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Quantifying Cognitive State from EEG using Phase Synchrony *

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Abstract— **Phase synchrony is a powerful amplitude-independent measure that quantifies linear and nonlinear dynamics between non-stationary signals. It has been widely used in a variety of disciplines including neural science and cognitive psychology. Current time-varying phase estimation uses either the Hilbert transform or the complex wavelet transform of the signals. This paper exploits the concept of phase synchrony as a mean to discriminate face processing from the processing of a simple control stimulus. Dependencies between channel locations were assessed for two separate conditions elicited by distinct pictures (representing a human face and a Gabor patch), both flickering at a rate of 17.5 Hz. Statistical analysis is performed using the Kolmogorov-Smirnov test. Moreover, the phase synchrony measure used is compared with a measure of association that has been previously applied in the same context: the generalized measure of association (GMA). Results show that although phase synchrony works well in revealing regions of high synchronization, and therefore achieves an acceptable level of discriminability, this comes at the expense of sacrificing time resolution.**

I. INTRODUCTION

The human brain is a massively complex system where billions of neurons and neural ensembles interconnect in a vast intricate network. It is the interaction between different brain regions that enables information processing and therefore, accomplishing complex tasks. In the past decades, considerable research has been directed towards exploring the brain connectivity in order to deepen the understanding of its cognitive processes [1], [2]. It has been also proved that brain areas which are coactive during cognition are most likely interdependent [3], which motivates using measures of dependence to detect functional interactions between these areas. Meanwhile, non-invasive techniques such as functional neuroimaging and electroencephalography (EEG) have made it possible to record the activity of human brain, and further help probe the brain dynamics during cognition. Electrophysiological signals have the distinct advantage of providing a particularly high time resolution, and enable exploring brain dynamics at small time scales. A previous study in our lab has shown that it is possible to discriminate two cognitive states in statistical terms, using dependence values estimated from processed scalp EEG signals [4]. The employed measures of dependence include linear measures such as cross-correlation [5], [6] or nonlinear measures such as mutual information [7], [8], besides a recently introduced measure that was termed generalized measure of association (GMA) [9], [10]. In addition to the aforementioned measures of dependence, we propose to apply a widely used concept that has been used to detect synchronizations in brain signals: phase synchrony [11], [12]. The reason phase synchrony seems particularly well suited for this work is that our ssVEP methodology focuses on a single frequency and the EEG is bandpass filtered around this frequency for further processing. This enables extracting the instantaneous phase and further studying the phase synchronization between pairs of signals from different recording sites. In this paper, we show how the performance of phase synchrony, in terms of discriminating two cognitive states, compares with that of GMA, a measure of statistical dependence that characterizes functional interactions in brain networks.

The rest of the paper is divided into the following sections. In section II, we briefly outline GMA which has been previously applied to estimate functional dependencies between different recording sites. Section III describes the methodology applied in this paper, including the signal processing approach and the phase synchrony measure. Simulations using the phase synchrony measure on EEG data are performed in section IV, and are further compared to the simulation results carried out using GMA. Section V provides a discussion and conclusion.

II. GENERALIZED MEASURE OF ASSOCIATION

The generalized measure of association or GMA is a promising dependence measure that enjoys the benefits of having no free parameters and being capable of capturing nonlinear interactions between two variables. The traditional association between two random variables usually tries to estimate how much large values on one random variable can be associated with large values on the other. GMA has generalized this concept by considering the distance between realizations instead of their absolute values. It computes a distribution of ranks based on the closeness between realizations, and then uses the skewness of that distribution to quantify dependence. A simple way of capturing the skewness of the ranks random variable is to calculate the area under its empirical cumulative distribution function. The steps of computing GMA between two time series have been thoroughly described in previous publications [4], [9].

GMA satisfies the boundedness and invariance properties of a measure of association, and is not necessarily symmetric. GMA assumes values between 0.5 and 1. Two independent random variables will cause the ranks to be uniformly distributed, and a GMA value close to 0.5 is obtained in that case. On the other hand, in the case of highly dependent random variables, GMA is closer to 1. Unlike other measures

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of dependence, it is parameter-free, and has the ability to compute association between two variables defined on *two different metric spaces*.

