# Functional Connectivity from EEG Signals during Perceiving Pleasant and Unpleasant Odors

*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 odor 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 pleasant and unpleasant emotions from olfactory perceptions can be better classified if we see the brain as a nonlinear small-world network. By extracting appropriate features from functional connectivity networks, we manage to classify pleasant and unpleasant olfactory perceptions with an average Kappa value of $0.11 \pm 0.17$, which is significantly non-random.**

*Index Terms*—**functional connectivity, odor pleasantness, EEG, nonlinear regression analysis, Granger causality**

## I. Introduction

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 [1], food intake [2], languages [3], etc.

Since multimedia systems are increasingly becoming immersive by rendering more realistic user-experience, which makes it better in evoking strong emotions. To study the emotion reactions to differnt multimedia contents can help us better understand, recognize and interpret the emotion responses to them, and further more can help us to simulate human affects to multimedia contents. 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., [4]–[6]), 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 [7].

Although pleasantness perception has been thoroughly analysed for various, especially audiovisual, stimuli, it has received less attention during experience of odors. Research on pleasantness detection and classification has been carried out by analyzing brain activity using various brain imaging techniques(e.g., [8]–[10]). Various Electroencephalography (EEG) studies on investigating odor pleasantness have analysed brain activation in terms of power spectral density features in frequency domain. To better understand and classify the pleasantness during odor perceiving, more information on how olfactory perception can affect emotions need to be discovered. To contribute to this study, we proposed to investigate the functional connectivity patterns in remote brain locations during olfactory perception process. Our hypothesis is that there are differences in the functional connectivity patterns when subjects experience pleasant and unpleasant odors.

In order to validate our hypothesis, we designed experiments to record EEG signals during olfactory perception. Subjects' feedbacks on each ordor were self-reported after the perception process. Functional connectivity patterns of recorded EEG signals were calculated. To test if different connectivity patterns exist between pleasantness and unpleasantness, we extracted features from functional connectivity patterns and trained classifiers with these features. The evaluation of the classifier is subject-independent, in order to study if there are any common features we could find across all subjects during olfactory perception and emotion generation. This model can be further generalized and benefit other emotion recognition studies. Details on the methods we used are explained in the rest of this paper. Section II explains the background concept of functional connectivity and the concept of network feature of functional connectivity patterns, which will be used for pleasantness classification. Section III describes the experimental protocols and methods for constructing and measuring functional connectivity maps from EEG signals. Section IV provides the classification results on pleasantness by using network-based features extracted from the functional connectivity patterns. Section V gives the conclusions of this work.

## II. Background

### A. Functional Connectivity

Brain connectivity refers to a pattern of anatomical links (anatomical connectivity) or of statistical dependencies (functional connectivity) between neural assemblies. The connectivity pattern is formed by structural links such as synapses or represented by statistical or causal relationships measured as cross-correlation, coherence or information flow [11]. Brain connectivity is a crucial concept to elucidate how neural networks process information. A neurophysiological concept of functional connectivity is introduced by A.A Fingelkurts [12]. According to Fingelkurts' concept, functional connectivity is described as the mechanism for the coordination of activity between different neural assemblies in order to achieve a complex cognitive task or perceptual process. However, since the dependence between different sub-regions of the brain can be interpreted in different ways, there exist different models of estimating functional connectivity in the brain. Widely used models include time-domain estimations such as *Linear Granger Causality* [13], *Nonlinear Regression Analysis* [14], *Transfer Entropy* [15] and frequency-domain estimations such as *Spectral Coherence* [16].

The concept of functional connectivity has been largely used in neuro-imaging analysis in the study of major depression [17] and epilepsy [18]. To our knowledge, little work has been done on emotion recognization on olfactory perception by analysing functional connectivity patterns. Thus in this paper, we introduce the concept of functional connectivity to investigate the connctivity patterns between brain regions during odor pleasantness perception. We applied and compared two time-domain functional connectivity models: *Linear Granger Causality* and *Nonlinear Regression Analysis*. By comparing the performances of the two models, we can better understand the arrangement of connections between brain regions during olfactory perception and emotion generation. The differences of connectivity patterns between pleasant and unpleasant ordor perceptions can be generalized to other emotion study and also help us process or stimulate human affects in the future work.

