Real-time Measures for Brain Activity Detection to Live Indian Classical Music Stimulus

Satyam Panda
Department of Civil Engineering
Indian Institute of Technology Guwahati
India, 781039
Email: panda18@iitg.ac.in

Dasari Shivakumar
Neural Engineering Lab
Department of Biosciences and Bioengineering
Indian Institute of Technology Guwahati
India, 781039
Email: d.shivakumar@iitg.ac.in

Yagnyaseni Majumder
Head of Hindustani classical music (vocal)
World Forum for Art and Culture
India, 700078
Email: yagnyaseniclassicalvocal@gmail.com

Cota Navin Gupta
Neural Engineering Lab
Department of Biosciences and Bioengineering
Indian Institute of Technology Guwahati
India, 781039
Email: cngupta@iitg.ac.in

Budhaditya Hazra
Department of Civil Engineering
Indian Institute of Technology Guwahati
India, 781039
Email: budhaditya.hazra@iitg.ac.in

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Abstract*—Numerous studies have explored the intriguing relationship between music and the brain, providing compelling evidence that listening to music has a profound impact on brain activity and stimulation. These investigations have uncovered intricate details about how the brain processes and responds to music, leading to a more nuanced understanding of the intricate relationship between music and the human brain. Despite extensive research on the subject, there remains a gap in our understanding of the specific effects of Indian classical music (ICM) as well as its therapeutic applications. This study proposes a real-time energy and distance measures for determining the brain areas that are activated by live ICM, while simultaneously accounting for musical impulse and EEG response uncertainty. For this, the authors used recursive Mahalanobis distance and energy measurements by finding recursive covariance matrix. Focusing on the Hindustani classical music (HCM) form of ICM, this study uses two chosen ragas with similar ascending-descending structure but differing in two normal and flat notes: Yaman and Puria Dhanashree (PD). Two of the volunteers involved in this study had prior musical knowledge on ICM and three had none. To precisely collect brain responses from different parts of brain regions, authors used a 24-channel electroencephalogram (EEG) cap to record brain responses. The results of this work show that different brain regions will get activated for different ragas. The listener's knowledge on ICM also affects the regions of brain evoked. For the volunteer with knowledge in HCM, parieto-occipital region is evoked for both ragas. The one with carnatic music knowledge has more right temporal activation for both the ragas and the volunteers with no musical knowledge showed more activation in parieto-occipital region for PD. In summary, the relationship between music and the brain has the capacity to enhance mental productivity, induce relaxation, and contribute to both mental and physical well-being.

***Index Terms*—Electroencephalography, Indian classical music, Mahalanobis distance, Energy**

I. INTRODUCTION

Scientists and researchers are intrigued by the brain and how it works. This has led to a deep desire to understand the complexities of the brain. Over the years, scientists have devised various methods to investigate the electrical activity of the brain. One of these methods is electroencephalography (EEG), which allows for the study of brain's electrical signals. EEG is a non-intrusive procedure that involves the placement of electrodes on the scalp to detect, measure, and record the brain's electrical activity in the form of brain waves [1], [2]. Richard Caton was the first person to observe electrical activity in the brains of animals and this is when EEG was originally discovered. A scalp EEG recording consists of a range of electrical impulses from the different parts of the brain as well as from external, non-brain sources. The contributions of the various signals cannot be separated due to their overlap. The emission of electrical potentials from specific cortical regions results in brain signals, which can be distinguished from recordings of non-brain signals like eye blinking, lateral eye movements, muscle tension, and other things [3]. These brain signals captured through EEG recordings can be classified into distinct frequency bands: delta, theta, alpha, beta, and gamma whose frequency bands are 1-3 Hz, 4-7 Hz, 8-13 Hz, 14-30 Hz, and 31-50 Hz, respectively [4].