III. METHODOLOGY

A. Signal Processing

We use the same EEG data obtained from the experiment described in [4]. In the experiment, the electrode net of 129-channel Hydro-Cell Geodesic Sensor Net (HCGSN) [13] was applied, and the recordings were continuously made using C_z as the recording reference. Steady-state evoked potentials (ssVEPs) were generated by flickering visual stimuli with a frequency at 17.5 Hz in front of a human subject. An image of a neutral human face was presented to the subject on a monitor, and the same procedure was repeated with a control stimulus showing a Gabor patch. Both images were matched for luminance, average contrast and mean spatial frequency, to preclude systematic differences with respect to these parameters. Epochs of 4200 ms after stimulus onset were extracted from the recorded signals. For the two conditions, a total of 15 trials were performed. The EEG data was collected with a sampling rate of 1000 Hz.

Since the frequency response of the EEG data displays strong noise components at 60 Hz and its odd harmonics (180 Hz and 300 Hz), notch filters were used to process the signals, and they were then fed to a band-pass filter to extract the narrow frequency band of interest. The filter's order and quality factor were chosen from a set of values proven to maximize the discriminability between the two conditions [9]. In this paper, we use a 150-order filter with a quality factor equal to 1.5.

B. Phase Synchrony Measure

Phase synchrony is defined as the process by which two oscillators tend to repeat a sequence of relative phase angles with independent amplitudes. In order to measure the phase synchrony between two signals, the instantaneous phase of each signal has to be estimated around the frequency of interest. The two mostly used approaches to extract the instantaneous phase of the signal are the Hilbert transform and the complex wavelet transform [14]. Both methods try to express the signal in the form $x(t,\omega) = a(t)\exp\left(j(\omega t + \phi(t))\right)$, where $a(t)$ refers to the instantaneous amplitude and $\phi(t)$ refers to the instantaneous phase at the frequency of interest ω. The formulation can be repeated for different frequencies to obtain a time and frequency dependent phase estimation.

Once the phase difference between two signals is estimated, it becomes possible to quantify the amount of synchrony. Here, we use the phase synchronization index to quantify the synchrony based on the relative phase difference. This index is also known as "phase-locking value" or PLV, and can be defined over the time series using the following average:

$$PLV(t) = \left|\sum_{n=1}^{N} \exp(j\theta(t,n))\right| \tag{1}$$

where $\theta(t,n)$ is the time-varying phase difference between two signals for the n^{th} trial which is equal to $\phi_1(t) - \phi_2(t)$, and N is the number of trials. If the phase difference varies little across the trials, PLV is close to 1 indicating a pair of signals with higher phase synchrony.

In this paper, we extract the phase information of the signal from its wavelet transform, which is the convolution of the signal with a complex wavelet. To simplify the calculation, we compute the product of the Fourier transform of the signal with the wavelet generated in frequency domain. A Morlet wavelet is chosen for this analysis, because of the good balance it offers between the time and frequency localization. It can be expressed in the frequency domain as follows:

$$g_{f_0}(f) = A \cdot \exp\left(\frac{(f-f_0)^2}{2\sigma_f^2}\right) \tag{2}$$

where $\sigma_f = \frac{f_0}{m}$, $A = \frac{1}{\sqrt{\sigma_f \cdot \sqrt{\pi}}}$, σ_f is the width of the wavelet in the frequency domain, and f_0 is the center frequency of the wavelet. m should be selected carefully to achieve good time and frequency resolution in the frequency band of our interest. The m-value is usually greater than 5 and is suggested to be 7 according to Grossman et al. [15]. In this paper, the m-value is chosen with the discriminability between the two stimuli conditions in mind, the latter being evaluated with the result of the Kolmogorov-Smirnov test. The KS-test is applied by scanning different m-values (from 5 to 12) on the EEG time series windowed by 228 ms. Results show that $m = 9$ gives the best tradeoff between time and frequency resolutions, and thus better discriminates the face and Gabor patch condition. Therefore, a value of $m = 9$ was picked in our simulations with a wavelet width of 2 Hz in the frequency domain. Assume $W_x(t,\omega)$ to be the convolution of the signal x with the wavelet, then:

$$W_x(t,\omega) = a(t)\exp(j(\omega t + \phi(t))) \tag{3}$$

where $a(t)$ is the time-varying instantaneous amplitude and $\phi(t)$ is the instantaneous phase at the frequency of interest ω. Then the phase difference between two signals $x_1(t)$ and $x_2(t)$ can be computed by:

$$\phi_{12}(t,\omega) = \arg\left(\frac{W_1(t,\omega)\cdot W_2^*(t,\omega)}{|W_1(t,\omega)|\cdot|W_2(t,\omega)|}\right) \tag{4}$$

Thus, according to (1), the PLV can be further calculated using:

$$PLV_{12}(t,\omega) = \frac{1}{N}\left|\sum_{n=1}^{N} \frac{W_1(t,\omega)\cdot W_2^*(t,\omega)}{|W_1(t,\omega)|\cdot|W_2(t,\omega)|}\right| \tag{5}$$

This calculation procedure can be repeated for all pairs of channels and at several frequencies to study the phase synchrony between channels over a broader frequency range.

