Functional Connectivity from EEG Signals during Perceiving Pleasant and Unpleasant Odours

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***Abstract*—The olfactory sense is strongly related with memory and emotional processes. Studies on the effects of odour perception from brain activity have been conducted by using different neuro-imaging techniques. In this paper, we analyse electroencephalography (EEG) of 23 subjects during perceiving pleasant and unpleasant odour stimuli. We describe the construction of brain functional connectivity networks measured by most commonly used models. We discuss the network-based features of functional connectivity, as well as design classifiers by applying different functional connectivity network features. Finally, we show that by applying functional connectivity methods and network features to EEG signals, we manage to classify pleasant and unpleasant olfactory perceptions with a significantly non-random average Kappa value of 0.11 ± 0.17.**

I. Introduction

Emotion is involved in every aspect of human life, thus, it has gained attention in many research disciplines, including computer science. For instance, multimedia systems are increasingly becoming immersive, in order to evoke strong emotions and render user-experience more realistic. Traditionally, multimedia systems include video and audio contents, they, thus, mainly stimulate the visual and auditory senses. Nevertheless, recently odors have started to be incorporated into multimedia systems (e.g., [1]–[3]), since they directly stimulate memories and elicit strong emotions. However, emotion elicitation from odors has not been adequately investigated, although the primary response to smell is related to pleasantness perception [4].

Perception of pleasantness from various stimuli has been investigated by various researchers through different means. Many studies have been conducted on the investigation of pleasantness perception through facial expressions [5], food intake [6], languages [7], etc. Research on pleasantness detection and classification has been carried out by analyzing brain activity, especially using Positron Emission Tomography (PET) [8] and functional Magnetic Resonance Imaging (fMRI) [9]. EEG approaches in emotion detection and recognition have been also conducted by various research groups to classify the emotional responses of pleasantness from various affective stimuli (e.g.,).

Although pleasantness perception has been thoroughly analysed for various, especially audiovisual, stimuli, it has received less attention during experience of odors. Moreover, various EEG studies on investigating odor pleasantness have analysed brain activation in terms of power spectral density features, but further information from EEG could equally or better contribute to a deeper understanding of pleasantness perception from odors. For instance, a question that still remains unanswered is regarding the way in which odor pleasantness influences functional connectivity patterns in remote brain locations. The hypothesis is that there are differences in the functional connectivity patterns when subjects experience pleasant and when they experience unpleasant odors.

In general, there are different levels of connectivity in the brain, ranging from the connections between neighbouring neurons to the connections between different segregated brain regions. The concept of functional connectivity describes the dependence between the activities of different neuron assemblies. The functional connectivity map describes the dependency between all the sub-regions of brain (all the electrodes in EEG signals) regardless of whether they are structurally linked or not. The concept of functional connectivity maps has been largely used in neuro-imaging analysis (EEG, fMRI, PET and etc), to study major depression [10] and epilepsy [11] disorders with respect to control states. Based on the neurophysiological principle [12], brain can be viewed as a complex network. Thus in this paper, we will introduce the concept of functional connectivity map to understand the networking of the brain during odor perception.

Since the dependence between different sub-regions of the brain can be interpreted in different ways, there exists different models of estimating the functional connectivity map of the brain. Widely used models include *Granger Causality* [13], *Transfer Entropy* [14], *Nonlinear Regression Analysis* [15] and *Spectral Coherence* [16]. In this paper, we applied and compared two different models in estimating functional connectivity maps. To have a better view of what is happening during the processes of odour perception and emotion generation, we also applied network-based features to estimated functional connectivity maps including *characteristic path* [17], *local and global efficiency*, *clustering coefficient* [18], *shannon entropy* and *von Neumann entropy* [19]. The extracted features were then used for classification of the pleasantness of odor perception, which is also a target of this paper.

The rest of the paper is organised as follows: Section II describes the experimental protocols and methods for constructing and measuring functional connectivity maps from EEG signals. Section III provides the classification results on pleasantness by using the network based features extracted from functional connectivity maps. Section IV gives the conclusion of this work.

