# Characterization of functional brain networks and emotional centers using the complex networks techniques

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**Abstract.** The study of complex systems such as brain, using Network science framework has offered deep insights into its structural and functional organization. In this work, we construct functional networks of the human brain using the coherence measure on the EEG time series data, in response to external audio-visual stimuli. These stimuli were nine different movie clips selected to evoke different emotional states. The constructed networks for each emotion were characterised using network measures such as clustering coefficient, small worldness, efficiency of information propagation, etc. in different frequency bands corresponding to brain waves. We used a community detection algorithm to infer segregation of functional correlations in the brain into modules. Further, using the variation of information measure, we compare and contrast the modular organizations of different brain networks. We observe that the different brain networks are closest in their organization into modules in alpha frequency band while they farther apart in other bands. We identified crucial network nodes or hubs using centrality measure, and find that most of the hubs were common for all networks and belong to specific location on the brain map. We also find that functional connectivity is suppressed in high-frequency wave bands such as beta and gamma and vice-versa. In summary, our work demonstrates utilization of the network theoretical and statistical tools for understanding and differentiating different brain networks corresponding to perception of varieties of emotional stimuli.

**Keywords:** Brain networks, Functional Connectivity, Modular Organization, Hubs

## Introduction

In the recent years, analysis of brain networks constructed from EEG and advanced brain imaging techniques has contributed to the understanding of the complex structure and functioning of the human brain [(9;45)] and has given clues to understanding its higher cognitive exhibits such as emotions and reasoning abilities [(30;40;32)]. The functional brain networks studies have given credible evidence against the locationist approach of functional segregation of brain regions, in favour of constructionist approach where different emotions involve brain circuits comprising of brain areas not specific to a particular emotion [(31;40;41)]. Emotional stimuli affect large scale functional brain networks which can be evaluated in terms of parameters such as node betweenness and network efficiency [(42)]. The human brain can be decomposed into multiple, distinct, and interacting networks such as salience network, executive control network and task negative network, and emotional stimuli can differentially affect these subnetworks [(51;42;32)]. For example, strong changes in salience networks have been reported during watching an aversive movie segment as compared to watching a neutral movie segment through fMRI studies [(24)].

Studies on emotion, based on the analysis of single-electrode level EEG in the frequency domain have demonstrated the association of emotion with asymmetric activity in the frontal brain in alpha band. It has also been demonstrated that different patterns of functional connectivity are associated with different emotional states in either single or combined frequency bands ascertaining distinct response patterns of the central nervous system to different emotional stimuli [(30)].

In previous studies on classifying emotions, researchers have largely focused only on a few contrasting dimensions such as threat-safe, sadness-happiness, positive-negative-neutral and with a small number of recording sites of EEG activity [(35;13;30)]. Also, the film-based studies on emotions and functional response of brain has been previously carried out primarily based on the western classification of emotions which are happiness, sadness, fear, anger, surprise, disgust [(14;15)]. However, audio-visual stimuli such as film viewing are capable of evoking sentiments which might be due to the interplay of the basic emotions (dominant states), and transitory and temperamental states

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of emotions. In a recent study [10], authors reported the existence of 27 different emotional experiences based on reports of emotional states elicited by a large number of emotionally evocative videos. Many of these emotional experiences were not discrete but were linked to each other through a smooth gradient.

In this paper, we aim to use tools from network theory to explore any consitent patterns or differences in brain network structures when participants are evoked with various emotional stimuli. The nine dimensions of emotions studied here correspond to the sentiments or *Rasa*'s described in the *Natyasastra* evoked through audio-visual stimuli such as performing arts (here movie clips) [18]. The *Rasas* can be understood as a superposition of basic emotional states (see methods for details) such as anger, disgust, fear, happiness, sadness, and surprise as described by Ekman [15].

We have analysed the patterns of brain activity and examined whether these activities show specific neural signatures in viewers, in different frequency bands corresponding to the brainwaves [48]. Different network measures were used to characterize the structural and functional differences among these emotional states. Modular organization of functional connectivity of the brain for different *Rasas* networks were extracted using community detection algorithms. These networks were then compared using information flow measure to quantify the difference between the their modular organizations, across all frequency bands. Central nodes for information propagation were identified using the leverage centrality measure for each of the networks, enabling us to find the most significant nodes for emotion perception and segregate designated areas for processing of a particular emotion. The current work, though relates to *Rasa* theory and emotional states, it offers a generic approach to characterizing brain networks (corresponding to different tasks), and in different frequency wavebands.

## Data and Methods

Prior to conducting EEG experiments, ethical clearance was taken from the Institute Ethical Committee (IEC) of Indian Institute of Technology Gandhinagar. Informed consent was obtained from all the participants before conducting experiments.

### Subjects

Participants were 20 healthy, right-handed students from Indian Institute of Technology Gandhinagar (mean age: 26 years, 16 males; 4 females). All of the participants were proficient in Hindi and English languages. They were all informed about the task and were asked to remain attentive while watching the film clip. An independent ranking of many movie clips corresponding to each category of emotion was done by on small number or subjects. Only those clips were selected which were ranked best suited to evoke a particular response for all the categories.