### B. *Network Features*

The functional connectivity gives us a view of how channels communicate information with each other, thus we can consider the whole connectivities over brain as a kind of brain network. For an N-channel EEG signal recording, functional connectivity estimates the connectivity between each channel combination, which results in an $N \times N$ connectivity network. With the increase of number of channels $N$, the brain network will become larger and more difficult to be analyzed directly. Thus, we proposed to extract network-based features from the brain network. The extracted network-based features from original functional connectivity over brain can provide a higher-level view on the characteristics of the brain network.

Some research groups see the brain network as a kind of small-world network [19] while some others view it as a scale-free network [20]. A small-world network is a kind of network with its nodes are not neighbours of one another but most of them can be reached from every others by a small number of steps. A scale-free newtork is a kind of network most of whose nodes have only a few connections, while only a small number of nodes have a lot of connections. The degree distribution of a scale-free network follows a power law [21].

Both scale-free network and small-world network can provide features based on their own characteristics. Small-world network can provide features as *characteristic path* [22], *local and global efficiency*, *clustering coefficient* [23]. Scale-free network can provide features as *shannon entropy* and *von Neumann entropy* [24]. In this paper, we extracted both types of features for training the classifiers. The performances of the classifiers can help us understand which type of network the functional connectivity network can be considered as.

## III. Materials and Methods

### A. *Experiments*

A total of 23 right-handed subjects took part in the experiment (9 females, 14 males, $24 \pm 4.6$ 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. None of the participants in experiment were wearing perfumed products on the day of experiment.

10 different odors 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 the EEG recording system, subjects were asked to relax and close their eyes. One odor bottle was randomly selected and provided to the subject's nostrils at 1-2 cm. The subjects were not informed about the name of the odor during the experiment. The same odor was presented for about 15 times, leading to about 15 trials. Each trial consisted of 6 seconds baseline and 6 seconds odor experience. After experiencing an odor, 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.

Regarding the equipment, 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.

### B. *Pre-processing of EEG Signals*

After the pre-cleaning and synchronization of recorded 256-channel EEG signals by GES-300 system, a total of 12 seconds EEG segment is kept for each trial. It contains 6 seconds of baseline (resting state) and 6 seconds of activity (odour perception). Signals from 40 electrodes which locate on face muscles and around eyes are rejected in order to reduce muscle and eye 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 0-50Hz. Small laplacian filter is applied for each electrode in order to reduce volume conduction effects [25]. Remaining Eye-movement artifacts are rejected manually by using Independent Component Analysis (funcitons are provided by EEGLAB© toolbox [26]). Topographic maps of ICA components are plotted for each trial, components showing strong activities around eye-region are examined and rejected if their statistics confirms that they are artifact components [26]. The number of components removed varies for each trial of each subject.

### C. *Construction of Functional Connectivity Networks*

Functional connectivity can be estimated in various ways. Two time-doman functional connectivity models were applied and compared in this paper, which are Linear Granger Causality model [27] and Nonlinear Regression Analysis model [28]. We applied both models to our 216-channel EEG signals and the performances of estimated functional connectivity networks were analysed by the classification on pleasantness during olfactory perception. The details on how to estimate functional connectivity networks by using these two models are described below.

*1) Linear 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 various neurophysiological studies. 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 optimal, 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 time series $X_t$ and $Y_t$ are represented by the signals from 2 different channel signals in our 216-channel EEG signal recordings. In this paper we used the Vector Auto-Regression model (VAR) [29] to estimate Granger causality since it provides better computational efficiency and numerical accuracy [29]. We used the MVGC toolbox [29] to estimate the parameters in the VAR model and to compute Granger causality. Details on the computing of Granger causality can be refered to [29].

For our 216-channel EEG signals for each experiment trial, the Granger causality of each channel combination are computed, thus formed a $216 \times 216$ Granger causality matrix. This matrix describes the functional connectivity patterns among these 216 channels of each ordor presentation trial.

*2) Nonlinear Regression Analysis:* Nonlinear regression analysis is also a commonly used model to estimate the functional connectivity. This model is introduced by Pijin and Lopes Da Silva for EEG analysis [14]. 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 measures the *correlation ratio* between two signals $x$ and $y$. The *correlation ratio* ($\eta^2$) describes the dependency of signal $y$ on signal $x$. 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:

$$\mu_{y|x} = \int_{-\infty}^{\infty} y p(y|x) \mathrm{d}y, \tag{1}$$

and $\mu_{y|x}$ describes the predicted value of $y$ given $x$. By this definition, we can calculate the correlation ratio ($\eta^2$) by predicting $y$ value using $\mu_{y|x}$. $\eta^2$ is expressed as:

$$\eta^2 = \frac{Explained\ Variance\ of\ y\ giving\ x}{Total\ Variance\ of\ y} \tag{2}$$

Explained variance is the variance calculated from $y$ according to $\mu_{y|x}$. In this paper, the nonlinear regression analysis algorithm is implemented by fieldtrip toolbox© [30].