II. Materials and Methods

A. Participants

A total of 23 right-handed subjects took part in the experiment (9 females, 14 males, 24 ± 4.6 years old). All subjects were non-smokers and without respiration problems. According to their self-reports, none had a history of injury in the olfactory bulb or incapability of smelling. Subjects were informed about the experimental protocol and the purpose of the study. During the experiment, subjects were seated in a comfortable chair with recording devices. None of the participants in experiment were wearing perfumed products on the day of experiment.

B. Experimental Setup

An EGI's Geodesic EEG system (GES) 300 was used to record, amplify and digitalize the EEG signals. EEG signals were recorded from a 256-channel EEG Net Amps 300 cap with sampling frequency of 250Hz.

C. Experimental Protocol

10 different odours were provided for the experiment, including rose water, lavender oil, jasmine oil, chocolate powder, mint oil, valerian pills, garlic powder, star anise, rotten cooked cauliflower and baby shampoo. The odorants were placed inside covered bottles so as to avoid effects of their visual characteristics

After the set up of EEG recording system, subjects were asked to relax and close their eyes. One odour bottle was provided to the subject's nostrils at 1-2 cm. The subjects were not informed about the name of the odour during the experiment. The same odour was presented for about 15 times, leading to about 15 trials. Each trial consisted of 6 seconds baseline and 6 seconds odour experience. After experiencing an odour, the subjects were asked to rate it in terms of pleasantness, using a 5-point Linkert scale that ranged from very unpleasant to very pleasant. More details about the experiment design can be found in [20].

D. Pre-processing of EEG Signals

Signals from 40 electrodes which are placed on face muscles and around eyes are manually rejected for all subjects due to movement artifacts. Signals from the remaining 216 electrodes are kept for further analysis.

A bandpass filter (4th order butterworth) is applied for the EEG signals with pass-band 3-47 Hz. A small laplacian filter is applied for each electrode in order to reduce volume conduction effects [21]. Further artifacts are rejected by using Independent Component Analysis (functions are provided by EEGLAB© toolbox [22]).

E. Construction of Brain Networks

Brain connectivity refers to a patter of anatomical links (anatomical connectivity) or of statistical dependencies (functional connectivity) between neural assemblies. The functional connectivity pattern is represented by statistical or causal relationships estimated using measures such as cross-correlation, coherence or information flow [23]. Brain connectivity is a crucial concept to elucidate how neural networks process information. In this paper, we investigate functional connectivity and use this information to interpret how brain functions during perception of pleasant and unpleasant odours.

Functional connectivity can be estimated in various ways. For instance, a neurophysiological concept of functional connectivity is introduced Wendling's group, who utilised the Nonlinear Regression Analysis as a measure of functional connectivity [24]. The notion of Granger Causality [25] has been also extensively used to estimate functional connectivity.

1) Granger Causality: Granger causality is first proposed by C.W.J. Granger in investigating causal relations in econometric models in 1969 [13]. Decades later this concept is introduced into the neurophysiology study. It is used to measure the causality between activities in different neuron assemblies, which estimates the functional connectivity over brain regions.

Suppose we have two time series X_t and Y_t. Let U_t denote all the information accumulated from both time series since time $t-1$, and $U_t - Y_t$ denotes all this information apart from the specified series Y_t. $\sigma^2(X|U)$ is the variance of $\epsilon_t(X|U)$, in which $\epsilon_t(X|U) = X_t - P_t(X|U)$ and $P_t(X|U)$ represents the optimum, unbiased, least-squares predictor of X using the set of values U.

Definition of Causality: If $\sigma^2(X|U) < \sigma^2(X|\overline{U-Y})$, then Y is causing X, denoted by $Y_t \Rightarrow X_t$. Under the notion of Granger causality,Y_t is causing X_t if X_t is better predicted using all available information than if the information from Y_t is excluded.

