ANALYZING DEPENDENCE STRUCTURE OF THE HUMAN BRAIN IN RESPONSE TO VISUAL STIMULI

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ABSTRACT

Communication between cortices mediated by deep brain structures such as the amygdala and fusiform gyrus has been suggested to explain the enhanced perception of stimuli bearing emotional content or having facial features. In this paper, we analyze the dependence structure of the relevant brain regions to assess their connectivity in response to a facial stimulus, and to discriminate it from a *mock* stimulus. The proposed approach treats the brain as a graphical network where vertices correspond to locations of electroencephalogram (EEG) recordings, and weights of the edges correspond to dependence values. We employ a novel measure of dependence, called generalized measure of association (GMA), due to its underlying simplicity, and compare its performance against Pearson's correlation. The performance is assessed in terms of the discriminability between the face and mock stimuli. We observe that GMA successfully exhibits higher dependence in regions that might reflect the activity of the amygdaloid complex and the right fusiform gyrus when the stimulus is face. Furthermore, the distributions of the dependence values show that GMA also achieves a better separation between face and mock, compared to correlation.

***Index Terms*—** Brain Connectivity, Dependence Measures, Electroencephalograhy (EEG), FIR Least-Square Filter, Generalized Measure of Association.

1. INTRODUCTION

Graph theoretical methods have been proposed as a tool to analyze structural, functional and effective brain connectivity [1], where vertices correspond to brain regions or neurons, and edges represent synapses or paths of pronounced statistical association between neural elements. Previous studies have noted higher activity in the occipitotemporal cortex where the visual cortex is excited with face and non-face stimuli [2], whereas a face stimulus has been noted to entail further activation in or near the fusiform gyrus. In this paper, we address the problem of assessing functional connectivity in the human brain in response to two different visual stimuli, face and mock with the goal of (1) assessing the enhanced connectivity to facial stimulus, and (2) automatically classifying the stimuli without relying on human experts.

The experimental setup exploits the steady-state visual evoked potential (ssVEP), a well-known physiological tool in human brain studies [3]. ssVEPs are continuous brain responses caused by flashing visual stimuli, generally modulated in intensity with a fixed rate, falling mostly from 6 to 30 Hz. These scalp potentials are observed to oscillate with a fundamental frequency equal to the stimuli flashing rate, and therefore we focus our analysis only on and around this particular frequency.

Numerous methods have been developed to estimate functional dependence, for example, mutual information [4], coherence measures [5, 6] and correlation in time or frequency domains [7]. The measure of dependence we use in this context is a novel measure proposed in [8], called the generalized measure of association (GMA). A particular advantage of this approach is that it is parameter-free. We compare the performance of GMA against the standard Pearson's correlation, and observe that GMA produces better conclusions.

This paper is organized as follows. In Section II, we briefly describe the experimental setting and outline the preprocessing performed on the recorded EEG scalp potentials. In Section III, we describe the methodology to compute dependencies among transformed EEG recordings. In section IV, we compare the performances of GMA and correlation, and in section V we present some general discussions and concluding remarks.

2. EXPERIMENTAL PROCEDURE AND PREPROCESSING

2.1. Setting

The electrode net of a 129-channel Hydro-Cell Geodesic Sensor Net (HCGSN) montage [9] was employed to record neural activity at scalp locations for a duration of 5 seconds with a sampling frequency $F_s = 1000$ Hz. 15 trials were performed

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in which the participants saw two different types of pictures. The first one shows a neutral human face while the second one shows a Gabor patch with similar luminance and contrast as the first figure. Artifacts were reduced by explicitly asking the subjects not to blink during the recordings. In the following sections, we will refer to the facial stimulus as "Face" and the Gabor patch as "Mock".

It is known that the electrical conduction property of the human head would hinder any meaningful interpretation of dependencies between scalp potentials. To reduce the effect of volume conduction, we transform our data into current source density space following the procedure described in [10]. This implementation relies on a spherical layered model of the human head (scalp, skull, cerebro-spinal fluid and brain) to yield reference-free signals. The noise at odd multiples of 60 Hz originating from power lines were attenuated using notch filters.

