2014 International Joint Conference on Neural Networks (IJCNN)
July 6-11, 2014, Beijing, China

Detection of Signaling Pathways in Human Brain during Arousal of Specific Emotion

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***Abstract*—Neuroscientists usually determine similarity between EEG electrode signals, by a measure of pairwise linear dependence among them. However, recent research indicates the drawbacks of analyzing the pairwise dependence of signals instead of analyzing the simultaneous joint interdependence among them. To overcome this problem we propose a novel similarity measure known as probabilistic relative correlation. Our approach is unique because our similarity measure allows the electrodes to have probabilistic similarity measures and recognizes emotion dependent structures even from mismatched sequences of correlation. We further validate our proposed similarity measure by testing it on the well-known emotion recognition problem. Our experiments have noteworthy implications towards realizing the neural signatures of discrete emotions and will allow for the better understanding of neurological pathways associated with different emotional states. To identify the most active neurological pathways in brain during an emotion, we adapt the minimal spanning tree algorithm.**

Keywords— Emotion recognition; Brain Maps; Support Vector Machine; Similarity Measures; Brain-computer interface; Electroencephalography

I. Introduction

The ease with which the brain completes seemingly complex tasks like pattern recognition and reasoning with words has fascinated scientists. Researchers have consistently argued that a thorough understanding of how the brain organizes computation, is a necessary prerequisite of building systems which can rival brain-like computation [18], [19]. This covers many aspects including synthesis and recognition of emotions. There has been widespread research aiming at emotion recognition from different modalities such as gestures, facial expressions and voice [1], [2]. Although these modalities can be used to recognize emotions, they can be controlled voluntarily. EEG signals, however, are beyond the control of an individual. There has been a lot of work in deciphering emotion from EEG signals [3], [4] as well as to determine the dependency of brain region activities on emotional states of a person [5]. However, deciphering neural signatures for different emotions has remained a difficult task, primarily because of a chain of interactions in the brain rather than just isolated activities of different brain regions, during emotion arousal [6]. Similarity measures of various types have been proposed to understand the relation in between EEG electrode signals [7], [8] but they were lacking in the fundamental requirement that brain signals exhibit not only pairwise but simultaneous interdependence [9].

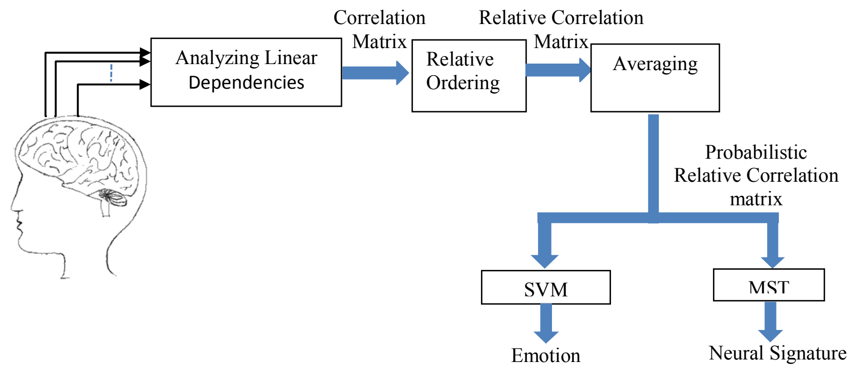
According to Davison's motivational model, left brain is associated with positive emotions and right brain is associated with negative emotions [10]. However there is not much agreement about this according to all researchers [11], [12].Our approach to decipher neural signatures of brain activity during emotion arousal is different. Here, we propose a new technique of decoding the neural signaling structure and effectively summarize the complex structure obtained to create a more comprehensible sub-structure. To examine the interdependency between brain signals obtained from various regions, we propose a new measure of similarity called as *probabilistic relative correlation*. This measure is dependent on linear correlation among brain signals and is more robust than other dependency measures primarily because of three factors.