### *Rasa* and *Natyasastra*: A background

A major source of the Indian system of classification of emotional states comes from the '*Natyasastra*' [50], the ancient Indian treatise on the performing arts, which dates back to 2nd Century AD (pg. LXXXVI: [18]). The '*Natyasastra*' speaks about 'sentiments' or '*Rasas*' (pg.102: [18]) which are produced when certain 'dominant states' (*sthayi bhava*), 'transitory states' (*vyabhicari bhava*) and 'temperamental states' (*sattvika bhava*) of emotions come together (pgs.102, 105: [18]). This *Rasa* theory, which is still widely followed in classical Indian performing arts, classifies eight *Rasas* or sentiments which are: *Sringara* (erotic), *Hasya* (comic), *Karuna* (pathetic), *Raudra* (furious), *Veera* (heroic), *Bhayanaka* (terrible), *Bibhatsa* (odious) and *Adbhuta* (marvelous). There was a later addition of the ninth sentiment or *Rasa* called *Santa* (peace) in later Sanskrit poetics (pg.102: [18]).

We drew inspiration from this classification system and selected movie clips corresponding to each of the nine *Rasas*. Please note that, as there are no standard movie clips for this classification system, our selection of movies is one possible set and is not stringent in any manner.

### Western emotional classification and *Rasa* theory

According to Western version of emotion classification by Ekman, there are basic or universal emotions [16;14], [15] which are happiness, sadness, fear, anger, surprise, disgust. However, there are also background emotion sets which are: wellbeing-malaise; calm-tense; pain-pleasure; [11] as well as self-referential social emotions which are: embarrassment, guilt, shame, jealousy, envy, empathy, pride, admiration. [36;6;12;20;29;47]. Also, there are pioneering works of scientists like Lisa Feldman Barrett [2] who questions Ekman's concepts of discreteness of emotions.

One can find startling similarities between the *Rasa* theory (its concepts of the generation of *Rasa*s from the Bhavas) with the works of Panksepp and Kagan [38;37;27;39]. However, there had been very little previous work done on the perception or brain science of emotional states based on *Rasa* theory mostly due to the lack of awareness regarding the science of the *Rasa* theory among the scientific community. One behavioural study was conducted by Hejmadi [23], which investigated the identification of these emotions across cultures. An image processing study was conducted in Ref. [46] for investigating the variations in facial features based on nine *Rasas*.

This study proposes a tool for the design of intelligent emotion recognition system but does not offer a psychophysical or brain-based perspective on how these individual emotions differ in the way they affect our perceptual process. There have been no brain-imaging based works on *Rasa*-theory comparable with similar works done on emotions based on Western literature. We recorded (through EEG) from participants, the patterns of brain activity generated while watching nine different emotional film clips categorized based on Indian *Rasa* theory. We then use tools from network theory and attempt to find out, whether these activities would show specific neural signatures across viewers.

### Movie Clips

Complex, naturalistic stimuli like film-viewing evoke highly reliable brain activity across viewers as per current research works [21]. In this work, we used nine film clips from Bollywood films (popular Indian Hindi language cinema) made between 1970's to the current time (see Table 1). Independent rating of the movies was done on a small number of subjects. The length of the movie clips varied from 42s to 2 mins 37s. Length of the film segments were not kept constant since the clips included a flow of narrative which was necessary to be shown till a certain length of time (different for each segment) to evoke a specific Rasa.

| ***Rasa* genre** | **Film name** | **Director** | **Year** | **Duration** | **Start time** | **End time** |
|---|---|---|---|---|---|---|
| *Adbhuta* | Mr. India | Shekhar Kapur | 1987 | 1m 48 s | 1 h 1 m 40 s | 1 h 3m 28 s |
| *Bhayanka* | Bhoot | Ram Gopal Varma | 2003 | 1 m 34 s | 1 h 2 m 57 s | 1 h 4 m 31 s |
| *Bibhatsa* | Rakhta Charitra | Ram Gopal Varma | 2010 | 1 m 12 s | 43 m 55s | 45 m 7 s |
| *Hasya* | 3 Idiots | Rajkumar Hirani | 2009 | 2m 33 s | 59m 55s | 1 h 2 m 28 s |
| *Karuna* | Kal Ho Naa Ho | Nikhil Advani | 2003 | 2 m 37 s | 2 h 47m 41 s | 2 h 50 m 18 s |
| *Raudra* | Ghajini | A.R. Murugadoss | 2008 | 2m 9 s | 2 h 38 m 43 s | 2 h 40 m 52 s |
| *Santa* | Zindagi Na Milegi Dobara | Zoya Akhtar | 2011 | 2 m 22 s | 48m 22 s | 50 m 44 s |
| *Sringara* | Umrao Jaan | Muzaffar Ali | 1981 | 42 s | 43m 08 s | 43 m 50 s |
| *Veera* | Lagaan | Ashutosh Gowariker | 2001 | 2 m 3 s | 2 h 10 m 57s | 2 h 13 m |

Table 1: Table for the movie clips corresponding to each emotion

### EEG Experimental Procedure

We conducted the EEG experiment on the participants during which they were asked to watch chosen film clips representative of nine different *Rasa* Genres. The electrical activity of the brain was recorded using 128 channel high-density Geodesic EEG Systems$^{TM}$ with a sampling frequency of 250Hz. A representative diagram of the node placement (along with node numbers from 1 to 128) used in the present work for brain network visualization, is shown in Fig. 2 (a). The figure also depicts the electrode allocations to anatomical regions of the brain. The following abbreviations are used: F, P, O and T stand for Frontal, Parietal, Occipital and Temporal lobes; L and R represent Left and Right regions.