IV. SIMULATIONS

We apply the methodology described in the previous section on our problem. We first use time windows of 228 ms, or 228 samples. This duration corresponds to four cycles of a 17.5 Hz sinusoid and accommodates a scenario where a relatively high time resolution is needed, while still having enough samples for dependence computation. The

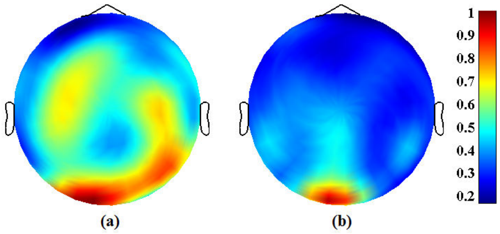

Fig. 1. The averaged phase-locking values between the reference channel and all the other channels for the Face condition (a) and Gabor condition (b). Whole time series were used to calculate the PLVs.

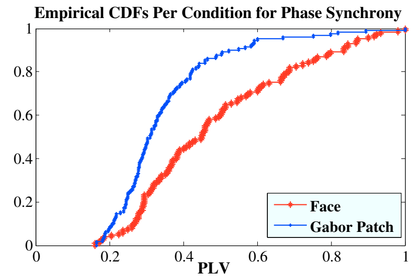

Fig. 2. Empirical cumulative distribution functions (CDFs) computed from PLVs across the 129 channel pairs per condition on the whole time series.

phase-locking values between channels are calculated and used to discriminate the two conditions. This procedure is repeated for several frequencies by using Morlet wavelets centered within the $[12.5, 22.5]$ Hz frequency range, with a step-size of 1 Hz. As already mentioned, this enables exploring a wider frequency range and further studying phase synchronization between different channel locations in both time and frequency. We also propose to apply the same methodology using the whole time series to further investigate its performance when more samples are available for computation.

Channel 72 in the 129-channel HCGSN system (or *POz*) is selected as a channel of particular interest. The rationale for this choice is that this is a central channel located in the occipito-parietal region where most of the ssVEP power is localized. Fig. 1 shows the averaged phase-locking values between channel 72 and all the other channels for the two conditions. Here, the phase-locking values are calculated by using the wavelet centered at 17.5 Hz on the whole time series without partitioning the series into smaller windows.

A. Statistical Analysis

To assess the synchrony maps quantitatively, we use the two-sample KS-test for statistical analysis. The two-sample KS-test is a non-parametric test that compares the cumulative distributions of two data sets. It reports the maximum vertical deviation between the two cumulative distributions which is known as KS statistic and calculates a p-value from the KS statistic and the sample size. The null hypothesis of the KS-test is that both groups were sampled from populations with identical distributions. If the p-value is smaller than a specified significance level, it could be concluded that the two groups were sampled from populations with different distributions. Here, we choose the significance level to be 0.05, and then apply the KS-test on the phase-locking values corresponding to the two conditions calculated by applying different wavelets on the 228 ms time windows. Results show that only the wavelet centered at 17.5 and 18.5 Hz could discriminate the two conditions. Meanwhile, the wavelet centered at the flickering frequency 17.5 Hz achieves the best discriminability with a p-value equal to 0.0058 and a KS test statistic of 0.2093, which coincides with our expectations.

We further apply the same wavelet processing on the whole time series of 4200 samples, and then calculate the phase-locking values for every pair of channels. Results of the KS-test show that the phase synchrony measure implemented on the whole time series outperforms in discriminability the one using 228 ms windows, for almost all of the wavelets centered in the frequency range $[12.5, 22.5]$ Hz. Further, the p-value drops to a near-zero value of 1.8×10^{-5} when using a wavelet centered at 17.5 Hz. This outperformance comes at the expense of the reduced time resolution. Furthermore, we plot the empirical cumulative distribution functions (CDFs) of the phase-locking values calculated on the whole time series using the Morlet wavelet centered at 17.5 Hz per condition, as shown in Fig. 2. No intersections can be observed between the two curves, which is an indicator of a good separability. Theoretically, we expect signals recorded for the Face stimulus to be more synchronized than those of the Gabor patch condition. Since the cumulative distribution function of the PLVs for the Gabor patch condition increases faster than that for face condition at the smaller PLV range, and slower at the larger PLV range, the PLVs between channels for the Gabor patch stimulus condition is mainly distributed at a small numeric range. Thus, the signals recorded for the Gabor patch condition are less synchronized than those for the Face stimulus, which confirms our expectations.