Carnatic music and Hindustani classical music (HCM) are both considered to be forms of Indian classical music (ICM). Both consists of same swaras known as notes. Each swara in a raga is associated with a specific frequency based on the scale in which the raga is performed. The Indian classical vocal melodies known as ragas [5]. Each raga comprises of notes in ascending and descending order. There are seven 'Suddh swaras' in ICM and they are: Sa Re Ga Ma Pa Dha Ni. Each swara has its own frequency. The swaras 'Sa' and 'Pa' are called natural swaras and they do not have any counterparts. The corresponding counterparts of the notes 'Re', 'Ga', 'Dha', and 'Ni' are referred to as 'Komal swaras'. The frequency of komal swaras is lesser than the frequency of their suddh swaras. The komal swaras are represented as: re (komal re), ga (komal ga), dha (komal dha), and ni (komal ni). The swara 'Ma' has a counterpart and called it as 'Teevra swara' and is represented as 'Teevra Ma' (Ma$^{\#}$), which will have the frequency greater than 'suddh Ma'. There are three octaves in ICM: lower, middle, and upper. The frequency of each note is different in each octave. Octave is represented as 'Sa to Sa'. The Fig. 1 shows all the notes and their corresponding frequencies in middle octave. From Fig. 1 it is observed that the frequency of Sa in middle octave is 240 Hz and the frequency of Sa in upper octave is double than the frequency in middle octave which is 480 Hz.

Frequency (Hz)		250	290	345	380	430		
Notes		re	ga	Ma$^{\#}$	dha	ni		
Notes	Sa	Re	Ga	Ma	Pa	Dha	Ni	Sa
Frequency (Hz)	240	270	300	320	360	405	450	480

Fig. 1. ICM notes in middle octave and their frequencies

The human brain processes music in a variety of areas, including the auditory cortex, motor cortex, and frontal cortex. [6]. Each musical note has a unique frequency and energy, which can be measured using an EEG. These differences in frequency and energy can have a discernible effect on the brain's electrical activity [7]. Recent studies have shown that music therapy can have a positive impact on the emotional and physical health of individuals, based on our understanding of brain responses and the frequency bands of melodic input [8].

There are several previous studies on music and EEG and the research studies were conducted by selecting ragas which evokes different emotions like, joy and sorrow [9]. Also by chosing ragas which are differed by one or two notes however, they evoke different emotions and performed analysis on different phrases [10]. There are some studies which used musical instruments to generate music [11], [12]. In some studies by varying some parameters like pitch and tempo using musical instruments [12]. In most of these studies the recorded musical input was presented to subjects/volunteers through speakers, earphones. However, ICM is essentially a performing art, hence in order to create an approach to therapy, appropriate performance exposure is needed [5]. In this study, the authors presented a live vocal stimulus for collecting the EEG data. Here, the analysis was performed on different swaras (notes).

II. Methodology

A. Volunteers:

For this study ten volunteers (8M, 2F) were recruited and one of them had prior musical knowledge on HCM and another volunteer had prior knowledge on carnatic classical music and the rest had no musical knowlege on ICM. All the experiments were approved by Institute Human Ethics Committee of Indian Institute of Technology, Guwahati, India. All the volunteers were free from neurological disorders and hearing problems. A detailed demonstration was given to all the volunteers prior to conducting the experiment. Volunteers were prepared for collecting the EEG data. For collecting the data a 24-channel EEG cap was used and the electrodes were placed based on 10-20 electrode positioning system. All the electrodes were cleaned with alcohol before applying conducting gel between electrodes and scalp to reduce the impedance. All the electrode impedances were maintained between 10-20 kΩ. Experiments were conducted based on the availability of the volunteers. Volunteers were asked for feedback when subject preparation was completed and after the experiment completion to see whether they felt any discomfort, however, none of them expressed any annoyance or pain. EEG data was recorded using mobile CameraEEG application [13] with a sampling frequency of 500 Hz.

B. Paradigm:

The authors proposed a paradigm for collecting the EEG data based on previous studies. The two ragas viz. Yaman and Puria Dhanashree (PD) are chosen for this study. These melodies differ only in two notes which are Re and Dha. The set of notes for the raga Yaman are: Ni Re Ga Ma Dha Ni and Sa, whereas for raga PD: Ni re Ga Ma dha Ni and Sa. To collect the EEG data, the paradigm was designed using two ragas, where, the vocalist starts with the initiation phase of 30 sec, then raga Yaman for 3 min followed by a relaxation phase of 2 min, thereafter a transition phase from raga Yaman (2 min) to PD (3 min), and finally a relaxation phase.