The definition of Granger causality represents a theoretic approach which is difficult to implement due to lack of knowledge of the distributions of the estimators. In order to solve this problem, different approaches for computing Granger causality have been developed. In this paper we use the Vector Auto-Regression model (VAR) [26] to estimate Granger causality since it provides better computational efficiency and numerical accuracy [26].

According to the VAR model, we suppose signals from two channels (i.e., two electrodes in our case) are $\mathbf{X_t}$ and $\mathbf{Y_t}$. Then

$$\mathbf{U_t} = \begin{pmatrix} \mathbf{X_t} \\ \mathbf{Y_t} \end{pmatrix} = \sum_{k=1}^{p} \begin{pmatrix} A_{xx,k} & A_{xy,k} \\ A_{yx,k} & A_{yy,k} \end{pmatrix} \begin{pmatrix} \mathbf{X_{t-k}} \\ \mathbf{Y_{t-k}} \end{pmatrix} + \begin{pmatrix} \epsilon_{\mathbf{x,t}} \\ \epsilon_{\mathbf{y,t}} \end{pmatrix} \tag{1}$$

U_t represents the combined time series by X_t and Y_t, which will be used in VAR model for regression and analysis of dependence between X_t and Y_t. The residuals covariance

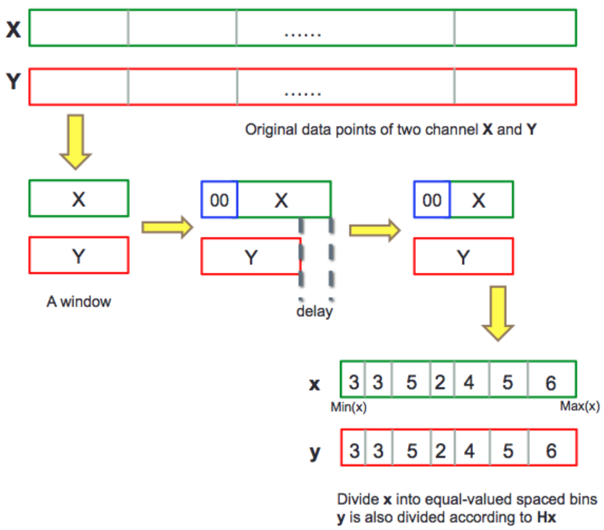

Fig. 1. An example of separating EEG time series into windows and bins for computing the nonlinear regression curves

matrix Σ from the residual terms in (1) is estimated as

$$\Sigma \equiv cov\begin{pmatrix}\epsilon_{\mathbf{x},\mathbf{t}}\\ \epsilon_{\mathbf{y},\mathbf{t}}\end{pmatrix} = \begin{pmatrix}\Sigma_{xx} & \Sigma_{xy}\\ \Sigma_{yx} & \Sigma_{yy}\end{pmatrix}. \tag{2}$$

In this paper we use the MVGC toolbox [26] to estimate the parameters in the VAR model. We first estimate the best model order *p* by using the AIC (Akaike Information Criterion). The minimum model order is selected by using a regression model of Morf's version of the LWR (the initials stand for Levinson, Whittle, Wiggins and Robinson) algorithm [27]. Similarly to the estimation of the model order, the LWR is also used for estimating the VAR parameters. The Granger causality from $\mathbf{Y_t}$ to $\mathbf{X_t}$ is then defined as:

$$F_{\mathbf{Y_t}\to\mathbf{X_t}} \equiv ln\frac{|\Sigma'_{xx}|}{|\Sigma_{xx}|}. \tag{3}$$

In Equation (3), $|\Sigma'_{xx}|$ represents the covariance matrix of the reduced regression (the regression contains only $\mathbf{X_t}$, and $\mathbf{X_t}$ is predicted only by information from its own past), while $|\Sigma_{xx}|$ represents the covariance matrix of the full regression (which contains both $\mathbf{Y_t}$ and $\mathbf{X_t}$). Thus, the value of F provides the "amount of information" transmitted from $\mathbf{Y_t}$ to $\mathbf{X_t}$ by estimating the reduction in the prediction error when $\mathbf{Y_t}$ is included in the prediction of $\mathbf{X_t}$. When there is no information transmitted from $\mathbf{Y_t}$ to $\mathbf{X_t}$ (i.e., $|\Sigma'_{xx}| = |\Sigma_{xx}|$), then $F = 0$. There is no upper limit on the values of F.