2.2. Signal Processing

The motivation of this particular experimental set-up is to excite the visual cortex with a stimulus whose response has defined and "traceable" characteristics i.e. the frequency at which the stimulating pictures flicker. Therefore, we only concentrate on a specific frequency band centered around this *flickering* frequency. A linear-phase FIR least-squares filter is used for bandpassing. A detailed account of the filtering steps can be accessed in [11], which suggests using a length-50 filter with a unity quality factor (Q). Fig. 1 shows the original signal for a sample channel, with the resulting FFT after notching and bandpassing.

Prior to computing dependencies, we embed each processed time series in $\tau = 8$ dimensions to account for the propagation delay among neighboring channels. As a result, we obtain at each electrode location k a time series X_k embedded in τ-dimension.

3. THE DEPENDENCE GRAPH

Dependence graphs have proved their usefulness in describing dependence relations between random variables [12]. We model the electrodes network as a complete undirected graph $G = (V, E)$, where V is the set of vertices and E is the set of edges. For each edge e_{ij} between two vertices i and j, we assign a value m_{ij} representing the dependence between X_i and X_j. Note that for correlation, m_{ij} exists in the interval $[-1, 1]$, whereas for GMA it lies in the interval $[0.5, 1]$. We assume that the graph is undirected since our goal is to quantify dependencies between brain regions, which does not account for direction. To relax this assumption, measures of causality and a subsequent directed graph can be considered for assessing effective connectivity.

Choosing the dependence measure is crucial for our approach. Correlation can be used in this regard, but since it only captures second order interactions, it performs rather poorly for time series featuring higher order interactions. We employ a novel rank-based measure of dependence capable of capturing nonlinear structure called generalized measure of association (GMA) [8]. The main advantage of GMA over other measures of dependence is that it is parameter-free, which alleviates the problem of choosing specific parameters such as the kernel size for mutual information. The steps involved in computing GMA between two time series are outlined in Algorithm 1.

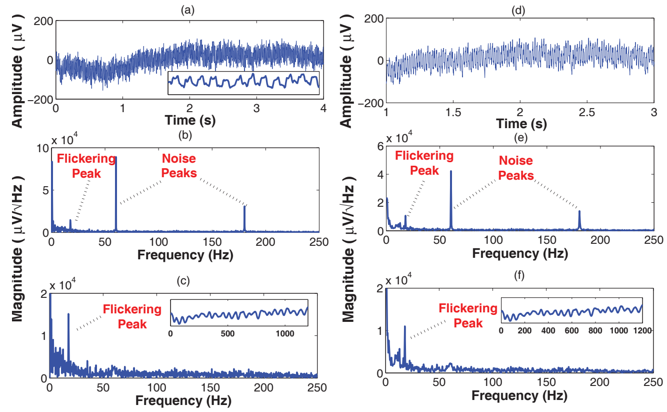


Fig. 1. *(a) Original signal for channel 75 and trial 7 over a 4 sec duration and window showing the same signal at a lower time scale. (b) Frequency components of the signal in (a). The noisy spikes mask the flickering peak at 17.5 Hz. (c) Frequency spectrum after cleaning noisy components and resulting time domain filtered signal. (d,e,f) Same procedure for a smaller window size.*

Algorithm 1: Generalized Measure of Association

Input: Bivariate time series $\{x_t, y_t\}_{t=1}^n$ assuming values in the joint space $\mathcal{X} \times \mathcal{Y}$

Output: Estimated dependence $d \in [0.5 : 1]$

- Assign $P(R = r) = 0 \,\forall\, r \in \{1, \dots, (n-1)\}$

for $i \in \{1...n\}$ **do**

  Find x_{j^*} ($j^* \in \mathcal{J}$) closest to x_i, equivalently $j^* = \arg\min_{j \neq i} \delta_x(x_i, x_j)$, where δ_x denotes Euclidean distance in $\mathcal{X}$.

- For all $j^* \in \mathcal{J}$, find the spread of ranks, i.e. $r_{i,max}$ and $r_{i,min}$ of y_{j^*} in terms of δ_y such that:

$$r_{i,max} = \#\{j : j \neq i, \delta_y(y_j, y_i) \leq \delta_y(y_{j^*}, y_i)\}$$
$$r_{i,min} = \#\{j : j \neq i, \delta_y(y_j, y_i) < \delta_y(y_{j^*}, y_i)\}$$

- For all rank values $r_{i,min} < r \leq r_{i,max}$, assign: $P(R = r) = P(R = r) + 1/|\mathcal{J}|/(r_{i,max} - r_{i,min})/n$

- Compute C as the empirical CDF of $\{r_1, \dots, r_n\}$. d is the area under C normalized by $(n-1)$

We compute the dependence values per time window corresponding roughly to the propagation from the occipital to the frontal region, which is 114 ms [11]. Therefore, m_{ij} can be denoted as m_{ij}^t, where t refers to the time window index. Since the time series is 4600 ms after removing the *baseline*, we have a total of 40 time windows. Besides GMA, we use Pearson's correlation for comparison purposes.