First it considers not only the pairwise interdependence between brain signals but the relationship of a signal with all other signals as a whole. Secondly, it is tolerant to the intra-emotion changes in correlation patterns because it uses the concept of relativity rather than absolute values. Lastly the similarity measure allows the electrodes to have probabilistic relationships, such that some relationships are stronger than the others. We have compared our results with well-known similarity measures like linear correlation, correntropy [8], coherence [7] and Itakuara distance [17]. Our method of similarity measurement has outperformed all the other four similarity measures in the domain of emotion recognition. Finally we compute a summarized structure to propose the signaling pathway which is most likely to be associated with a specific emotion.

II. Principles And Methodology

In our experiments, we attempt to decode the chain of signaling pathways that is active in the brain during the arousal of a specific emotion. To find out if the different brain

Fig. 1: General Scheme adopted. MST: Minimal Spanning Tree, SVM: Support Vector Machine.



regions are interdependent (exchanging signals), we analyze the linear correlation among the different EEG signals specific to the considered brain regions. Next to overcome the problems associated with pairwise dependency measures, we propose probabilistic relative correlation. The probabilistic relative correlation is a measure of the probability that an EEG signal from an electrode position is relatively more linearly correlated to another. Our next task is to classify emotion from the obtained probabilistic relative co-relation matrices. The probabilistic relative correlation matrices may be viewed as adjacency matrices which indicate brain region connectivity and may be used to create brain region connectivity graph. Finally to conclude about the most active neurological pathways associated with an emotion, we need to eliminate undesirable connectivities in the brain map. To do so, we employ the minimal spanning tree algorithm such that it creates a spanning tree which connects the strongest pathways in the brain region connectivity graph. The details of implementation are given in the following sub-sections. The overall scheme is indicated in Fig. 1.

A. Analyzing linear interdependencies

In order to identify the mutual interrelationship between brain signals of different regions, we adopt the well-known linear dependency measure known as Pearson's correlation coefficient. The correlation between any two pairs of electrode signals called cross-correlation. Thus for the set of 14 electrode channels we have a 14×14 matrix in which each correlation coefficient with respect to all other electrode signals is stored The Pearson's correlation coefficient is evaluated as follows [13]:

$$R_{x,y}=\frac{n\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2(y_i-\bar{y})^2}}$$

Here, $R_{x,y}$ is the Pearson's correlation coefficient, which indicates linear dependence between signals x and y. $\bar{x}$ is the average value of signal x, $\bar{y}$ is the average value of the signal y, n is the number of samples of the signal that we have, x_i is the ith value of the signal x and y_i is the ith value of signal y. It may be noted here that the correlation matrix obtained will be symmetric because the linear correlation between any two signals is bi-directionally same. For instance the sample correlation between four electrode signals for the emotion fear is given in Table I.

B. Creating Relative Correlation Adjacency Matrix (RCAM)

From our experiments it was observed that the order in which the electrodes were linearly dependent was more relevant to the emotional state than the correlation values themselves. It was further observed that the ordering of linear dependencies was not strict but vague. Hence we coined the expression of relative correlation by which, for a given reference electrodes we would identify the 7 most linearly dependent electrode connections (among the considered 14 electrodes) as strong connections.

C. Creating Probabilistic Relative Correlation Adjacency Matrix (PRCAM)

It was observed that though the dependency graphs of the same emotions are similar but not the same. Thus it was concluded that some dependencies which mostly hold are relatively stronger than the others dependencies which do not hold in most cases. Thus we constructed PRCAM which would contain the probabilities of a connection to hold for each specific emotion. In order to construct the PRCAM we show the subject five different video clips eliciting the same emotion. For each of the five clips we construct an adjacency matrix .The PRCAM for an emotion is constructed by taking the element-wise average of the five obtained relative correlation adjacency matrices. A sample calculation of a probabilistic dependency graph according to three RCAMs is shown below. From n RCAM we create a single PRCAMs by constructing a matrix C such that $C_{i,j}=\frac{\sum_{k=1}^{n}{}^{k}b_{i,j}}{n}$

where, n is the number of RCAMs considered,
${}^{k}b_{i,j}$ is the element of the kth adjacency matrix which

belongs to row i and column j.