Similarly to the functional connectivity network construction using Granger causality, the estimation of functional connectivity network using Nonlinear regression analysis is done for all the channel combinations in our 216-channel EEG signals. The functional connectivity network for each ordor presentation trial is also of size $216 \times 216$ .

### D. Significance Check

The significance check is similar 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 *Bonferroni* 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". In this paper, we assume that the connectivity values emanate from a normal distribution and the $p$-value that rejects the null hypothesis is set to $p = 0.05$. 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 functional connectivity maps that passed significance check are kept for feature extraction and classification in later steps. The significance check was run after the estimation of functional connectivity maps for each trial of each subject. Thus the number of values that passed significance check were different across all trials.

### E. Network Feature Extraction

As described in the Background section, it is difficult to analyse a functional connectivity network of size $216 \times 216$. The better way to evaluate such a large network is to extract useful features from it. Thus we introduced two types of network features to represent the functional connectivity networks.

*1) Small-World Network Features:* The brain is considered as a small-world network by some group [19]. Different aspects of small-world network has 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* [22] [23].

*Characteristic path* represents the average 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 [23] 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 subgraphs of the neighbours of a vertex $i$ in the graph (details of computing subgraphs can be referred to [31]). The subgraphs 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 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 is given by Watts and Strogatz [22] as the average of the local clustering coefficients of all vertices.

The mathmatical presentations and calculations of these 4 small-world network features can be refered to [32].

*2) Scale-Free Network Features:* A few studies have shown that brain functional connectivity can also be considered as a scale-free network. Groups of CJ Stam [21] 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 two.

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 [33].

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 [33]). If a network has a smaller Shannon entropy, it will have more constrains on its structure, which shows this network is more optimal.

*Von Neumann entropy* has been defined by von Neumann for proving the irreversibility of quantum measurement processes. Recently it is also shown that von Neumann entropy can also be applied to network analysis [24]. It has been shown that von Neumann entropy is a measure of regularity of networks [24]. 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 [24] and [33].

The mathmatical presentations and calculations for Shannon entropy can be refered to [34], while the presentations and calculations for von Neumann entropy can be referred to [24].

Thus, to sum up, we provided two types of network features to measure the characteristics of our functional connectivity networks from different aspects of view. These networkfeatures including characteristic path, local efficiency, global efficiency, clustering coefficient, Shannon entropy and von Neumann entropy were extracted from the estimated functional connectivity networks for classification purposes. In particular, network features of Linear Granger Causality estimated functional connectivity networks and network features of Nonlinear Regression Analysis estimated functional connectivity networks were extracted separately for classification. We compared these two functional connectivity models by evaluating the classifiers' performances.

### *F. Classification*

Network features of previously estimated functional connectivity networks were extracted for both pleasant and unpleasant trials. For the purpose of classification, pleasant trials were labelled as 1 while unpleasant trials were labelled as 0. The whole dataset containing extracted features of 23 subjects is split into three parts. Feature data of 1 subjects formed the testing set, the left feature data of 22 subjects were further split into two subsets: training set and validation set. Validation set was used for selecting the best parameter of the classifier. Of the 22 subjects data, each time 1 subject was picked out and used as validation set while the others were used as training set (leave-one-subject-out cross-validation strategy). The parameter validation process was run for 22 times until all 22 subjects data were used for validation. The best parameter was selected based on which parameter value gave the best performence acrossing 22 validations.

Support vector machine with a *Gaussian radial basis function* kernel is used for classification. We tested 13 different values of parameter $\sigma$ ranged from 0.01 to 2 with regular space of 0.15. This range was selected based on try and trials. We tried the parameters ranged from 0.01 to 10 and found the best parameters always fell into the range of 0.01 to 2. Cohen's kappa $\kappa$ [35], as a measure of agreement between two viewers, and was used to evaluate the classifier's performance. 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).

Since we had data from 23 subjects and each time we used 1 of them for testing the performance of the classifier, to evaluate the overall performance of the classifier, the classification process was run for 23 times. Each time 1 subject's data was selected as testing set, while the others for training and parameter validation. After 23 times, all 23 subjects' data were used for testing the classifier and the evaluation was based on the 23 resulting Cohen's kappa values.