2) Nonlinear Regression Analysis: Nonlinear regression analysis is also a commonly used way to estimate the functional connectivity, which is represented by statistical coupling between EEG signals. This method is introduced by Pijin and Lopes Da Silva for EEG analysis [15]. Nonlinear regression analysis can quantify the relationships between different EEG signals in order to determine whether activity in one neuron assembly depends on that of other assemblies. Suppose we have two channels of EEG signals x and y, then nonlinear regression analysis provides a measure called *correlation ratio* η^2, whose estimator is called h^2. η^2 (or h^2) gives a statistical measure that describes the dependency of signal x on y. Assume the amplitude of signal y is a function of the amplitude of signal x. The expectation of y given a value of x is denoted as $\mu_{y|x}$ where:

$$\mu_{y|x} = \int_{-\infty}^{\infty} yp(y|x)\mathrm{d}y, \tag{4}$$

and $\mu_{y|x}$ describes the predicted value of y given x. By this definition, we can calculate η^2, which represents the reduction of variance of y that obtained by predicting y value using $\mu_{y|x}$. η^2 is expressed as:

$$\eta^2 = \frac{Total\ Variance - Unexplained\ Variance}{Total\ Variance} \tag{5}$$

Explained variance is the variance calculated from y according to $\mu_{y|x}$. In this paper, nonlinear regression analysis algorithm is implemented by fieldtrip toolbox© [28].

F. Significance Check

The significance check runs for the same processes for both methods (Grancer causality and Nonlinear Regression Analysis) and is split into two main parts: (1) p-value calculation for samples based on theoretical asymptotic null distribution; (2) statistical significance adjusted for *Bonfferroni* correction. The rationale behind applying a significance check is to keep only the significant connections.

The *null hypothesis* H_0 is set to "there is no functional connectivity between two channels". The final conclusion after the test is given in terms of the *null hypothesis*, i.e. we either *reject* H_0 or *do not reject* H_0. In this paper, we assume that the connectivity values come from normal distribution with known mean and standard deviation and set the $p-value$ to 0.05 for testing threshold. The commonly used F-statistics is applied for estimating the $p-value$ both for Granger Causality and for Nonlinear Regression Analysis.

All the values in funcional connectivity maps that passed significance check were kept for feature extraction and classification in later steps. We categorise the resulting functional connectivity maps which containing all the significant values into two types – unweighted maps and weighted maps. To construct an unweighted functional connectivity map, we keep all the significant nodes with value equal to 1 (shown in 2). Unweighted maps are only made of 0s and 1s, which can provide us a clear idea of where the significant connections occur. To have a better view of how strong those connections are, we need to implement weighted maps. All the nodes in weighted maps keep the original values from functional connectivity maps that passed significance check (shown in 3).

G. Network Feature Extraction

The functional connectivity maps gives us a view of how channels communicate information with each other, thus we can consider this map as a network. In this case, we can extract network features to analyse the functional connectivity maps.

	1	2	3	4	5	6
1	0	1	0	0	1	0
2	1	0	1	0	1	0
3	0	1	0	1	0	0
4	0	0	1	0	1	0
5	1	1	0	1	0	0
6	0	0	0	1	0	0

(a)

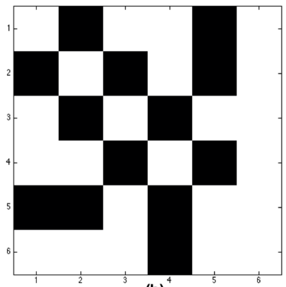

Fig. 2. An example of unweighted functional connectivity map construction of size 6×6. Nodes in (a) with value 1 represents the nodes that passed significance check. (b) is a visual expression of unweighted functional connectivity map.