D. Classification of an unknown emotion by using Probabilistic Relative Correlation Matrices

Each subject is shown five videos which would induce the subject with specific emotion, say fear. For each of the video clip, we can construct a RCAM. By consulting the five RCAMs we now construct a PRCAM. An unknown person is shown five videos inducing an emotion. The PRCAM is similarly computed for the unknown person. A sample 3D surface plot of PRCAM for emotion fear is shown in Fig. 2. In order to classify the emotion indicated by the PRCAM obtained from EEG Signals we first train a Support Vector Machine (SVM) classifier with the PRCAM of all the emotions (Fear, Happy, Sad, Relax). Since SVM is a linear classifier we reshape the m×n PRCAM into a 1×m.vector and use it for training. This reshaping is done by placing all rows sequentially in the new row vector of (1×mn) dimension. The SVM classifier is then asked to classify the reshaped probabilistic adjacency graph of the test emotion. Since SVM is a binary classifier, first the emotions are classified as fear and non-fear category, the non-fear category is then subsequently divided into two sub-groups and so on till all the emotions have been classified.

E. Summarizing Signaling Pathways from PRCAMs

To plot the connections between any two electrodes, say i and j, we connect them with a color which represents the maximum strength of connection among the connections i to j and j to i. The connection strength is obtained from the PRCAM. We draw these connections in Fig. 3 with colored edges such that blue represents weak connections while green represents strong connections. Next we draw a filtered connectivity map of those connections whose probabilistic values are greater than 0.5(threshold value). To create a summarized signaling pathway we choose those edges from the connectivity graph, which have been selected by an adapted version of minimal spanning tree algorithm (Fig. 4).

Fig. 2: 3D surface of sample PRCAM

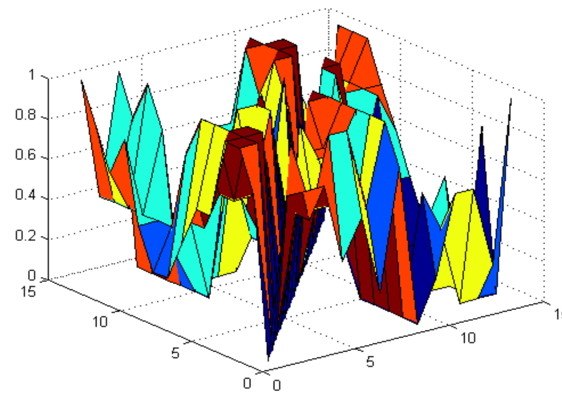


Fig. 3: Signal Connectivity (based on relative correlation for Fear a) before Thresholding b)after Thresholding (1 to 14 denote the electrode positions)

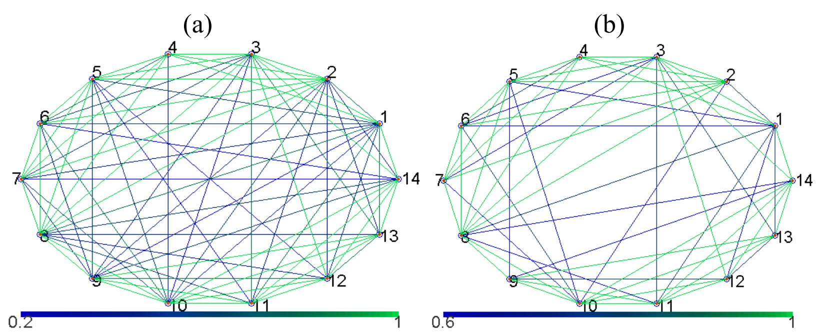
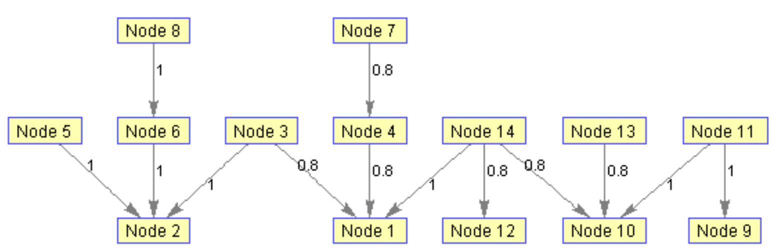