## IV. Results and Discussion

The classification results for the features extracted from the functional connectivity maps are shown in Fig. 1. Higher kappa values indicate better classification performance. A kappa value $k = 0$ indicates a random decision. According to Figure 1, a higher classification performance is achieved with Nonlinear Regression Analysis (NRA) compared to Granger's Causality (GC). One-way *Student-t test* was applied to test the significance of non-randomness. The null hypothesis is that the kappa values for each case follow a Student distribution with zero mean. The NRA results sucessfully passed the test with $p < 0.05$ (with $\kappa$ value $\mu = 0.06, \sigma = 0.14$, 14 out of 23 subjects have kappa values larger than zero). The null hypothesis is not rejected for the GC case. The higher kappa values from NRA network classifiers indicate that nonlinear patterns occur in the functional connectivity of neural assemblies, who able to discriminate between pleasantness and unpleasantness during olfactory perceptions.

TABLE I

KAPPA DESCRIPTIVES FOR EACH CLASSIFICATION SCENARIO. MIN STANDS FOR MINIMUM KAPPA VALUE, MAX FOR MAXIMUM KAPPA VALUE, AND SD FOR STANDARD DEVIATION. ONE ASTERISK INDICATES SIGNIFICANCE WITH $p < 0.05$, AND TWO ASTERISKS WITH $p < 0.01$.

| Features | Min | Max | Mean | SD |
|---|---|---|---|---|
| **GC** | -0.2 | 0.77 | 0.07 | 0.23 |
| **NRA*** | -0.2 | 0.19 | 0.06 | 0.14 |
| **GC+NRA*** | -0.07 | 0.18 | 0.05 | 0.08 |
| **NRA(Characteristic path**)** | -0.1 | 0.45 | 0.096 | 0.15 |
| **NRA(Local efficiency**)** | -0.14 | 0.37 | 0.09 | 0.14 |
| **NRA(Global efficiency**)** | -0.17 | 0.5 | 0.11 | 0.17 |
| **NRA(Clustering coefficient**)** | -0.15 | 0.5 | 0.11 | 0.16 |
| **NRA(Shannon entropy)** | -0.13 | 0.34 | 0.07 | 0.12 |
| **NRA(von Neumann entropy)** | -0.13 | 0.3 | 0.01 | 0.12 |

The most representative kappa descriptives are summarised in Table I. **GC** represents the network features (both small-world and scale-free types) extracted from Linear Granger Causality functional connectivity network. **NRA** represents the network features (both small-world and scale-free types) extracted from Nonlinear Regression Analysis functional connectivity network. **GC+NRA** represents the combined network features from both functional connectivity networks. Since the NRA network gives a better kappa performance, we further investigated the classification performance of each single network feature of the NRA functional connectivity network, using the same scenario of classification and statistical tests as described in previous sections. The results reveal that the small-world network features (characteristic path, local efficiency, global efficiency and clustering coeeficient) have a better classification performance compared to scale-free network features. This result indicates that odor 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.

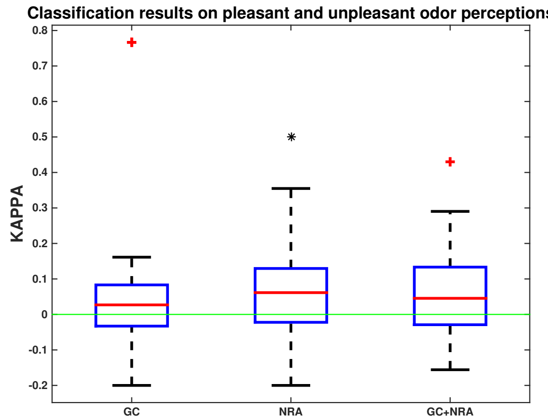


Fig. 1. Cohen's Kappa results boxplots. On each box, the central (red) line represents the median value, the upside and downside edges represent the 25th and 75th percentiles, and the red crosses represent outliers. The green line represents the random decision, $Kappa = 0$. GC refers to the kappa values estimated for features extracted from the functional connectivity maps estimated using Granger Causality. NRA refers to the kappa values estimated for features extracted from the maps estimated using Nonlinear Regression Analysis. GC+NRA refers to the kappa values estimated using features both from Granger Causality and from Nonlinear Regression Analysis.

Additionally, free-scale networks are known for their property of self-similarity in finer scales. However, in our case free-scale network features did not lead to significantly non-random results, indicating that self-similar properties of functional connectivity maps may not be responsible for odor pleasantness discrimination.