The participants were shown all the film clips in random order. A white fixation cross with a black screen for ten secs was shown before each clip. Initial few seconds of the time series recordings were neglected before analysis to avoid major fluctuations due to adjustment. Signals beyond 60 Hz frequencies were filtered out to avoid noise effects. The design of the experiment was done in E-prime$^{TM}$ and synced with Net-station$^{TM}$ acquisition software. The entire study on the collected data from the EEG experiment is summarised in Fig. 2(b).

## Construction of Brain Network

Standard time series analysis measures such as Coherence [8], Phase Synchronization [52], Mutual Information [44], and Granger Causality [25] offer a huge depth into understanding the synchrony and information propagation in the

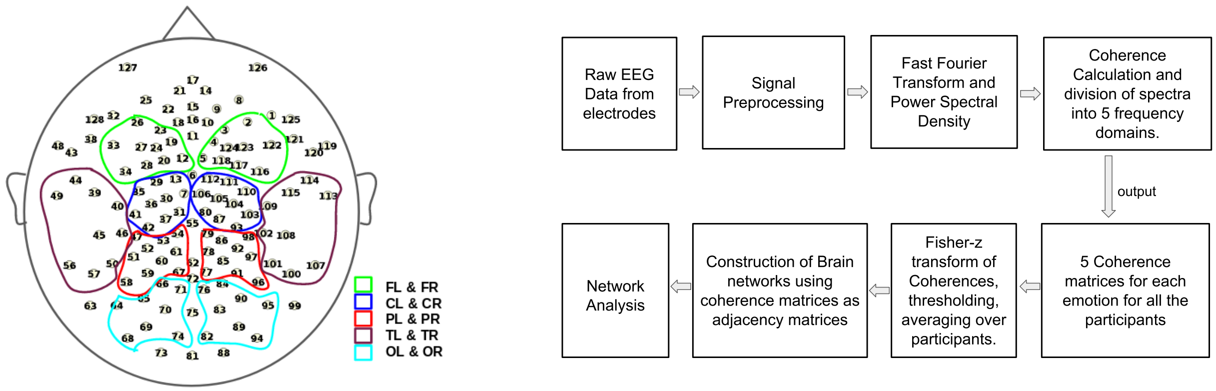



Fig. 2: (a) A brain map of the electrode positions of the EEG cap. All the Brain networks and extracted communities in the present work follow this Node placement. (b) Workflow structure governing EEG data recording, pre-processing, network construction and analysis.

functional brain. We use Electroencephalographic Coherence that is used as a metric for deriving functional brain connectivity i.e. the degree of association between any two brain regions (whose electrical activity is recorded by electrodes in the signal space). Holding values between 0 (nil coherence) and 1 (complete coherence), it compares similarity of the power spectra (measured in microvolts squared, $\mu V^2$ ) of the time-series recorded by these electrodes. The regions showing highest coherence are assumed to be the most synchronized functionally and vice-versa. The coherence measure (Eq. 1) between two time series $X$ and $Y$ is defined as,

$$C_{XY}(f) = \frac{|G_{XY}(f)|^2}{|G_{XX}(f)G_{YY}(f))|}, \tag{1}$$

where $G_{XY}(f)$ is the cross-power spectral density and $G_{XX}(f)$ and $G_{YY}(f)$ are the respective auto-power spectral densities[(49)].

The time series data (recorded by the electrodes, in microvolts, $\mu$V) was transformed to frequency domain via Fast Fourier Transform (FFT) and the power in different frequency bands[(48)]: $\delta$ (1-4 Hz), $\theta$ (4 - 8 Hz), $\alpha$ (8 - 12 Hz), $\beta$ (12 - 40 Hz) and $\gamma$ (40 - 60 Hz), corresponding to different brain waves was calculated. The coherence spectra, thus decomposed into five frequency bands resulted in five ($128 \times 128$) coherence matrices and these were obtained for each of the nine stimuli. The frequency decomposition of the spectrum was crucial to estimating the power in each of the bands, capturing the brain state. Apart from powers in individual bands, we also used average coherence across the whole spectrum in the analysis. The coherence matrix was mapped to a weighted adjacency matrix, and the corresponding brain network was constructed with $N = 128$ nodes. In this network, the nodes are the electrode locations on the scalp and edges are connections between them measured by the coherence values. For the overall networks construction in each frequency band, corresponding to each *Rasa*, the edges weights (coherences) representing functional correlations are Fischer Z-transformed and then averaged over all the participants. Thus, a total of 45 ($9 \times 5$) weights networks were constructed, where weighted edges represent the strength of coherences between the nodes.