Fig. 4: Spanning tree for emotion fear



(Node 1 to 14 denote electrode positions. To construct the spanning tree we use Prim's algorithm, which is a greedy algorithm as it selects the locally available edge with least weight and adds it to the spanning tree. This process is repeated till the all the vertices of the graph have been joined. Time complexity is O (E*log(N)), where N and E are the number of nodes and edges respectively.)

F. *Illustrative examples*

Example 1: Suppose, we analyze the cross-correlation among the EEG signals generated by each any four electrode positions, say 1, 2, 3 and 4 and record them as in Table I .The relatively correlation adjacency matrix (Table II) is simply formed by creating another table in which the highest two cross-correlations in each row (of Table I) is marked as 1 and rest are marked as 0. The RCAM named r' thus created stores the relatively stronger connections among the all possible electrode connections. Similarly for, a table containing cross-correlations among 14 electrode positions, we may choose to represent the 7 strongest cross-correlations as 1 and rest as 0.

TABLE I : CORRELATION MATRIX R

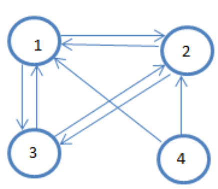
	1	**2**	**3**	**4**
1	0	0.99986	0.99971	0.9987
2	0.99986	0	0.9887	0.9624
3	0.99971	0.9887	0	0.9512
4	0.9987	0.9624	0.9512	0

TABLE II: RELATIVE CORRELATION ADJACENCY MATRIX R'

	1	**2**	**3**	**4**
1	0	1	1	0
2	1	0	1	0
3	1	1	0	0
4	1	1	0	0

It may be noted here that the RCAM will not always be symmetric like the linear correlation matrix because in example 1 we observe that the cross-correlation of electrode 1 is maximum with electrode 3 and 2.For electrode 4, electrodes 1, 2 hold the highest cross-correlation among other electrodes. From this RCAM we can now construct a dependency graph (Fig. 5). The link from node i to node j indicates that i is relatively more correlated to node j as element $x_{i,j}$ of RCAM is 1. Here i indicates column number and j indicates row number.

Fig. 5: Dependency graph obtained from table II



Example 2: Let The RCAMs obtained for 3 video clips for the emotion fear be matrices A1, A2, A3 (Table III)

TABLE III A: MATRIX A1

	1	**2**	**3**	**4**
1	0	1	1	0
2	0	0	1	1
3	1	1	0	0
4	0	1	1	0

TABLE III B : MATRIX A2

	1	**2**	**3**	**4**
1	0	1	1	0
2	0	0	1	1
3	1	1	0	0
4	1	1	0	1

TABLE III C:MATRIX A3

	1	**2**	**3**	**4**
1	0	1	1	0
2	1	0	1	0
3	1	1	0	0
4	1	1	0	0

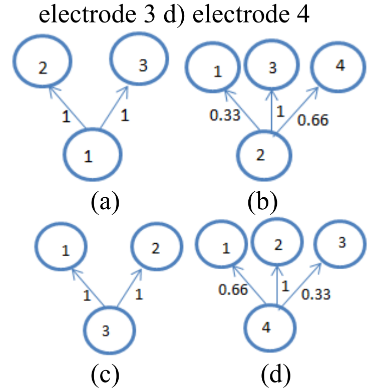
After adding the matrices element wise and dividing each element with 3(number of matrices) we obtain the probabilistic adjacency matrix. C (Table IV). Each element in the matrix C is represented by $c_{i,j}$ were i indicates row number, j indicates column number.