During the initiation phase, the vocalist will start singing with a single or dual notes for a duration of 30 seconds. Following the initial 30 seconds, the vocalist will proceed to perform raga Yaman for a span of 3 minutes. Following this, there is a period of restfulness lasting 2 minutes, during which the singer will abstain from singing, however, the EEG data will be captured. After the period of rest, the transition stage will commence, during which the vocalist will begin singing with raga Yaman for a duration of 1 minute. Subsequently, the vocalist will transition into raga PD and continue singing in PD for 3 minutes. This will be followed by another 2 minute relaxation period. The distance between the subjects and the vocalist while capturing the EEG data was around 1-1.5 meters. The EEG data was collected while the volunteers were seated in a comfortable chair facing towards the vocalist. The EEG data was recorded in a mobile phone using the CameraEEG application [13], and also the audio file of the vocalist was recorded on another mobile and the sampling frequency of the audio file was 48 kHz. Both EEG data and audio files were started recording at the same time.

C. Data preprocessing:

In data preprocessing stage all the recorded EEG data was converted from .bdf format to .mat format using EEGLAB in MATLAB2021. The electrodes which are not working are removed from the analysis. The 24 electrodes used in the study are: Fp1, Fp2, F7, F8, F3, F4, Fz, AFz, T7, T8, C3, C4, Cz, CPz, M1, M2, P3, P4, P7, P8, O1, O2, Pz, and POz. Out of these electrodes by selecting the electrodes which belong to particular brain regions, four brain regions were created. The created brain regions are: frontal, right temporal, left temporal, and parieto-occipital (PO). In order to preserve the authenticity of the music-listening experience, EEG artifact removal was not considered into account in this study.

D. Energy and Distance Measurements:

In this study, the brain activity detected while listening to a particular note (swara). This is achieved by measuring the energy and Mahalanobis distance [14]. Mahalanobis distance (MD) is widely known distance measure, which is used to detect the dynamic changes in brain activity. Mahalanobis distance considers the covariance matrix of provided input which makes it a suitable choice for assessing multivariate data. For the present study, this statistical measure is essential for understanding the correlation of 24-channel EEG data. This study employes the MD and its recursive version by taking reference electrode position Cz (which is in the center) to examine brain responses in the previously mentioned brain regions to ICM stimuli. It can be used to measure the brain's response to new information. The larger the MD, the more active the brain is in processing new information. This suggests that the brain is more active during the processing of melodic transitions than during the steady-state portions of the music. The MD, D_M for a 24-channel EEG data $Y = [X_1, X_2, ...X_k]^T$, the mean $\vec{\mu} = [\mu_1, \mu_2, ...\mu_k]^T$, $k = 1, 2, ...K$ and covariance matrix $\mathbf{W}$, is defined as [14]:

$$D_M(Y, \vec{\mu}) = \sqrt{(Y - \vec{\mu})^T \mathbf{W}^{-1} (Y - \vec{\mu})} \tag{1}$$

The dissimilarity between EEG responses in different brain regions can be easily measured by MD. It is calculated using Eq. (1), which takes into account the covariance of the data. The traditional MD is calculated for batch data, which is not suitable for real-time or automated applications. To address this, the recursive MD is employed for the present work. In order to derive the recursive update expressions, the data are first centered to zero by subtracting the mean from each data point. The data are then scaled to unit variance by dividing each data point by its standard deviation, as

$$\mathbf{Y}_1 = \left(\mathbf{Y}^0 - I_{n_1}\mu_1^T\right) \Sigma_1^{-1} \tag{2}$$

