EEG Responses for Dhrupad Stimulus: A Case Study

Anand Thyagachandran, Gowriprasad R, Saish Jaiswal, R Aravind and Hema A Murthy Indian Institute of Technology Madras tanand@cse.iitm.ac.in, ee19d702@smail.iitm.ac.in, cs20d405@smail.iitm.ac.in aravind@ee.iitm.ac.in, hema@cse.iitm.ac.in

Abstract—Music possesses the capacity to affect the human brain deeply, weaving together elements like melody, rhythm, timbre, lyrics, and pitch to elicit a wide range of emotional and cognitive responses. This study delves into the impact of Dhrupad, a genre within Indian classical music known for its meditative qualities, on the EEG responses. The EEG data were collected while participants immersed themselves in serene melodies of a Dhrupad alāp performance on the Rudra Veena — a choice made for its gradual and soothing nature. Using 128-channel EEG, the signals from different brain regions are analysed. Multitaper spectrograms are employed to analyse the evolution of mental states. The proposed research reveals consistent patterns in the EEG signals for different levels of attentiveness. Especially, patterns correlate across different attentive subjects and suggest that the responses may be related to cognition.

I. INTRODUCTION

Music, a timeless art form, has captivated humanity for its aesthetic qualities and, notably, its therapeutic potential across diverse musical traditions worldwide [1]. Music's profound impact is recognized even in the earliest stages of life, as research suggests that music appreciation begins during prenatal development [2]. This art form can remarkably influence an individual's temperament and emotional state, a phenomenon well-documented in studies [3]. These investigations not only provide insights into the intricate neuronal connections within the brain but also hold promise for enhancing brain-computer interfaces (BCIs) [4], [5], [6], [7] and could foster innovative technological applications based on brain responses. Electroencephalography (EEG), a non-invasive method to capture brain electrical activity, has emerged as a convenient tool for studying the brain's responses to music. The integration of advanced signal processing and machine learning has bolstered EEG's status as a valuable neuroimaging tool, offering improved spatial and temporal resolution [8]. This technological progress has also spurred the development of cost-effective wireless EEG sensors, particularly beneficial for mobile cognitive monitoring tasks [9], [10].

Recent research suggests that music can impact brain function. For example, Schellenberg and colleagues found that music can boost cognitive performance [11]. Studies exploring the neural underpinnings of music have revealed intriguing insights, such as the brain's ability to anticipate melodic information before it is presented [12]. EEG responses have shown synchronization with musical rhythms, highlighting the connection between gamma activity and rhythm perception



Fig. 1. Data Collection Protocol

[13]. Research on music tempo extraction from EEG signals has emphasised the influence of music on tempo estimation quality [14]. Moreover, brain responses to music entrainment directly align with beat frequency, shedding light on neural synchronization [15]. While some studies have used canonical correlation analysis to examine music's correlation with EEG data [16], [17], research on brain activity patterns during music listening and recognition is still nascent. Deciphering these complex patterns is challenging, compounded by the subjectivity of aesthetic experiences associated with music [18].

Our study ventures into the realm of brain activity when exposed to a carefully crafted, soothing Dhrupad music stimulus. Dhrupad, an ancient Indian Art Music form, remains relatively unexplored through EEG analysis. We chose the slow, nonmetric alap section of a Dhrupad concert for stimulation, known for its meditative qualities [19]. Our main goal is to investigate neural responses to Dhrupad music. To achieve this, we selected excerpts from a rendition of Rag Bilaskhani Todi, Varadani, and Yaman performed instrumentally on Rudra Veena by Ustad Bahauddin Dagar, Zia Mohiuddin Dagar, respectively. A thorough analysis is performed on EEG responses to Bilaskhani Todi, which has an intricate melodic structure and is used in both classical and light music. By opting for instrumental music, we minimize the impact of voice timbre and lyrics. Employing signal processing techniques, our analysis aims to unveil the intricate relationship between Dhrupad music and the human brain's responses.¹

The following sections provide a comprehensive account of our study's methodology and findings. Section II details the

¹A similar analysis has been performed for two other $R\bar{a}gs$, namely Yaman and Varadani. These results are available in the supplementary material.



Fig. 2. Multi-taper Spectrogram depicting spectral evolution showcasing attentiveness based on the α activity.

EEG data collection protocol, including participant selection and data acquisition methods. Section III presents the EEG data analysis results, encompassing the spatial and spectral analyses to uncover the evolving mental states influenced by Dhrupad music. We also discuss interesting EEG response patterns, focusing on distinguishing between attentive and partially attentive listeners. Finally, Section IV offers a concise analysis and discussion of our findings and concludes with insights into the connections between Dhrupad music and the human brain's reactions, throwing light on the intersection of music, cognition, and neuroscience.