## Brain Network Characterization

Functional properties of complex networks are largely determined by the statistical properties of its structure. We have calculated six well-known network measures on the networks: Clustering Coefficient ($CC$), Characteristic Path Length ($L$), Network Density ($d$), Local and Global efficiency ($LE, GE$), and Small-worldness index ($SW$) using Area Under Curve[(3)] method. In the AUC procedure, two cutoffs (one upper and one lower) on the edge strengths, are consistently determined for each network, such that a range of important connections are retained, and only important network structure is dealt with. The upper bound in this threshold range, $\kappa_+$, is an edge weight at which network is fully connected and the lower bound, $\kappa_-$ is the threshold at which the network just gets disconnected. The network is binarised at each threshold within this range, retaining only edges with weights larger than the threshold value and eliminating the remaining ones and network metric ($M$) is evaluated at each connection density. This

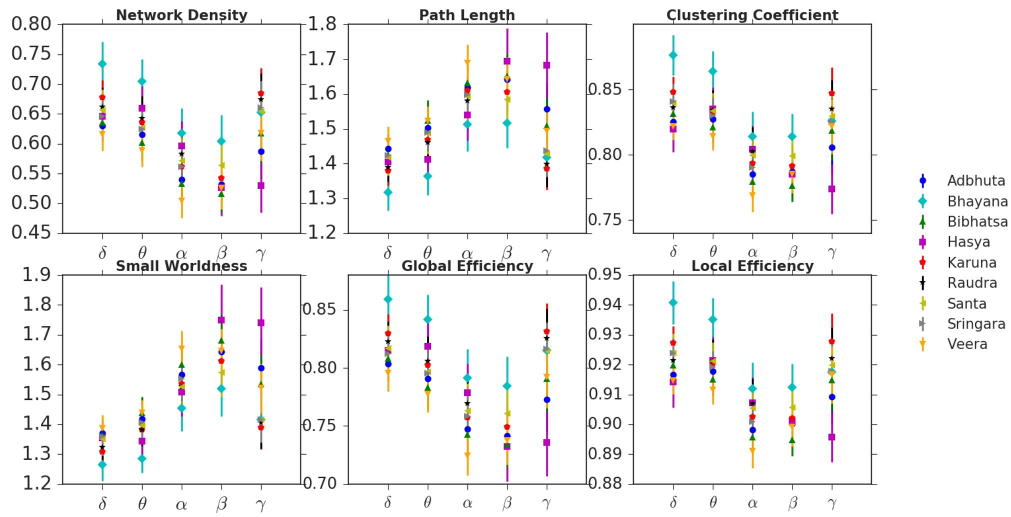



Fig. 3: Network measures Network Density (d), Path Length (L), Clustering Coefficient (CC) , Small Worldness , Global Efficiency (GE), and Local Efficiency (LE) (see text for details) of brain networks corresponding to different *Rasas* across the five frequency bands ($\delta, \theta, \alpha, \beta$ and $\gamma$) along with their error bars.

results in a curve showing the variation of $M$ with edge weights lying in the threshold range. The curve was then integrated over all these thresholds to yield the AUC value of the metric $M$.

In Fig. 3, we plot the six aforementioned measures for all the *Rasas* networks across all frequency bands. Network density (d) for all the networks has values $d > 0.45$, indicating that they are dense. Average shortest path length lies between 1.2 to 1.8, indicating the ease of information propagation. Network density decreases monotonically with increasing frequency in different bands, except in the gamma band - where it switches to higher values than its previous frequency band (beta). Conversely, we see a rise in path length values with increasing frequency, until the beta band, after which it drops in gamma band. Clustering coefficient for all networks shows small variations from 0.75 to 0.9. Gamma band has greater spread (over different networks) in the network metrics than all other bands. *Veera* and *Bhayanaka* networks shows the maximum difference across $\delta, \theta, \alpha$, and $\beta$ bands. SW is greater than one for all *Rasas*, indicating deviation from randomness as well as absolute regularity of connections as in the brain. Global efficiency of the networks is high - ranging from 0.7 to 0.87. Local efficiency is even higher- 0.88 to 0.95, indicating high robustness to the failure of nodes. The trend (increase or decrease of network measures with frequency) is flipped at high frequency i.e in the $\gamma$ band. This is seen for all the *Rasas* and for each network metric, suggesting a dynamic reorganisation of structure at high frequency. in other words, the information flow at gamma frequency requires a special structural organisation of networks, quite different from the one at just lower frequency band.