Considering, $\mathbf{Y}_{k+1}^0 = \begin{bmatrix} \mathbf{Y}_k^0 & \mathbf{Y}_{n_{k+1}}^0 \end{bmatrix}^T$, for all the $k+1$ sample points, the next sampled mean is related to current sampled mean as follows,

$$\mu_{k+1} = \frac{\sum_{i=1}^{k} n_i}{\sum_{i=1}^{k+1} n_i}\mu_k + \frac{1}{\sum_{i=1}^{k+1} n_i}\left(Y_{n_{k+1}}^0\right) \tag{3}$$

Thereafter, the data matrix is recursively updated as,

$$\begin{aligned} \mathbf{Y}_{k+1} &= \left(\mathbf{Y}_{k+1}^0 - I_{k+1}\mu_{k+1}^T\right)\mathbf{\Sigma}_{k+1}^{-1} \\ &= \begin{pmatrix} \mathbf{Y}_k\mathbf{\Sigma}_k\mathbf{\Sigma}_{k+1}^{-1} - I_k\Delta\mu_{k+1}^T\mathbf{\Sigma}_{k+1}^{-1} \\ \mathbf{Y}_{n_{k+1}} \end{pmatrix} \\ &= \begin{pmatrix} \left(\mathbf{Y}_k^0 - I_k\mu_k^T\right)\mathbf{\Sigma}_k^{-1}\mathbf{\Sigma}_k\mathbf{\Sigma}_{k+1}^{-1} - I_k\Delta\mu_{k+1}^T\mathbf{\Sigma}_{k+1}^{-1} \\ \left(\mathbf{Y}_{n_{k+1}} - I_{n_{k+1}}\mu_{k+1}^T\right)\mathbf{\Sigma}_{k+1}^{-1} \end{pmatrix} \\ &= \begin{pmatrix} \mathbf{Y}_k^0\mathbf{\Sigma}_{k+1}^{-1} - I_k\mu_k^T\mathbf{\Sigma}_{k+1}^{-1} - I_k\Delta\mu_{k+1}^T\mathbf{\Sigma}_{k+1}^{-1} \\ \mathbf{Y}_{n_{k+1}}\mathbf{\Sigma}_{k+1}^{-1} - I_{n_{k+1}}\mu_{k+1}^T\mathbf{\Sigma}_{k+1}^{-1} \end{pmatrix} \end{aligned} \tag{4}$$

where, $\mathbf{\Sigma}$ is the diagonal matrix of standard deviation and $\Delta\mu_{k+1} = \mu_{k+1} - \mu_k$. Following the same line of reasoning, the recursive estimation of the covariance matrix can be expressed as,

$$\begin{aligned} &\left(\textstyle\sum_{i=1}^{k+1} n_i - 1\right)\mathbf{W}_{k+1} = \mathbf{Y}_{k+1}^T\mathbf{Y}_{k+1} \\ &-\left(\textstyle\sum_{i=1}^{k} n_i - 1\right)\mathbf{\Sigma}_{k+1}^{-1}\mathbf{\Sigma}_k\mathbf{W}_k\mathbf{\Sigma}_k\mathbf{\Sigma}_{k+1}^{-1} \\ &+\textstyle\sum_{i=1}^{k} n_i\mathbf{\Sigma}_{k+1}^{-1}\Delta\mu_{k+1}\Delta\mu_{k+1}^T\mathbf{\Sigma}_{k+1}^{-1} + \mathbf{Y}_{n_{k+1}}^T\mathbf{Y}_{n_{k+1}} \end{aligned} \tag{5}$$

For the current data, which are the EEG responses, the recursive covariance matrix follows only rank one update. In the recursive framework, instead of updating the model entirely, it is updated at every time instant as the new data streams in, therefore reducing the computational complexity. Eq. (5) is then reduced to the following form,

$$\begin{aligned} \mathbf{W}_{k+1} = \; &\tfrac{k}{k+1}\mathbf{\Sigma}_{k+1}^{-1}\mathbf{\Sigma}_k\mathbf{W}_k\mathbf{\Sigma}_k\mathbf{\Sigma}_{k+1}^{-1} \\ &+\mathbf{\Sigma}_{k+1}^{-1}\Delta\mu_{k+1}\Delta\mu_{k+1}^T\mathbf{\Sigma}_{k+1}^{-1} + \tfrac{1}{k+1}\mathbf{Y}_{k+1}\mathbf{Y}_{k+1}^T \end{aligned} \tag{6}$$