TABLE IV: MATRIX C (PRCAM)

	1	**2**	**3**	**4**
1	0	1	1	0
2	0.33	0	1	0.66
3	1	1	0	0
4	0.66	1	0.33	0

From the PRCAM obtained we construct a probabilistic dependency graph by assigning the weight c_{ij} to the directed node which goes from node i to j. Thus for the PRCAM given in table IV we obtain a graph as indicated in Fig. 6. The graph is divided into 4 parts (each part representing the connections of a single electrode with others) for the sake of clarity in representation.

Fig. 6: Strong connections of a) electrode 1 b) electrode 2 c) electrode 3 d) electrode 4



It is observed from the maps that all the brain regions intercommunicate when a subject feels an emotion. However we need to summarize the sequence of these connections so that we can arrive at a conclusion about the most probable pathways that that are activated in brain during arousal of a specific emotion. To do so, we find out the minimum spanning tree of the probabilistic dependency graph obtained from PRCAM of each emotion. A spanning tree is a tree which connects all the vertices. A minimal spanning tree is the spanning tree which has minimum weight among all other spanning trees. But in our case, we need to find a spanning tree in which the edges with maximum weights are connected. To do this we take the PRCAM and simply reverse the weights by subtracting them from 1 and adding a small constant *a* so that weights which are 1 do not become zero. After this we find the minimal spanning tree. Finally we reverse the weights of the edges again and hence get a spanning tree in which edges with highest probabilities are connected. The direction of edges is chosen arbitrarily, later the direction of edges is adjusted by considering occipital lobe as the source of signals, since the stimulus is visual. For e.g. spanning tree obtained for the emotion fear is indicated in Fig. 4. Similarly, we construct spanning tree for all other concerned emotions. Since the subjects are shown visual stimuli, the emotion is considered to originate at occipital lobe. From the connectivity tree obtained we infer the probable pathways which occur during the arousal of an emotion. It may be noted that in Fig. 4 the arrows are drawn for brevity and do not represent which node is source and which one is sink. The results obtained by considering occipital lobe as the source is indicated in Fig. 10 (a) for emotion Fear.

III. EXPERIMENTS

A. Stimulus Preparation

The stimulus set is prepared by collecting 10 videos of the following emotions (i) Happiness (ii) Sadness (iii) Fear (iv) Relaxation. Between each video there is a blank frame of 30 seconds. 5 of the videos of each emotion is shown to a subject to prepare the training probabilistic dependency graph. To make sure that this dependency graph obtained represents the emotion and not the stimuli, EEG responses corresponding to the 5 remaining videos are used to make the test probabilistic dependency graph for each specific emotion. Some sample video stimuli are shown below (Fig. 7).

B. Data Acquisition and Filtering

The subjects are shown the prepared visual stimuli in a noise-free environment. Special seating arrangement is made for the subject with cushion and armrests. The subject receives audio visual stimuli from a laptop equipped with high quality graphics and headphones .The experiment is conducted on 10 subjects: 5 male and 5 female in the age group 24±5. The data is acquired using 14 channel wireless Emotive headset [14]. Alpha band is found to have significance in emotional feelings of a person [15], [16].Hence we design a band-pass Chebyshev filter of order 10 to filter the alpha band. We now use the filtered raw signals for further analysis. For construction of relative correlation adjacency matrix we consider the relative correlation of all the 14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4) with each other. We thus have a 14×14 matrix containing relative correlation values.