II. DATA COLLECTION

Fig. 1 depicts the EEG data collection protocol. EEG data were captured using a 128-channel HydroGel Geodesic Sensor Net (GSN) 130 device with stable 250 Hz sampling, ensuring uniform spatial distribution across the scalp. Continuous monitoring minimized artefacts from voluntary movements. We collected data from 15 subjects for the instrumental rendition of Rāg Bilaskhani Todi as a stimulus. However, the presence of artefacts due to motor movements or electrode placements led to the inclusion of eight subjects (5 males and 3 females) within the final dataset. These participants, aged 18 to 35, were all healthy, with no neurological history. Data collection took place in an anechoic chamber to eliminate external influences. Each session, lasting about 12 minutes, focused on the Rāg Bilaskhani Todi, although we extended our research to include multiple ragas and subjects. The protocol ensured participant comfort, with eyes closed and minimal voluntary movement. Each session began with a 60-second baseline to acclimatize participants before presenting the audio stimulus.

Bilaskhani Todi stimulus is of duration 12 minutes and corresponds to the slow Dhrupad alāp, which primarily is improvised music (or rather unwritten music), generated extemporaneously by the artist, and relates to the nuances of the $R\bar{a}g$. The audio volume gradually rose to a stable 68dB and faded out, followed by a 60-second end baseline. Our study



Fig. 3. Evolution of sub-band power computed over α and δ regions

included 19 sessions across eight subjects, some of whom are avid listeners of Indian classical music, resulting in around 228 minutes of EEG recordings (5 subjects with 2 sessions and 3 subjects with 3 sessions). Ethical approval was obtained from the Institute Ethics Committee. The data acquired during this study will be made publicly available for research purposes upon request, further contributing to the scientific community's understanding of the neural responses to Dhrupad music.

III. ANALYSIS

A. Spatial Analysis

Different parts of the brain are responsible for various tasks [20]. For instance, the frontal lobe is associated with reasoning, motor abilities, higher-level cognition, and expressive language [21], [22], while the occipital lobe analyses visual stimuli. The temporal lobe is responsible for processing audio information, whereas the parietal lobe is responsible for language comprehension, sound interpretation, and speech perception [20], [23]. This study primarily focused on the temporal and parietal lobes owing to the use of music stimulus.



Fig. 4. DTW Paths, represented as different coloured lines, between pairs of independent sessions for AL and PAL

A systematic approach is adopted to extract meaningful insights from the 128-channel EEG data. Representative signals for each brain lobe are obtained by averaging the channels corresponding to the respective lobes to suppress the noise in individual channels (for detailed methodology, please refer to the supplementary material: supplementary material). This comprehensive approach allowed us to dissect and understand the nuanced neural responses to meditative Dhrupad music stimulus. The original objective of this study was to relate the EEG responses to the musical content, as done in [20], where responses were correlated with syllables in speech, where it was shown that syllables in speech had consistent signatures across subjects. Similar to speech, music consists of a sequence of notes, where a note has an onset, attack, and decay similar to that of a syllable in speech. Unfortunately, consistent annotation is unavailable for the stimulus provided owing to the extensive use of ornamentations called gamakas² in Dhrupad. Nevertheless, consistency in cognitive signatures across attentive listeners to the music is established, suggesting that further analysis may lead to the presence of atoms of music, similar to syllables as the fundamental units of cognition in speech.

B. Spectral Analysis

EEG signal is defined by rhythmic patterns in oscillatory bands like delta δ (0-4Hz), theta θ (4-8Hz), alpha α (8-12Hz), beta β (12-30Hz), and gamma γ (30-120Hz)[24], [25]. This study focuses on the α and δ sub-bands as α subband energy reflects calm attentiveness, while increased δ subband energy may indicate drowsiness [25], [26].

Short-term spectral analysis using Multi-taper Spectrograms (MTS) [27] is performed to uncover the evolving EEG responses to the Dhrupad music stimulus as shown in Fig. 2. MTS multiplies the signal by orthogonal taper windows, generating independent projections. These projections are then averaged to create the final spectrum, reducing variance. For the slow-paced Dhrupad music, the following MTS parameters were used: a 5-second window length (1250 samples, 1-second shift), resulting in 2 Hz spectral resolution, with nine tapers (default MATLAB parameters). MTS provides a better spectral resolution for different sub-bands. α and δ sub-band

²this refers to ornamentation used in Indian Art Music which involves a significant variation in the pitch which could be both glides and oscillations



Fig. 5. Evolution of total power computed over α and δ sub-bands

energies are assessed to categorize subjects into attentive and partially attentive listeners (ALs and PALs). Higher α subband energies are indicative of attention, which aligns with prior research on EEG patterns during different wakefulness states [26], [28].

In addition, brain dynamics are visualized with the α and δ sub-band powers, computed using power spectral densities (PSD), for the parietal region, as shown in Fig. 3. A higher magnitude with consistent δ sub-band power is observed in PALs, indicating reduced attention, while a lower magnitude and more varying δ power is displayed by ALs, signifying alertness. In terms of α power, PALs consistently had lower levels with less variability, while ALs had higher α power. An insightful observation in Fig. 3 is a decline in α and an increase in δ power beyond the 300-second mark in both ALs and PALs. This could be due to factors like listener fatigue or individual differences in attention span. Further investigation is needed to understand the exact reasons behind this trend.