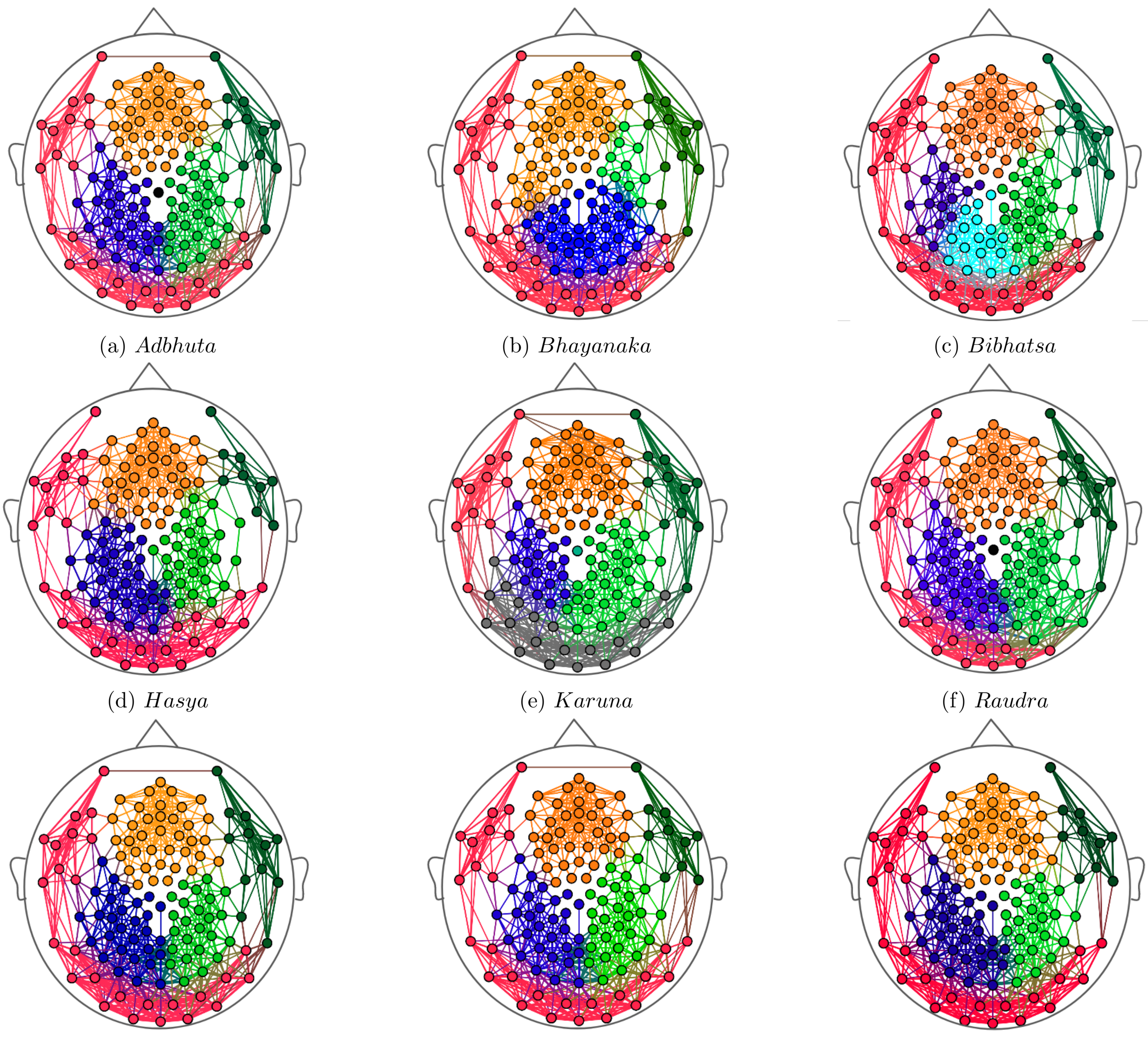
## Results of Network Analysis

Network analysis of the functional networks performed in the present study consists of five elements as explained in the following sections.

### Community Structure

Quantitative analysis of brain using complex networks measures has revealed the presence of highly connected hubs and significant modular architecture [1], apart from showing small-worldness. Modules are functionally specialised and spatially localised groups of nodes that function together in unison to integrate the information globally that they process locally.

In Fig. 4, we show community structure of brain networks corresponding to all the *Rasas*. Note that the networks show only top 10% of the edges. This was done for better visualization, as the unthresholded network is fully connected and hence very dense. The community structure was extracted using an algorithm based on the modularity optimization, in Gephi [5]. All the networks had modularity value, $Q \geq 0.58$, and had five to six communities in each case. Broadly, the community structure appears to be similar across all networks, with one major community in the frontal lobes (C1), two in the left and right hemisphere's central/parietal brain regions (C2, C3), one that encompasses a large area in the visual cortex in the occipital areas (C4) and two other smaller communities along the left and right temporal regions (C5, C6). The *Bibhatsa Rasa* shows split of the community in the parietal lobe. The communities C4 and C5 are merged into one for most of the graphs.



(a) *Adbhuta* (b) *Bhayanaka* (c) *Bibhatsa*

(d) *Hasya* (e) *Karuna* (f) *Raudra*

(g) *Santa* (h) *Sringara* (i) *Veera*

Fig. 4: Brain Networks for various *Rasas* with 10 per cent highest edge weight edges, organised into clear community structure. For all the *Rasas* the network is dissociated into 5 to 6 communities. One can notice the changes in the community structure from this figure, while there are a few clear communities consistently present across all the networks. The modularity value for network partition was above 0.5 for all the *Rasas*, depicting highly modular structure at the level of strongest connections in the network.