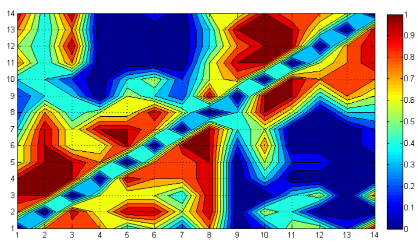
Fig. 7: Stimuli for emotion a) relax b) fear c) sad d) happy

(a) (b) (c) (d)

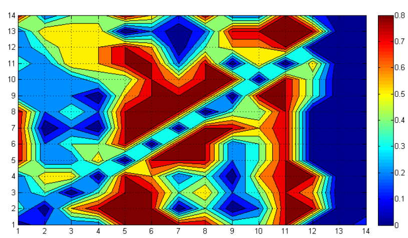
C. *Experimental Results*

For each emotion considered we construct a PRCAM, with the connection strength ranging between zero and one. Each of the numbers along the X and Y axes from 1 to 14 represent the 14 electrodes AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4 in sequence. PRCAM, we consult 5 RCAM. The connections which hold in all the 5 matrices are assigned a value of 1(represented by deep red), and the connections which do not occur in any of the graphs is assigned a value of 0(represented by deep blue) and so on. The 2D surface thus formed by representing the connection strength between electrode signals is represented as a contour. The sample 2D Surface maps obtained for emotions fear, sadness, happiness and relaxation are given in Fig. 8. It may be noted here that the connection strength of a node with itself (say 14 and 14) is always zero as auto co-relation is not considered. This gives rise to a diagonal sequence of blue squares across the map.

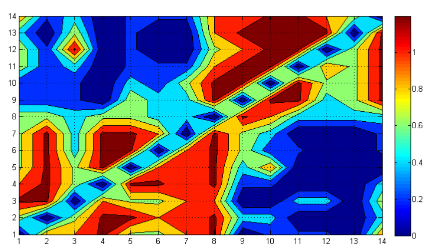
Fig. 8: 2D Surface plots of adjacency matrices of a) Fear, b) Happy, c) Relax and d) Sad



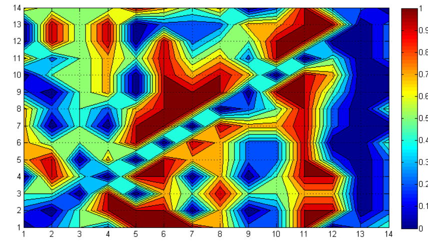
(a)



(b)



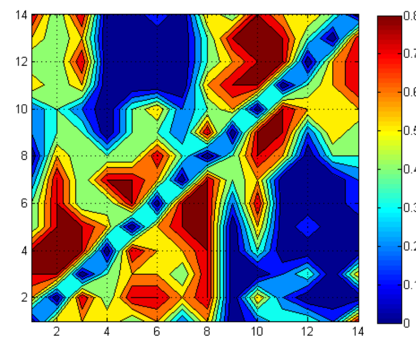
(c)



(d)

From the above surface plots of the adjacency matrix we find that most of the electrodes are linearly correlated. Almost each electrode is bi-directionally connected to every other electrode with varying strength. A sample 2D surface plot of PRCAM obtained for unknown emotion is indicated in Fig. 9.

Fig. 9: 2D Surface Plot of adjacency matrix of an unknown Matrix



D. *Performance Analysis*

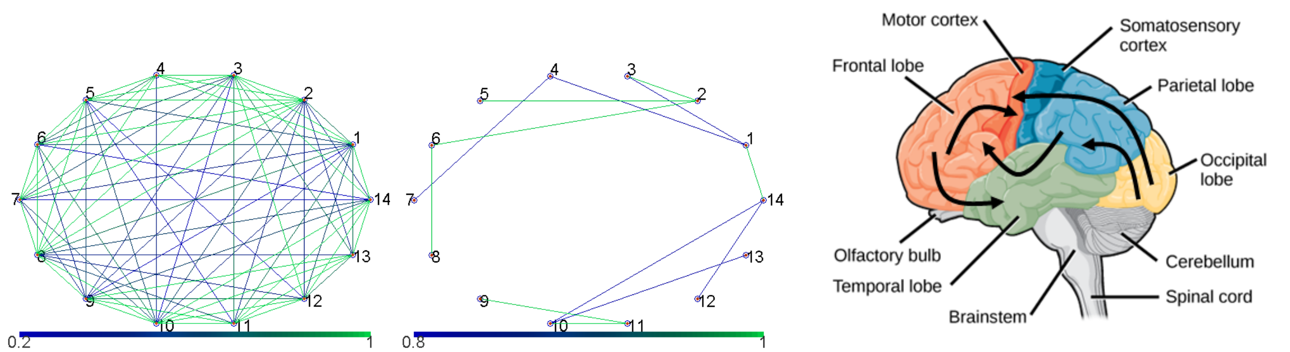
Each of the 10 subjects, are shown 10 videos inducing an emotion say fear. Thus we have a total of 100 instances for a given emotion. These instances are divided into subgroups of 5 instances, each to form a probabilistic adjacency graph. Thus we create 20 probabilistic graphs of the same emotion. 5 among the 20 graphs are used for training and the remaining 15 graphs are used for testing. The classification accuracies obtained for each emotion are listed in Table V.