C. DTW-based Correlation Analysis

Following the observation of spectral dynamics, our aim is to investigate the presence of correlations across different sessions and subjects for both ALs and PALs. In the literature, Dynamic Time Warping (DTW) is a widely used technique for assessing similarities between temporal sequences [29]. We apply DTW to evaluate intra- and inter-subject correlations across sessions using α sub-band energy features. The results are depicted in Fig. 4. Initially, we select a representative listener from both ALs and PALs and perform intra-subject DTW analysis across sessions (Fig. 4 (A) and (B), respectively). Each of the subjects was presented the same stimulus in three different sessions. In the case of ALs, DTW paths closely



Fig. 6. Evolution of DTW paths' Mean and Variance for ALs and PALs

align with the diagonal for intra-subject sessions, whereas PALs exhibit paths that deviate significantly from the diagonal. Furthermore, we perform inter-subject, inter-session DTW on all subjects' data for both ALs and PALs (Fig. 4 (C) and (D), respectively). A similar trend is observed for inter-subject sessions as well. ALs demonstrate a high correlation in α activity across sessions, while PALs exhibit more deviated DTW paths, indicating a lower correlation in their neural responses.

Building upon these findings, we sought to understand why PALs displayed greater DTW path deviations. We speculated that the relative decrease in α power might be a contributing factor, as observed in Fig. 3. To investigate further, we computed DTW costs for the initial 300 seconds and the entire session (Fig. 5). For the initial 300 seconds, the DTW costs for both ALs and PALs are similar with larger deviations in the case of PALs. However, over the complete session, the costs for ALs are notably lower than those for PALs. Additionally, PALs exhibit higher variance in DTW costs compared to ALs in both cases. A similar deviation was consistently observed across stimuli of other $R\bar{a}gs$ too. Interestingly, the presence of diagonals in the DTW plots for both ALs and PALs, without exception up to 5 minutes, suggests that the music may lead to similar cognitive patterns across subjects, depicting a universality in the stimulus. This could be culture-specific too, since all the participants were from the Indian subcontinent.

The path correlation across subjects from the AL category for the stimulus could perhaps lead to an understanding of the music, leading to atoms of music, which could relate to notes or phrases. Since Indian music does not have a score, the required ground truth is absent.

To visualize the evolution of DTW path deviations from the diagonal over time across ALs and PALs, we employed varplots as shown in Fig. 6. These plots reveal that up to the 300-second mark, the DTW paths for both ALs and PALs maintained minimal deviations from the diagonal. Beyond this point, there was a pronounced increase in path deviation, both in terms of mean and variance, for PALs. In contrast, ALs consistently exhibited lower path deviations throughout the session.

IV. DISCUSSION AND CONCLUSION

This study offers valuable insights into the relationship between Dhrupad music and the human brain's responses, particularly in the context of EEG data analysis. By delving into the EEG responses of individuals exposed to the meditative qualities of Dhrupad music, some interesting patterns in neural responses are observed.

The sub-band energy analysis, focusing on the δ and α subbands, unveils fascinating temporal dynamics. Higher energy levels in the α sub-band consistently correlate with a calm and attentive state. This observation aligns with existing research on EEG patterns during different states of wakefulness, further affirming the sensitivity of EEG measures to cognitive states.

DTW analysis further enriches our understanding of EEG responses. Notably, attentive listeners (ALs) exhibit highly correlated α activity across different sessions and across subjects, suggesting remarkable consistency in their responses to the musical stimulus. Conversely, partially attentive listeners (PALs) display less consistent α activity, reflecting variations in attentiveness across sessions. Even though the number of attentive subjects is small, more or less identical cognitive responses are seen across sessions for ALs, while the responses are quite random across PALs. This finding underscores the impact of individual attentiveness levels on EEG responses, emphasizing the need for nuanced analyses when interpreting music-induced brain dynamics.

The study's insights have broader implications, potentially extending to therapeutic and cognitive domains. Understanding how music modulates brain activity can inform the development of music-based interventions for various cognitive states and emotional well-being. In particular, the cognitive patterns of music and its relationship to the stimulus (notes, phrases) could be a useful direction of study. Our study provides preliminary analyses for future research to delve deeper into how music influences cognitive responses, as indicated by EEG data. As a part of future study, we aim to expand our analysis with a larger group of participants and to apply thorough statistical analysis to confirm our findings. Additionally, revisiting our approach to interpreting alpha and delta brainwaves with an expanded set of subjects with appropriate controls will enhance our understanding of attention in relation to music. Exploring how listening to music compares to other cognitive tasks can further uncover the specific impacts of music on attention and relaxation. Careful data preprocessing and applying proper statistical methods will ensure the reliability of our results and contribute significantly to this field of study.

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