Following the mean update from Eq. (3) and covariance update from Eq. (6), the MD (labelled as $D_M(k)$) on the EEG response at k^{th} instant can be evaluated as,

$$\begin{aligned} &D_M(k) = \\ &\sqrt{\begin{aligned} &\Big|(Y_k - \mu_{k-1})^T\Big[\tfrac{1}{(1-\lambda)}\mathbf{W}_{k-1}^{-1} - \tfrac{1}{(1-\lambda)^2}\mathbf{W}_{k-1}^{-1}\mathbf{Y}_k\Big(\tfrac{1}{\lambda}\mathbf{I} \\ &+\tfrac{1}{(1-\lambda)}\mathbf{X}_k^T\mathbf{W}_{k-1}^{-1}\mathbf{Y}_k\Big)^{-1}\mathbf{Y}_k^T\mathbf{W}_{k-1}^{-1}\Big](Y_k - \mu_{k-1})\Big| \end{aligned}} \end{aligned} \tag{7}$$

Apart from distance measure, energy is also calculated and in this study, the energy calculated is mean squared energy and which provides the brain activity information in distinct regions. The energy measurement is a way to quantify the strength of brain activation in specific regions. This is achieved by calculating the mean of the squared amplitudes of the brain reactions within a specific area. This provides an estimate of the total energy of the responses. In brain research, the mean squared energy method is widely employed to measure energy since it gives a squared approximation of the amplitude of the brain response [15]. The energy measurement provides valuable support as an additional approach to the MD, which is another way to quantify brain activation. The MD primarily emphasizes the covariance among responses, while the energy measurement focuses on the quantity of the responses. Both methods can be used to identify regions of brain activation, and they can be used together to provide a more complete picture of brain activity. It can be noted that, the energy measurement is a sensitive method, which means that it can detect even small changes in brain activity. This makes it a valuable tool for research on brain function. Moreover, the energy measurement is a relatively simple method to implement. This makes it a practical tool for use in clinical settings. The traditional mean squared response for different regions of the brain is given by Eq. 8 and is measured in microvolts square seconds,

$$E(r) = \frac{1}{N}\sum_{i=1}^{N}\left(\bar{Y}_i^r\right)^2 \tag{8}$$

In this context, the variable r represents the specific brain region, and $\bar{Y}_i^r$ refers to the brain response that surpasses a predefined threshold associated with region r. Following the similar line of reasoning as the Mahalanobis distance, the recursive measure of energy is necessary for the practical implementation of the algorithm. Towards this, the primary step is to obtain the batch energy measure using first few sample with the help of Eq. 8 towards initialization of the algorithm. Thereafter, the recursive energy measure is calculated as,

$$\mathbf{E}_k = \frac{k-1}{k}\mathbf{E}_k + \frac{1}{k}Y_kY_k^T \tag{9}$$

The brain response used to calculate energy should exceed a threshold value that is based on input from the user. The threshold is different for each subject and each note (swara) for both the ragas. Which implies for the same subject all the notes (swaras) are not evoking same energy. The utilization of this measurement can prove advantageous in detecting significant variations in energy levels within brain responses across different regions. Moreover, it can offer supplementary insights into the dynamics of brain activity when responding to the ICM stimulus.