	1	2	3	4	5	6
1	0	0.30	0	0	0.20	0
2	0.18	0	0.2	0	0.98	0
3	0	0.04	0	0.35	0	0
4	0	0	0.72	0	0.77	0
5	0.72	0.19	0	0.33	0	0
6	0	0	0	0.78	0	0

(a)

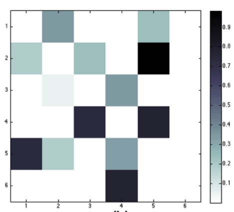

Fig. 3. An example of unweighted functional connectivity map construction of size 6×6. Nodes in (a) with values represents the nodes that passed significance check. The value of each node is taken from the value of the node from functional connectivity map. (b) is a visual expression of weighted functional connectivity map.

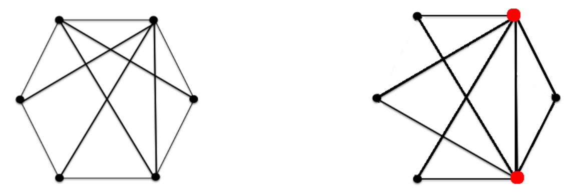

Fig. 4. An example of scale-free network (b) compared with a random network (a). Red nodes in (b) represents the hubs holding connections from subgraph.

Different ways of treating brain networks have been proposed by different groups. For instance, some research groups see the brain as a scale-free network [29], while others view it as a small-world network [30]. In this section, we introduce two categories of network features, based on the principles of scale-free networks and of small-world networks, namely – *physical statistics* features for scale-free networks, and *graph theory-based* features for small-world networks.

1) Small-World Network Features: A small-world network consists of nodes that can be reached from every other node with a small number of steps. Different aspects of small-world networks have been studied and here, based on the commonly used features in neural network studies, we introduce four features for analysing our functional connectivity maps which are *characteristic path*, *global efficiency*, *local efficiency* and *clustering coefficient* [17] [18].

Characteristic path represents the averaged shortest path of the network. The minimum value is achieved when the network is a complete graph (every pair of distinct vertices is connected by a unique edge). In our case, we can interpret the characteristic path as a feature representing the number of connections in the functional connectivity networks. The more the connections in the functional connectivity network, the smaller the value of the characteristic path, thus the faster the information that is transferred through the network.

The concept of *global efficiency* of a small-world network is introduced by Latora and Marchiori [18] and provides a measure of efficient behaviour of the network, by assuming that the network system is parallel (i.e., every vertex sends information concurrently through its edges in the network). The global efficiency of the network is higher when the characteristic path is short. Thus, global efficiency measures how efficiently the vertices exchange information through the network concurrently. Similarly with global efficiency, *local efficiency* is defined as the average efficiency of the subgraph of the neighbours of a vertex i in the graph (details of computing subgraph can be referred to [31]). The subgraph of i do not contain vertex i, hence, the local efficiency can show how efficient the communication is when i is removed from the network. Thus the local efficiency E_{loc} reveals how much the network is fault tolerant.

Finally, *clustering coefficient* of a network measures the degree to which vertices in a graph tend to cluster together. The overall level of clustering in a network measurement is given by Watts and Strogatz [17] as the average of the local clustering coefficients of all vertices.

2) Scale-Free Network Features: Although graph theory has been successfully used to describe brain functional connectivity networks, a few studies have shown that brain functional connectivity can also be considered as a scale-free network. The number of links k of a node in a scale-free network follows a power law destribution as (6).

$$P(a\ node\ having\ k\ links) \sim k^{-\lambda} \qquad (6)$$

where λ is a parameter valued in the range $2 < \lambda < 3$. Groups of CJ Stam [32] have found that brain functional connectivity network can be viewed as a scale-free network because the connectivity distribution followed a power-law scaling with an exponent close to 2, which suggests such functional connectivity network can be considered as a scale-free network topoloty [33]. Detailed analysis can also be found in Thivierge's work [34].