TABLE V: CLASSSIFICACTION ACCURACY OF THE PROPOSED TECHNIQUE FOR DIFFERENT EMOTIONS

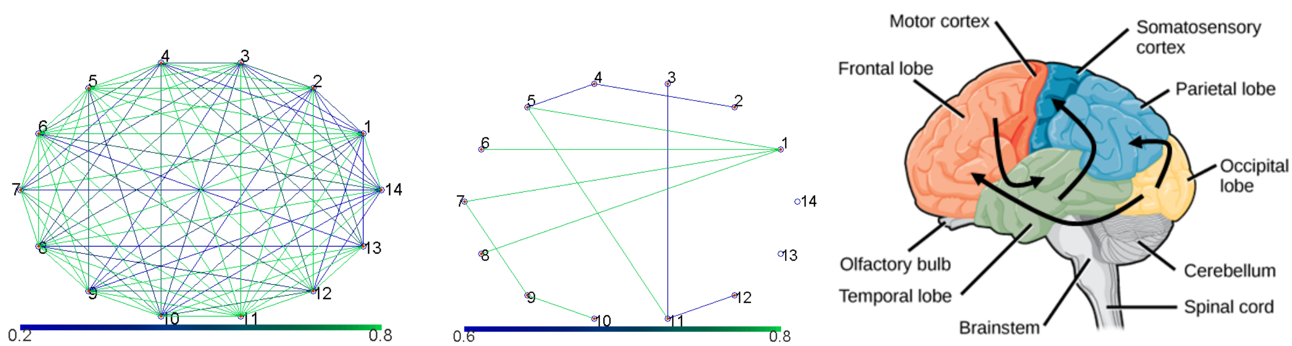
Emotion	Classification Accuracy
Fear	93.33%
Happy	86.67%
Sad	86.67%
Relax	60%
Average Accuracy	81.66%

Fig. 10: Signalling pathways and their summarizations(using spanning tree and thresholding) for emotions a)fear b)happy c)relax c)sad

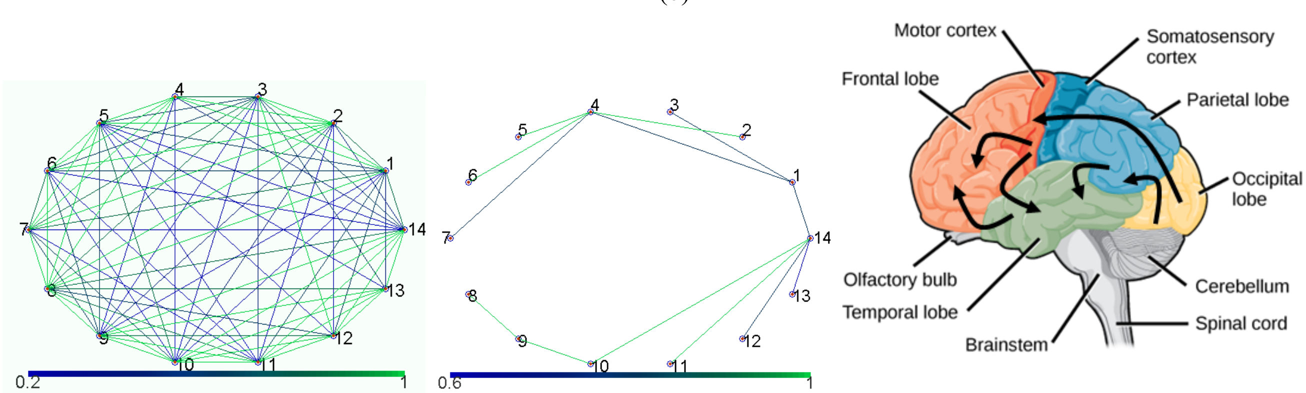
Connectivity Graph | **After Reduction(By thresholding and spanning tree)** | **Strongest Signaling Pathways**