For visualisation of dominant communities in the brain networks of all the *Rasas*, we used Gephi software which utilises a modularity optimisation algorithm [7] for detection of communities from the brain networks and Geolayout scheme for node positioning.

### Distance between Networks

To compare the similarities and differences in the network's modular organization (community structure), we used the Variation of Information (VI) measure [28] (See Eq. 2). The VI measure (defined below) signifies the difference in the modular organisation of the networks, summarising the differences in segregation of coherences between nodes. For calculation of VI measure, the community structure on the overall networks was evaluated using best partition routine of python library community [19].

Between two network partitions $X$ and $Y$, the $VI$ is defined in terms of the conditional entropy as below:

$$VI(X,Y) = H(X/Y) + H(Y/X). \tag{2}$$

The conditional entropy $H(X/Y)$ of partition $X$ given $Y$, with $M_x$ and $M_y$ modules can be computed as :

$$H(X/Y) = -\sum_{i=1}^{M_x}\sum_{j=1}^{M_y} p(x_i, y_i) \log p(x_i/y_j), \tag{3}$$

where $p(x_i, y_j) = n_{ij}/N$ is the joint probability of randomly selecting a node that belongs to modules $X_i$ and $Y_j$ and $p(X_i|Y_j) = n_{ij}/b_j$ is the conditional probability that a node belongs to module $X_i$ in partition $X$, given that it is in module $Y_j$ in partition $Y$, and $b_j$ is the number of nodes in community $Y_j$ of partition $Y$. $n_{ij}$ is the number of nodes that are simultaneously present in module $X_i$ and $Y_j$.

In Fig. 5, we show the VI measure based distance matrices for all *Rasas* networks' modular organization in different frequency bands. Networks that are farthest from each other are shown in brighter cell colour ($VI \simeq 0.5$), and those which are closest are shaded dark ($VI \simeq 0.0$). Six VI measure matrices were obtained - one corresponding to overall spectrum and five other corresponding to each of frequency bands (see Fig. 5). It can be seen that alpha frequency band shows maximum similarity in modular organization of all the brain networks.

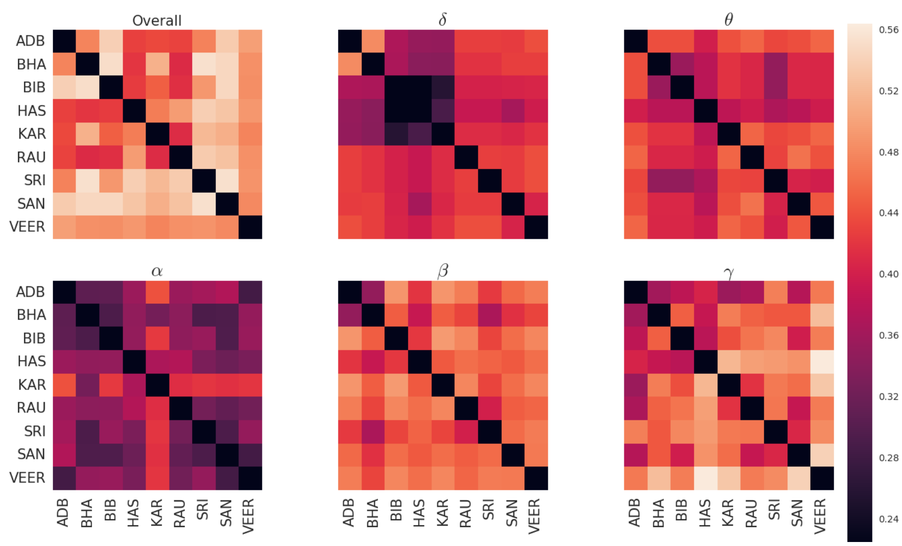



Fig. 5: Variation of Information (Eq. 2) matrices for various *Rasas* in different frequency bands arranged in order **overall,** $\delta$**,** $\theta$**,** $\alpha$**,** $\beta$ **and** $\gamma$, from left to right and top to bottom. It can be seen that *Rasas* have more similar modular organization in $\delta$ and $\alpha$ bands than in $\theta$, $\beta$ and $\gamma$ bands.

For all the pairs of *Rasas* networks, the VI falls in the range 0.22 to 0.56. The colour bar (common for all matrices) range is chosen to represent the maximum variation in VI. We observe that, for the full network, the dynamic range of VI variation is much small, hence we cannot infer much about the similarity or dissimilarity of different network organizations. In the lowest frequency $\delta$ band - *Bibhatsa*, *Hasya* and *Karuna* networks are closest to each other. Maximum distance is between *Adbhuta* and *Bhayanka* networks. For $\theta$ band- *Bhayanaka*, *Bibhatsa* , *Sringara* networks are relatively closest. Others are far from each other. The $\alpha$ band is the most distinctive frequency band where all the *Rasas* are much closer to each other (except the *Karuna* network). The $\alpha$ band activity for all the networks, except *Karuna* seems indistinguishable from each other. For $\beta$ band, the pairs *Adbhuta* and *Bhayanaka* and *Raudra*, and *Sringara* are the closest to each other, and *Hasya* and *Adbhuta* are the farthest. In the $\gamma$ band, *Veera* network is farthest from *Santa*, *Hasya* and *Bhayanaka* network. *Adbhuta* is much closer to *Bhayanaka* and *Karuna* networks.