In information theory, *entropy* plays an important role in measuring uncertainty. Recently, following theoretical and statistical mechanics paradigms, several entropy measures for complexity have been proposed for network structures, and these measures have shown good performance in quantifying the level of organisation encoded in structural features of scale-free networks. It is well known that *Shannon entropy* and *von Neumann entropy* are related to the information present in classical and quantum systems respectively. Both of them can be used to analyse the structural organisation of scale-free networks [35].

The amount of *Shannon entropy* has a correlation with the number of network structural constraints. Examples of network constrains include: a) fixed number of links per vertex, b) given degree sequence (a monotonic non-increasing sequence of the degrees of vertices in the graph), and c) community structure (vertices of the network can be easily grouped into sets of vertices such that each set of vertices is densely connected internally). From this point of view, we can conclude that Shannon entropy has a clear interpretation of quantifying the information presented in network structure (Detailed proof can be referred to [35]). If a network has a smaller Shannon entropy, it will have more constrains on its structure, which shows this network is more optimised.

Von Neumann entropy is defined by von Neumann for proving the irreversibility of quantum measurement processes at the beginning. Recently it is also shown that von Neumann entropy can also be applied to network analysis [19]. It has been shown that von Neumann entropy is a measure of regularity of networks [19]. For a fixed number of edges, regular networks (networks whose vertices have the same number of neighbours) have in general a higher von Neumann entropy. It is also shown that von Neumann entropy depends on the number of connected components, long paths and nontrivial symmetries. With a fixed number of edges, von Neumann entropy is smaller for networks with higher degree of cluster. The mathematical proofs can be found in [19] and [35].

Thus, to sum up, the network-based features including characteristic path, local efficiency, global efficiency, clustering coefficient, Shannon entropy and von Neumann entropy have been extracted from the estimated functional connectivity maps for further classification.

H. Classification

Support vector machine with a *Gaussian radial basis function* kernel is used for classification. The parameter selection of σ in RBF kernel is based on cross-validation. In particular, the dataset is split into three parts, namely training, validation and testing. Leave-one-subject-out (LOO) cross-validation is carried out to estimate the parameter σ. The testing is also carried out in a LOO cross-validation scheme. We tested 13 different values of parameter σ ranged from 0.01 to 2. More specifically, the parameter σ is selected based on the training and validation using data from 22 subjects, while one subject is left out for testing. The procedure is repeated until all subjects have been left out as test-subjects (i.e., the procedure is repeated 23 times).

Cohen's Kappa κ [36], is a measure of agreement between two viewers, and is calculated to evaluate the classifier's performance. Some researchers consider that Cohen's kappa can be used to evaluate the agreement by chance, i.e. if the viewers are randomly guessing for a decision. In our case the two viewers actually correspond to the ground truth and test labels. Cohen's kappa is considered an accurate metric for classification performance and takes into account unbalanced classes (i.e., classes with different number of samples).

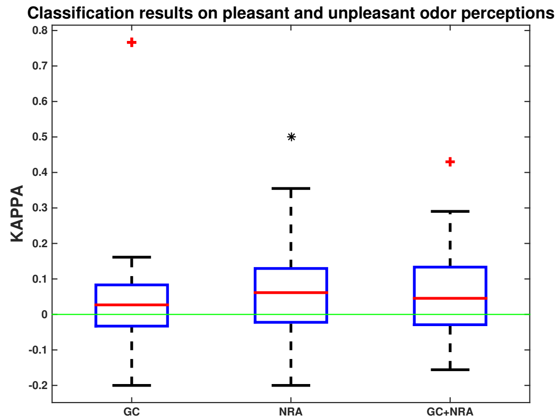

Fig. 5. Cohen's Kappa resluts boxplots. On each box, the central (red) line represents the median value, the upside and downside edges represent the 25th and 75th percentiles, and the red crosses represent outliers. The green line represents the random decision, $Kappa = 0$. GC refers to the kappa values estimated for features extracted from the networks estimated using Granger Causality. NRA refers to the kappa values estimated for features extracted from the networks estimated using Nonlinear Regression Analysis. GC+NRA refers to the kappa values estimated using features both from Granger Causality and from Nonlinear Regression Analysis methods.