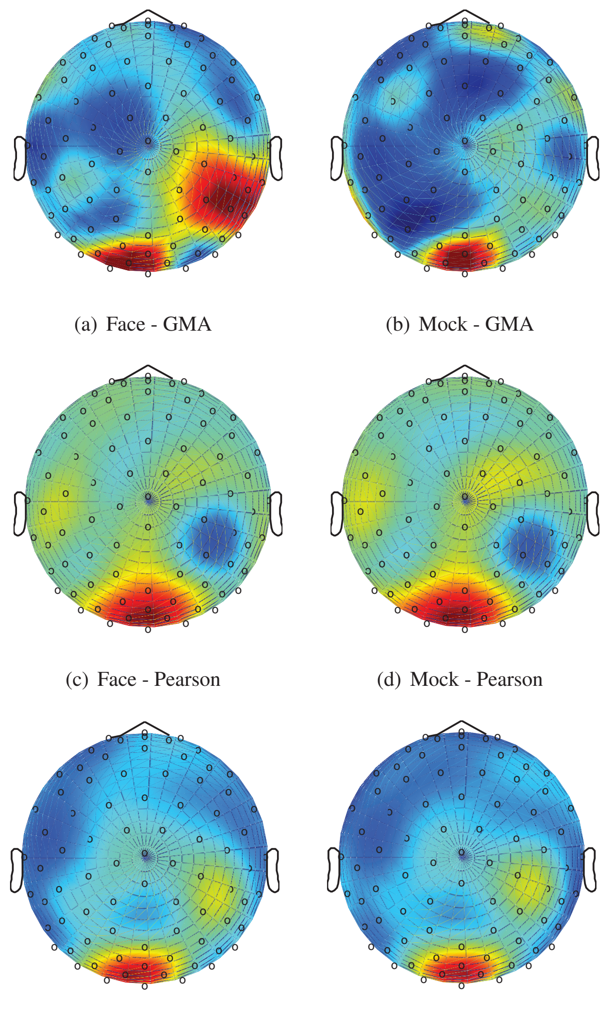
4. SIMULATION RESULTS

Due to the lack of ground truth, we select two criteria for validating our findings and assessing the performance of these dependence measures. The first criterion is the compliance with physiological understanding. For example, we expect the face stimulus to draw more activity in the fusiform gyrus region, especially in the right hemisphere. The second criterion is the ability to discriminate between the two stimuli. This can be inferred from observing the distribution of dependence values for the two stimuli, since the face stimuli should produce more dependence in specific brain regions sensitive to facial stimuli. Although such an approach does not take into consideration the spatial distribution of the vertices, it is simple, and works well for our preliminary evaluation.

We assess the dependence between electrode E72 and the rest since it is the best location for monitoring dependence with respect to the occipital region from which the ssVEP signal is known to emanate. Fig. 2 shows the obtained dependence structure for this channel for both measures of dependence, and for both stimuli. In the case of GMA, the activity in the right hemisphere for the Face stimulus is noticeable and suggests the activation of additional subcortical sources. However, the same thing is less noticeable for correlation, especially when looking at signed correlation values in the $[-1, 1]$ range instead of absolute values. The latter approach also exploits anti-correlation as measure of activation of brain regions. Fig. 3 further projects the obtained GMA measures to the brain surface [13].

Fig. 4 shows the empirical cumulative distribution functions (CDFs) for correlation and GMA per stimulus. GMA yields CDFs that can be easily discriminated whereas for correlation, the CDFs are overlapping and discriminability is less evident. Using the Kolmogorov-Smirnov (KS) statistic to assess these results, GMA gives a value of 0.8527 versus 0.1938 for correlation.

Finally, we study the impact of the free parameters of our implementation, namely the time window size and the embedding dimension. Table 1 shows that the impact of embedding is stronger for smaller time windows. Moreover, as can be seen in Fig. 5, the difference margin between the two stimuli is smaller for larger time windows. This behavior needs to be analyzed with more scrutiny. A plausible explanation is the non-stationarity of the time series and the change in statistical properties over different windows. Also, as we are working with time windows of around 114 ms (corresponding to the lower region of the curve), we should expect near-optimum discriminability between the two conditions.