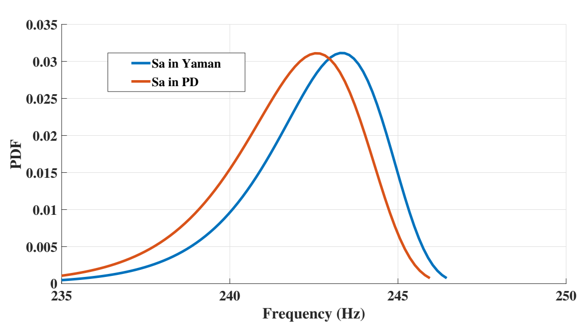

Fig. 2. PDF of Note Sa in both Yaman and PD

III. Results and discussion

From input audio file all the notes (swaras) are identified by listening to the audio file in both ragas. To gain insight into the probabilistic characteristics of the input notes in both ragas, probability density functions (PDFs) are estimated. These PDFs provide an estimation of the likelihood of different notes occurring in the input and help us understand the probabilistic nature of the notes within each raga. The notes in ICM supposed to have fixed frequencies however there will be some change in those frequencies for the same note in different ragas and this can be observed through PDFs. The PDF plots are generated using the Hilbert transform. The Hilbert transform technique is widely used to extract the instantaneous frequencies of a signal by calculating the analytic signal, and which gives the original and its Hilbert transform of the signal. By using this technique the instantaneous frequencies of different notes from both the ragas are obtained and which gives the useful information of audio signal. By using this the PDFs are generated. The

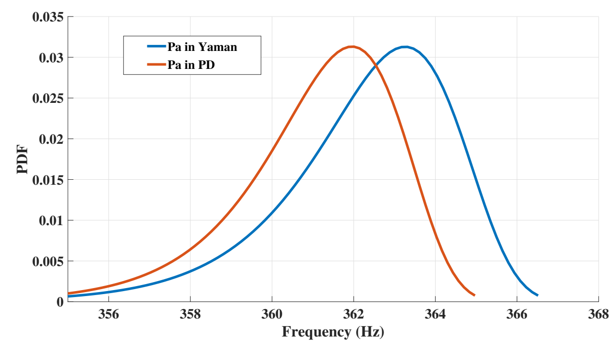

Fig. 3. PDF of Note Pa in both Yaman and PD

Figs. 2, and 3 shows the PDFs of natural notes Sa and Pa because the notes Sa and Pa don't have any counterparts. The PDFs are derived from the amplitude of audio files, which is measured in decibels (dB). The units for these PDFs are given in decibels inverse (dB^{-1}). From the Fig. 2 it is observed that, the frequency of swara Sa in yaman is centered around 244 Hz and the frequency in PD is centered around 242 Hz. The same thing can also be observed for swara Pa also in Fig. 3, the frequency is centered around 364 Hz in Yaman and the frequency is around 362 Hz in PD. Now, the Fig. 4 displays the topographical plots depicting the EEG responses to certain musical notes (swaras) in two different ragas: Yaman and PD. These topographic plots correspond to the alpha band of frequencies. Specifically, Fig. 4 depicts the topo plots of notes 'Dha' and 'Ga' for raga yaman, and the notes 'dha' and 're' for raga PD. Each column in Fig. 4 corresponds to the topo plots of a specific note. The topo plots in Figure 4 correspond to time points a, b, and c, respectively, and represent the EEG response to different notes played in two ragas. It is observed from the figure that the EEG response varies across notes and also between the two ragas. Moreover, the response is not uniform across all subjects even for the same note in the same

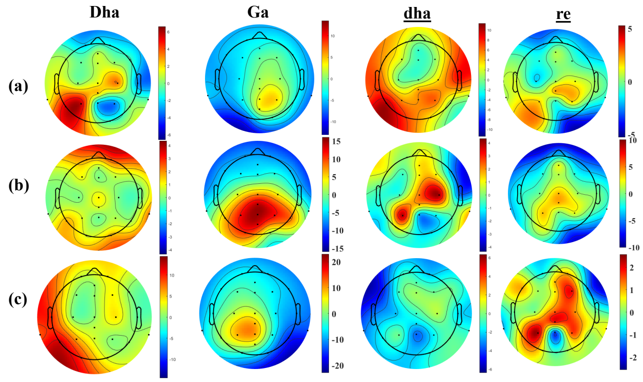

Fig. 4. Topoplots of different notes at different time plots in alpha band for both ragas. The time points are: Dha: 40, 40.5 and, 41 sec, Ga: 34.5, 35 and, 35.8 sec, dha: 106,107 and, 108 sec, re: 65.5, 66 and, 66.5 sec. The different colours in topoplots shows amplitude (microvolts) fluctuations.