III. Results and Discussion

The classification results are shown in Figure 5. Higher kappa values indicate better classification performance. A kappa value $k = 0$ indicates a random decision. According to Figure 5, a higher classification performance is achieved with Nonlinear Regression Analysis compared to Granger's causality. In order to investigate if the kappa values are significantly non-random, a one-way *Student-t test* is applied for each case. The null hypothesis is that the kappa values for each case follow a Student distribution with zero mean. The null hypothesis is rejected for the case of Nonlinear Regression Analysis ($p < 0.05$, κ values with $\mu = 0.07, median = 0.06, \sigma = 0.17$). Although this value is statistically significant, it is still close to zero. However, 14 out of 23 subjects have kappa values larger than zero. The null hypothesis is not rejected for the Granger causality case. This finding indicates that nonlinear patterns occur in the functional connectivity of neural assemblies, able to discriminate between pleasant and unpleasant odours.

In order to investigate the classification performance of the two feature-categories, namely the small-world network features and the free-scale network features, a SVM classifier is trained and tested as previously, for each feature-category. The results are presented in Figure **??**. In order to investigate if each feature-category leads to significantly non-random kappa values, a one-way *Student-t test* is applied as previously. The results reveal that the small-world network features lead to a significantly non-random performance, whereas this is not the case for the free-scale network features. This finding indicates that odour pleasantness perception can be depicted in small-world network features extracted from the functional connectivity across neural assemblies which is estimated using Nonlinear Regression Analysis.

TABLE I
KAPPA DESCRIPTIVES FOR EACH CLASSIFICATION SCENARIO. MIN STANDS FOR MINIMUM KAPPA VALUE, MAX FOR MAXIMUM KAPPA VALUE, AND SD FOR STANDARD DEVIATION. THE ASTERISKS INDICATE SIGNIFICANCE WITH $p < 0.05$.

Features	Min	Max	Mean	SD
GC	0.57	0	0.43	
NRA	0	1	0	
GC+NRA	0.58	0	0.42	
Small-world	0.57	0	0.43	
Free scale	0	1	0	
Characteristic path**	-0.1	0.45	0.096	0.15
Local efficiency**	-0.14	0.37	0.09	0.14
Global efficiency**	-0.17	0.5	0.11	0.17
Clustering coefficient**	-0.15	0.5	0.11	0.16
Shannon entropy	0	0	0.42	
von Neumann entropy	-0.13	0.3	0.01	0.12

Finally, in order to further explore which individual feature increases the classification performance, the same analysis as previously is carried out for each feature. The results are presented in Figure **??**. According to this figure, the global efficiency leads to the best average Kappa value $k = 0.1112 \pm 0.1673$, which is significantly non-random ($p < 0.01$). Table I presents the kappa descriptives (min, max, mean, and standard deviation) estimated for each case. One may notice from this Table that the global efficiency extracted from the brain network estimated using Nonlinear Regression Analysis leads to the best classification performance.

IV. CONCLUSION

For years the concept of functional connectivity maps has been used to study the brain activity but not for classification of emotions. In this paper, we studied the concepts of brain functional connectivity and compared different methods of estimating functional connectivity on EEG signals for 23 subjects in order to classify pleasant and unpleasant emotions during odour perception. By considering the maps as networks, physical statistics and graph theory based features are extracted and used for designing SVM classifiers with RBF kernel. The best classification accuracy based on Cohen's Kappa is achieved at 0.11 ± 0.17 , which is significantly non-random. The results indicates that features estimated from 216-channel Nonlinear Regression Analysis estimated functional connectivity can be used to classify pleasant and unpleasant emotions during odour perception with a higher accuracy.

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