(a) Face - GMA (b) Mock - GMA

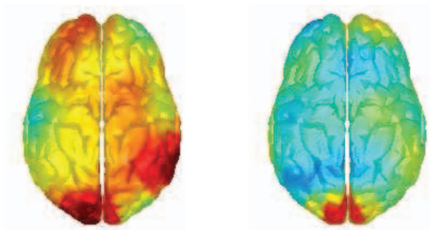
(c) Face - Pearson (d) Mock - Pearson

(e) Face - Pearson (Abs) (f) Mock - Pearson (Abs)

Fig. 2. *Dependence graphs for Face and Mock for the two dependence measures of interest. (a,b) GMA. (c,d) Correlation in a* $[-1, 1]$ *range. (e,f) Absolute correlation in a* $[0, 1]$ *range.*

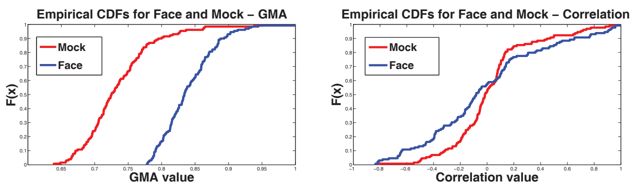
Table 1. GMA values between graph vertices $i = 72$ and $j = 78$ for different parameters ($T = 114$ samples)

Window Size	Embedding Dimension	GMA Value
228 ($2 \times T$)	1	0.6458
	4	0.7899
456 ($4 \times T$)	1	0.5803
	4	0.6659
1824 ($16 \times T$)	1	0.5562
	4	0.5989
3192 ($28 \times T$)	1	0.5515
	4	0.5862
4560 ($40 \times T$)	1	0.5337
	4	0.5550



(a) Face (b) Mock

Fig. 3. *Dependence graph projection over human brain topography using emegs2.4. Left (Face stimulus) and Right (Mock stimulus) using GMA. Note that the region neighboring the amygdaloid complex and the right fusiform gyrus is more active for the Face stimulus rather than the Mock stimulus.*



(a) Empirical CDFs using GMA (b) Empirical CDFs using correlation

Fig. 4. *Empirical distributions for the correlation and GMA measures over the dependence graph for one time cycle corresponding to 114 ms clearly show that GMA has an advantage in discriminating the two conditions. For (a), the KS statistic is 0.8527 and for (b) KS statistic is 0.1938.*

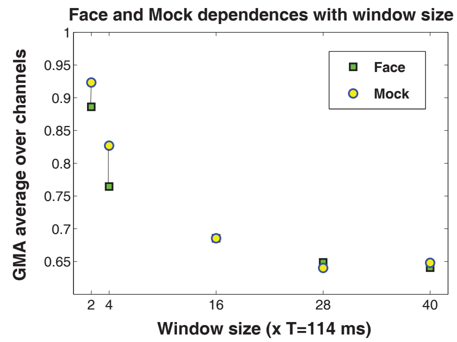


Fig. 5. *GMA values as function of samples used for computation. As sample size increases, the dependence margin between the two conditions shrinks, so does the dependence level. In this paper, a window length corresponding to $2 \times T$ is used. An analysis of the behavior for higher window sizes should be addressed in a later study.*

5. DISCUSSION

In this paper, we used a novel measure of dependence to assess the connectivity among different regions of the human brain in response to two different visual stimuli. Both indicate the presence of active regions in the occipitotemporal cortex. The first measure of dependence, GMA, additionally suggests the presence of active areas in the amygdaloid complex and the fusiform gyrus, which would be caused by subcortical sources in the corresponding brain regions for the Face stimulus. Correlation produces similar results for the Face and Mock stimuli and hence poorly discriminates between the two conditions. Results are also assessed from a statistical perspective using empirical CDFs that show a better discrimination for GMA, which earns a higher KS statistic.

Although we do not consider the whole graph connectivity for evaluation in this study, it would be interesting to assess the dependence values between all possible pairs of channels and use appropriate statistical methods to extract the most active edges. An important evaluation tool for a later study would be a procedure that automatically matches two graphs displaying dependence structure. Previous examples in the literature where graph comparison and matching methods were applied include [14] and [15].

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