However, the best obtained accuracy ($0.11 \pm 0.17$), although significantly non-random, is not very high. Compared with previous study on olfactory pleasantess perception using other methods such as power spectral density [10], our results are not outstanding. We expect that by integrating information from the brain functional connectivity with commonly used features for odor pleasantness perception (such as power spectral density features), the classification performance can be improved.

This work in analysing network features from functional connectivity networks in general can have a great impact in affective computing. The method we had proposed in this paper can help revealing additional knowldege about how information flows during underlying emotional processes. Due to the limitations of research on odors (still many questions open regarding exposition time, etc.), it would be very interesting to further explore if similar patterns occur and if the classification performance is increased using more conventional affective stimuli, such as video and audio.

## V. Conclusion

The concept of functional connectivity maps has been used to study the brain activity but it has not yet been used for classifying odor pleasantness perception. In this paper, we compared different methods of estimating functional connectivity from EEG signals for 23 subjects in order to classify pleasant and unpleasant odors. By considering the connectivity maps as networks, physical statistics and graph theory based features were extracted and used in SVM classifiers. The best classification accuracy based on Cohen's Kappa was achieved using nonlinear regression analysis and small-world network features to estimate the connectivity maps. The results indicated that nonlinear patterns occur in the connectivity maps during hedonic olfactory perception, able to classify odor pleasantness perception in a significantly non-random way.

## References


[1] M. Lyons, S. Akamatsu, M. Kamachi, and J. Gyoba, "Coding facial expressions with gabor wavelets," in *Automatic Face and Gesture Recognition, 1998. Proceedings. Third IEEE International Conference on*. IEEE, 1998, pp. 200–205.

[2] I. E. De Araujo, E. T. Rolls, M. L. Kringelbach, F. McGlone, and N. Phillips, "Taste-olfactory convergence, and the representation of the pleasantness of flavour, in the human brain," *European Journal of Neuroscience*, vol. 18, no. 7, pp. 2059–2068, 2003.

[3] F. S. Bellezza, A. G. Greenwald, and M. R. Banaji, "Words high and low in pleasantness as rated by male and female college students," *Behavior Research Methods, Instruments, & Computers*, vol. 18, no. 3, pp. 299–303, 1986.

[4] T. Nakamoto, H. Ishida, and H. Matsukura, "Olfactory display using solenoid valves and fluid dynamics simulation," *Multiple Sensorial Media Advances and Applications: New Developments in MulSeMedia*, p. 140, 2011.

[5] T. Nakamoto, S. Otaguro, M. Kinoshita, M. Nagahama, K. Ohinishi, and T. Ishida, "Cooking up an interactive olfactory game display," *Computer Graphics and Applications, IEEE*, vol. 28, no. 1, pp. 75–78, 2008.

[6] E. Richard, A. Tijou, P. Richard, and J.-L. Ferrier, "Multi-modal virtual environments for education with haptic and olfactory feedback," *Virtual Reality*, vol. 10, no. 3-4, pp. 207–225, 2006.

[7] C. S. Gulas and P. H. Bloch, "Right under our noses: ambient scent and consumer responses," *Journal of Business and Psychology*, vol. 10, no. 1, pp. 87–98, 1995.

[8] R. J. Zatorre, M. Jones-Gotman, and C. Rouby, "Neural mechanisms involved in odor pleasantness and intensity judgments," *Neuroreport*, vol. 11, no. 12, pp. 2711–2716, 2000.

[9] M. L. Kringelbach, J. ODoherty, E. T. Rolls, and C. Andrews, "Activation of the human orbitofrontal cortex to a liquid food stimulus is correlated with its subjective pleasantness," *Cerebral Cortex*, vol. 13, no. 10, pp. 1064–1071, 2003.

[10] E. Kroupi, A. Yazdani, J.-M. Vesin, and T. Ebrahimi, "Eeg correlates of pleasant and unpleasant odor perception," *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*, vol. 11, no. 1s, p. 13, 2014.

[11] O. Sporns, "Brain connectivity," *Scholarpedia*, vol. 2, no. 10, p. 4695, 2007.

[12] A. A. Fingelkurts, A. A. Fingelkurts, and S. Kähkönen, "Functional connectivity in the brainis it an elusive concept?" *Neuroscience & Biobehavioral Reviews*, vol. 28, no. 8, pp. 827–836, 2005.

[13] C. W. Granger, "Investigating causal relations by econometric models and cross-spectral methods," *Econometrica: Journal of the Econometric Society*, pp. 424–438, 1969.