### Hub Identification

For brain networks, work by Joyce *et al.* suggests that Leverage centrality [26] is computationally cheaper and more accurate for identifying hubs than other centrality measures (as revealed by their Receiver Operating Characteristic curves). Leverage centrality also incorporates information about local node neighbourhood, such that a node with high positive leverage centrality is more impactful to its neighbours so that its neighbours draw more information from it than any other nodes in their neighbourhood. In contrast, a negative leverage centrality node is influenced more by its neighbours than being an influencer node. In the present study, we designate central nodes as nodes with the largest positive and negative leverage centralities.

Leverage centrality (defined in Eq. 4),

$$l_v = \frac{1}{k_v} \sum_{N_v} \frac{k_v - k_w}{k_v + k_w} \tag{4}$$

measures the relationship between the degree of a vertex $k_v$ and the degree of each of its neighbors $k_w$, averaging over all the neighbors $N_v$. For the weighted network, as in our case, degrees are weighted degrees.

In Fig. 6, are shown a brain map with coloured nodes having the highest (top 12) positive and highest negative (top 12) leverage centralities. Colour coding is based on the *Rasas* as shown in the figure. Nodes shown in pink are consistently central across all the *Rasas*. For the positive centrality case, they all lie in the periphery of the brain map, mostly in the parietal brain regions indicating that most important information relay centres for the perception of emotions are located at the parietal regions of the brain. The central nodes with most negative leverage centralities are in the frontal and central brain regions demonstrating that nodes drawing maximum information from their neighbours are in these regions.

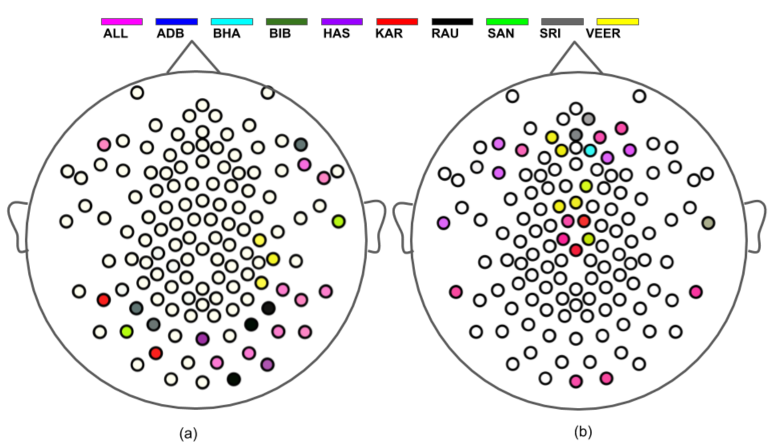
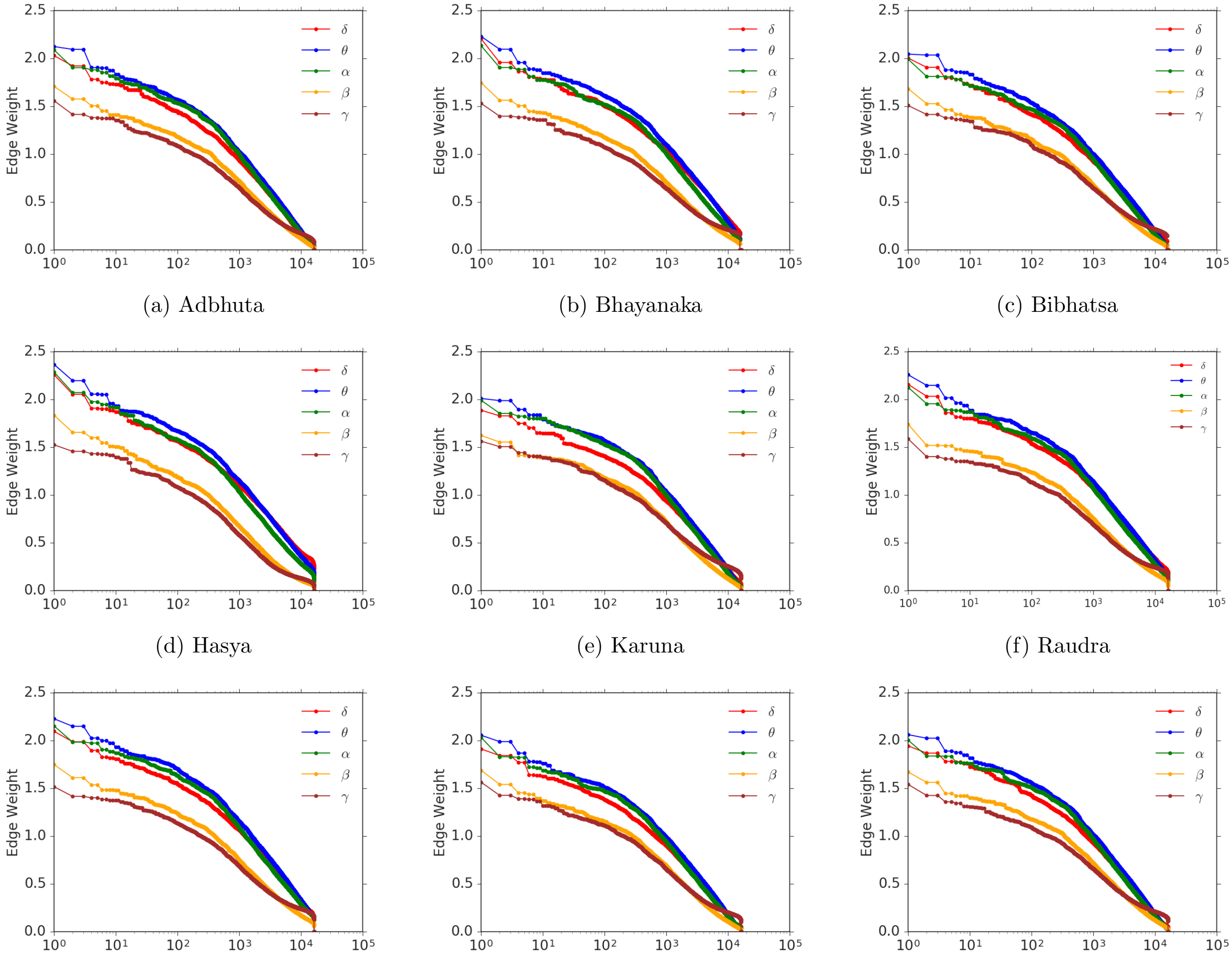