raga. Notably, the topo plots reveal that the response changes dynamically from one brain region to another over a short period of time. This suggests that the neural activity associated with processing musical notes is complex and involves the coordinated activity of multiple brain regions. The regions designed in (section II-C) are used to know which region is more active for a particular raga. Figs. 5 and 6 show bar

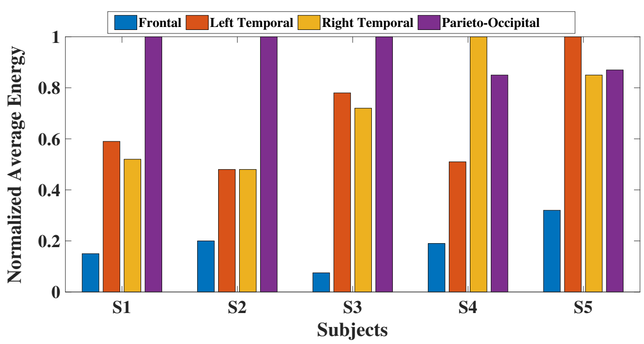

Fig. 5. Averaged Normalized Energy of all the subjects for raga PD. S1, S2,...and 55 represents subject 1, subject 2, ... and, subject 5

plots of the average normalized energies for ragas PD and Yaman, respectively. The plots are arranged by subject and display the average energy level normalized across all subjects. Among the participants, subject 1 had prior knowledge of HCM, while subject 4 had knowledge of carnatic classical music. The remaining participants had no musical background. It is observed that for raga PD from Fig. 5 parieto-occipital region is more evoked for subject 1 and for subject 4 right temporal region is more active. For rest of the subjects also parieto-occipital region is more active. The same thing is observed for raga yaman also in Fig. 6. From Fig. 6 it is observed that subject 1's parieto-occipital region is more active and for subject 4 right temporal response is more. For rest of the subjects also right temporal region is more active. From both the Figs. 5 and 6 it

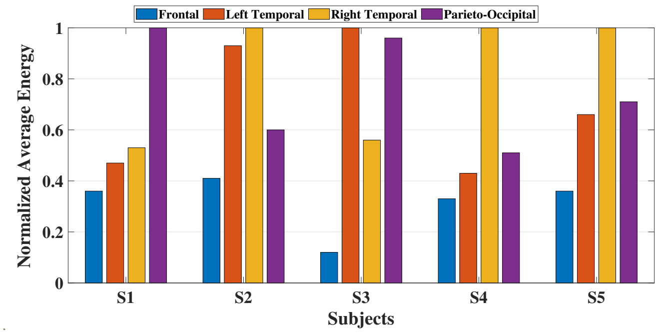

Fig. 6. Averaged Normalized Energy of all the subjects for raga Yaman

is clearly observed that, the volunteers with prior knowledge on ICM, their region of response is not changing for both the ragas and is majorly observed in only one region. For knowledge on HCM subject in both the ragas parieto-occipital region was active and for carnatic musical knowledge person right temporal region was more active. However, for subjects with no musical knowledge on ICM, their response is changing from one region to another region differently for both the ragas. Which is evident that different subjects are processing the music differently. These analysis however are not amenable

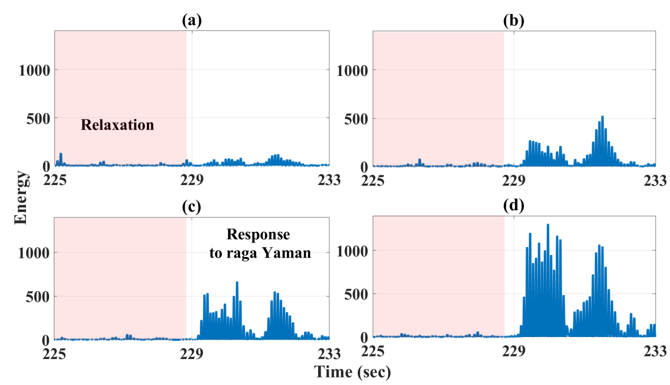

Fig. 7. Recursive energy measure of (a) Frontal, (b) left Temporal, (c) right Temporal and (d) Parieto-Occipital regions for relaxation (225s - 229s) to raga Yaman (229s - 233s)

