP1 and F3 electrodes were indicated as predictors while for valence, FP2 and F7 were indicated as predictors. A high connectivity further existed between F3 and F7. Activation of frontal electrodes reflects emotional processing in the brain. Temporal lobe electrodes too were indicated as predictors in musicians and were highly connected. These results were absent in non-musicians due to lack of familiarity of music.

Electrodes regions that were not predicted had high correlation and regions with high node strength were not indicated as predictors. This suggests that predictors did not depend on node strength. The present study considered only a total of 20 samples of which 10 were musicians and 10 non-musicians. In order to make the results more convincing, more number of samples should be considered and various types of music stimuli should be used.

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