[14] J. Pijn, P. Vijn, F. Lopes da Silva, W. Van Ende Boas, and W. Blanes, "Localization of epileptogenic foci using a new signal analytical approach," *Neurophysiologie Clinique/Clinical Neurophysiology*, vol. 20, no. 1, pp. 1–11, 1990.

[15] T. Schreiber, "Measuring information transfer," *Physical review letters*, vol. 85, no. 2, p. 461, 2000.

[16] F. T. Sun, L. M. Miller, and M. D'Esposito, "Measuring interregional functional connectivity using coherence and partial coherence analyses of fmri data," *Neuroimage*, vol. 21, no. 2, pp. 647–658, 2004.

[17] M. D. Greicius, B. H. Flores, V. Menon, G. H. Glover, H. B. Solvason, H. Kenna, A. L. Reiss, and A. F. Schatzberg, "Resting-state functional connectivity in major depression: abnormally increased contributions from subgenual cingulate cortex and thalamus," *Biological psychiatry*, vol. 62, no. 5, pp. 429–437, 2007.

[18] A. B. Waites, R. S. Briellmann, M. M. Saling, D. F. Abbott, and G. D. Jackson, "Functional connectivity networks are disrupted in left temporal lobe epilepsy," *Annals of neurology*, vol. 59, no. 2, pp. 335–343, 2006.

[19] D. S. Bassett and E. Bullmore, "Small-world brain networks," *The neuroscientist*, vol. 12, no. 6, pp. 512–523, 2006.

[20] V. M. Eguiluz, D. R. Chialvo, G. A. Cecchi, M. Baliki, and A. V. Apkarian, "Scale-free brain functional networks," *Physical review letters*, vol. 94, no. 1, p. 018102, 2005.

[21] C. J. Stam, "Functional connectivity patterns of human magnetoencephalographic recordings: a small-worldnetwork?" *Neuroscience letters*, vol. 355, no. 1, pp. 25–28, 2004.

[22] D. J. Watts and S. H. Strogatz, "Collective dynamics of small-worldnetworks," *nature*, vol. 393, no. 6684, pp. 440–442, 1998.

[23] V. Latora and M. Marchiori, "Efficient behavior of small-world networks," *Physical review letters*, vol. 87, no. 19, p. 198701, 2001.

[24] F. Passerini and S. Severini, "The von neumann entropy of networks," *arXiv preprint arXiv:0812.2597*, 2008.

[25] C. Wolters and J. C. de Munck, "Volume conduction," *Scholarpedia*, vol. 2, no. 3, p. 1738, 2007.

[26] S. J. Luck, *An introduction to the event-related potential technique*. MIT press, 2014.

[27] A. Roebroeck, E. Formisano, and R. Goebel, "Mapping directed influence over the brain using granger causality and fmri," *Neuroimage*, vol. 25, no. 1, pp. 230–242, 2005.

[28] G. Bettus, F. Wendling, M. Guye, L. Valton, J. Régis, P. Chauvel, and F. Bartolomei, "Enhanced eeg functional connectivity in mesial temporal lobe epilepsy," *Epilepsy research*, vol. 81, no. 1, pp. 58–68, 2008.

[29] L. Barnett and A. K. Seth, "The mvgc multivariate granger causality toolbox: A new approach to granger-causal inference," *Journal of neuroscience methods*, vol. 223, pp. 50–68, 2014.

[30] R. Oostenveld, P. Fries, E. Maris, and J.-M. Schoffelen, "Fieldtrip: open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data," *Computational intelligence and neuroscience*, vol. 2011, 2010.

[31] J. R. Ullmann, "An algorithm for subgraph isomorphism," *Journal of the ACM (JACM)*, vol. 23, no. 1, pp. 31–42, 1976.

[32] M. Rubinov and O. Sporns, "Complex network measures of brain connectivity: uses and interpretations," *Neuroimage*, vol. 52, no. 3, pp. 1059–1069, 2010.

[33] K. Anand and G. Bianconi, "Entropy measures for networks: Toward an information theory of complex topologies," *Physical Review E*, vol. 80, no. 4, p. 045102, 2009.

[34] J. Lin, "Divergence measures based on the shannon entropy," *Information Theory, IEEE Transactions on*, vol. 37, no. 1, pp. 145–151, 1991.

[35] J. S. Uebersax, "Diversity of decision-making models and the measurement of interrater agreement." *Psychological Bulletin*, vol. 101, no. 1, p. 140, 1987.