towards practical implementation owing to their offline nature and require tailoring. To this end, as mentioned in section II-D, the online version of energy measure i.e., recursive mean square and recursive Mahalanobis distance are formulated. In the present work, recursive energy measure provides a mean for detection and quantification of the brain activity in distinct regions. This measure if then corroborated by the recursive Mahalanobis distance which assess the difference in pattern of current state to previous state. This validation is carried out through a case study focusing on the transition of brain activity from a relaxed state to an active state. To accomplish this, a specific 8 second segment of the experiment (225s to 233s) is analyzed. During this segment, the brain is initially in a relaxed

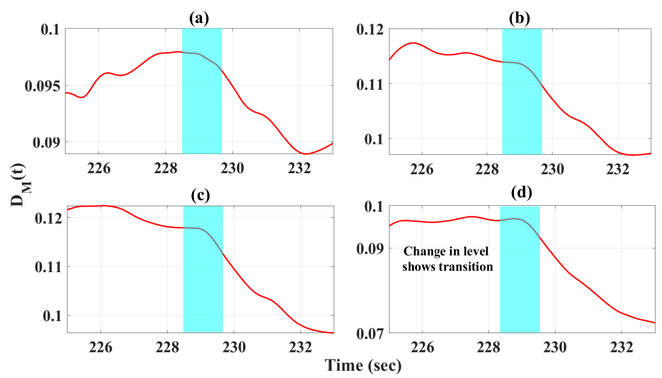

Fig. 8. Recursive Mahalanobis distance of (a) Frontal, (b) left Temporal, (c) right Temporal and (d) Parieto-Occipital regions for relaxation (225s - 229s) to raga Yaman (229s - 233s)

state, and the raga Yaman begins at 229s. Fig. 7 presents the recursive energy measure for relaxation (225s - 229s) to raga Yaman (229s - 233s) of distinct brain regions. It can be clearly observed from the figure that the for the relaxation phase all the regions are relatively less active than that in the melodic phase. The other observation is that the parieto-occipital region (Fig. 7(d)) is more active than other regions. The same can be corroborated from the recursive Mahalanobis distance shown in Fig. 8, where a sudden change in the level of recursive MD at 229s shows the transition of brain response from relax to active state. The results of brain activity detection in an automated framework provides a base towards feedback driven music therapy, where a particular melody can lead to localized activation of the brain.

IV. Conclusion

To conclude, while listening to ICM, the subjects with different prior musical knowledge on ICM showed the activation of different brain regions. For musically trained subjects for both the ragas same brain region is more active however for subjects with no musical training on ICM showed activation of different brain regions for different ragas. Subjects with training on HCM showed more activation of parieto-occipital region and for subject with musical knowledge in carnatic music showed activation of right temporal region. Subjects with no musical knowledge showed activation of right temporal and parieto-occipital region. Furthermore, it is worth noting that the practical implementation of the offline algorithm is not feasible, leading to the formulation of online energy and distance measures. The recursive energy measure effectively detects and quantifies brain activity in distinct regions, while the recursive Mahalanobis distance further assesses the differences in patterns between current and previous states. A qualitative case study is provided to validate the efficacy of the recursive frameworks. These findings provide a foundation for the development of feedback-driven music therapy, enabling the targeted activation of specific brain regions through the use of particular melodies.

V. Author Contribution

SP: Data collection, investigation, methodology, validation, formal analysis, data curation, writing - original, and edited draft. DS: Data collection, investigation, methodology, validation, formal analysis, data curation, writing - original, and edited draft. YM: Conceptualization, data generation. CNG: Conceptualization, supervision, resources, draft review. BH: Writing edited draft, conceptualization, supervision, draft review.

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