Fig. 6: Brain map showing nodes with (a)highest positive leverage centralities (b) highest negative leverage centralities for all the *Rasas*. Pink coloured nodes are the one which are consistently central for at least eight *Rasas*, other colors are for *Rasas* as shown in the color panel above.

### Edge Weight distribution

Edge weights denote the strength of connections between the nodes. The cumulative edge weight distribution of all *Rasa* networks is shown in 7. We find that edge weights are considerably high for $\delta$, $\theta$ and $\alpha$ bands for all networks and lower for $\alpha$ and $\beta$ bands. Through this we infer that functional connectivity is stronger in $\delta$, $\theta$, and $\gamma$ bands whereas the pathways have lesser average information flow in $\alpha$ and $\beta$ frequency regimes. We also observe that *Raudra*, *Bhayanaka* and *Hasya* networks have higher correlations specially in $\delta$, $\theta$ an $\alpha$ bands as compared to other *Rasas* networks.




(a) Adbhuta (b) Bhayanaka (c) Bibhatsa

(d) Hasya (e) Karuna (f) Raudra

(g) Santa (h) Sringara (i) Veera

Fig. 7: Edge weight distribution matrix for various Rasas in different frequency bands.

## Discussion

In this work, we have used concepts and tools from complex networks to understand the functional connectivity and structural organization of the brain subjected to audio-visual stimuli. The stimuli used in the EEG experiment was chosen to correspond to the nine *Rasas*, capable of evoking different emotions, as described in the Indian *Natyasastra*. To the best of our knowledge, this is the first attempt to design a network analysis probe to identify neural signatures for different *Rasas*. We have characterized how the emotional states are similar or dissimilar by measuring network segregation in different frequency bands. Our main findings, across all Rasa genres are 1) community structure in the alpha band is most similar and 2) lower synchrony of nodes in higher frequency bands and vice versa. Previous studies have reported higher correlations for negative or stress full visual stimuli [(33)] for lower frequency bands. In line with this, our results indicate higher coherence in these bands for *Raudra* and *Bhayanaka Rasas* emotions (considered as negative emotions).

Our coherence analysis has also shown higher synchronization among nodes in lower frequency bands: delta, theta and alpha and weaker correlations in beta and gamma bands for all the networks. We have identified the community structure of the brain for different *Rasas* at the level of strongest links. Using this, we tracked the community evolution such their birth, growth, merger and collapse across all the *Rasas*. We find the existence of four dominant communities consistently across all *Rasas* and localisation of hubs on brain map.

There are a few limitations to our current work which we would like to highlight here. Our observations are based on the analysis of the signal space of electrodes placed on the scalp which does not have a clear source mapping inside the brain. Hence, we refrain from making inferences on the source space and only present the analysis in the signal space. However, EEG based correlations have been successfully used to extract functional connectivities as well to distinguish different emotional states [30], even at the signal space. Also, we used only one movie clip corresponding to each *Rasa* that was ranked best to elicit a particular emotion. There can be other sets of movie clips for each category. Hence, there is a need for better standardization audio-visual stimuli for *Rasas* used. We also, did not distinguish between the emotional perception ability between classes such as gender and age group. We hope that the current work sets a precedent for using network tools for a more detailed analysis of the neural signatures of emotions based on audio-visual stimuli.

To conclude, we like to say that the western classification of emotions such as those by Ekman has been studied for decades using various imaging methods and analytical tools by researchers in various disciplines. However, we find very limited literature on the quantitative study of *Rasas* based on brain imaging or EEG. Through this study using a complex network approach, we hope that our work will trigger interest in the research community to explore the scientific study of *Rasas* further.

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