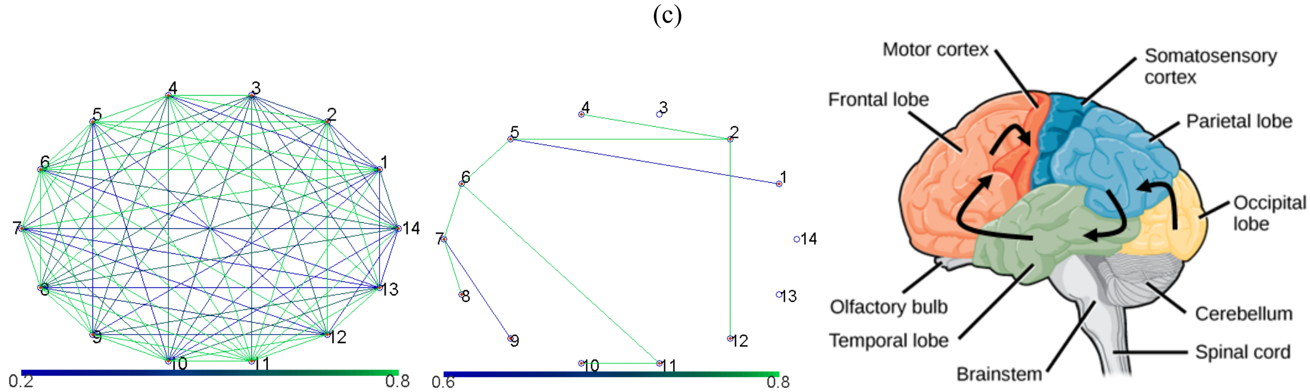
(a)



(b)



(c)



(d)

To test the validity of probabilistic relative correlation, we tested how it performed in classifying emotions in comparison to other dependency measures. The results of our analysis as tabulated in Table VI. In our experiments with non –relative dependency measures (Correlation, Coherence, Crossentropy), we did not construct adjacency graphs, rather we fed the SVM directly with the absolute dependency metric values. It was hence concluded that the relative dependency rather than absolute dependency was more relevant to find out emotional states.(Table VI)

TABLE VI: COMPARISON OF DIFFERENT SIMILARITY MEASURES AND PROPOSED SIMILARITY MEASURES

Emotion	**Classification Accuracy**
Correlation	72.21%
Coherence	73.58%
Crosscorrentropy	75.33%
Itakuara Distance	79.75%
Probabilistic Relative Correlation	81.66%

IV. CONCLUSION

In this paper we have proposed a novel approach to emotion recognition as well as we have outlined how the well-established linear correlation can be adapted to give rise to probabilistic relative correlation which can serve as a simple and robust measure for establishing neural signatures. There is still scope to establish in a similar fashion, the probabilistic relative coherence and probabilistic relative crosscorrentropy, which are expected to further better the results of emotion recognition. However correlation being the simplest and most trusted measures of linear dependence has been used in this study. In our studies we have considered only EEG signals. fNIR or fMRI are expected to give better results as they have better spatial resolution.

ACKNOWLEDGEMENT

Funding by University Grant Commission, India for the Project: University with Potential for Excellence Program in Cognitive Science (Phase II) granted to Jadavpur University, India is gratefully acknowledged.

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