B. Time-Frequency Analysis

As discussed, we use wavelets centered at different frequencies, resulting in frequency-dependent phase-locking values. The time-varying phase-locking values recorded between the reference channel and a specified channel can be seen in Fig.3. Channel 76 is located in the occipital zone and very close to the reference channel site, while channel 78 is in the parietal zone which is farther from *POz* than 76.

It can be seen from Fig. 3 that more synchronization between different electrode sites is present near the flickering frequency of 17.5 Hz. Fig. 3 (a) also suggests higher phase synchronization at 12.5 Hz, 13.5 Hz and even 21.5 Hz, which fall outside the anticipated frequency range for high phase synchronization, given the bandwidth of the wavelet used was 2 Hz. Since the two channels under consideration (76 and 72) are within close proximity, the higher PLV values can be explained by spurious synchrony due to volume conduction [11]. Corresponding spurious synchrony does not appear on channel 78 because of its farther distance from 72.

Fig. 3 also shows that the phase-locking values fluctuate along the time series, especially towards the beginning and the end. To evaluate the stability of the computed values, we further average the PLVs across time windows of 228 ms. Results shows that the obtained PLVs reside within 0.2, which reflects a relative stability in time.

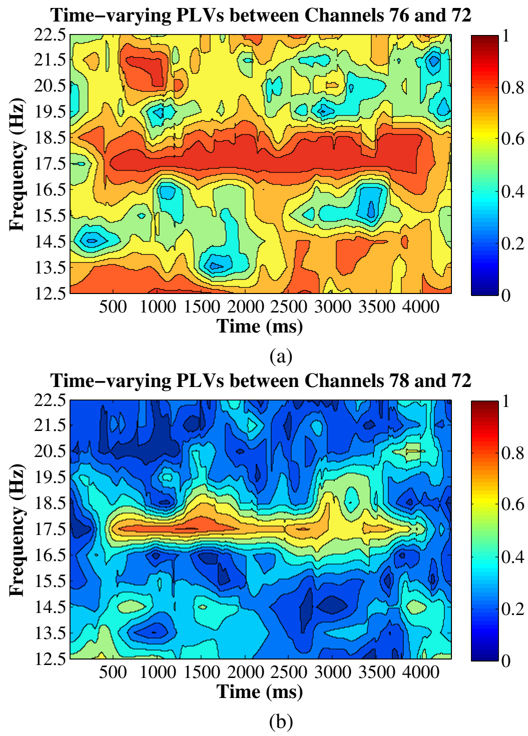

Fig. 3. Time-varying phase-locking values (a) between channel 76 and the reference channel, (b) between channel 78 and the reference channel calculated on the whole time series for Face condition.

C. Comparison with GMA

Fig.4 shows the empirical cumulative distributions per condition for GMA and phase synchrony when applied on 114 ms time window, which has been previously used with other measures of dependence. GMA discriminates the two conditions distinctly, whereas phase synchrony does not achieve satisfactory discrimination between the conditions. The KS-test statistic for GMA is 0.9125, which also performs well among other dependence measures. However, phase synchrony breaks down using 114 ms time windows, which suggests the need for more samples when estimating the instantaneous phase quantities. As a result, applying phase synchrony to detect dependencies with a higher time resolution achieved a worse performance than GMA.

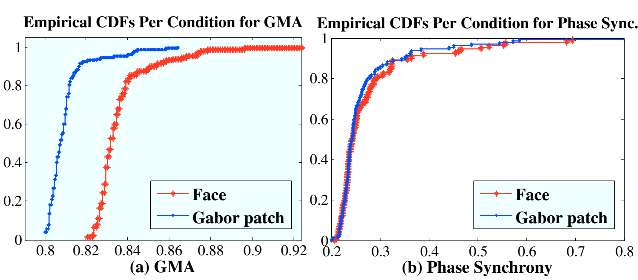

Fig. 4. Empirical cumulative distribution functions (CDFs) generated from dependency values computed per condition using 114 ms time windows across the 129 channel pairs for: (a) GMA, (b) phase synchrony.

V. Conclusion

In this paper, we addressed the problem of discriminating two cognitive states by measuring phase synchrony between EEG recording sites. We further compared the obtained results to those previously obtained using other measures of dependence. The proposed method achieves good performance when discriminating the two conditions of interest, especially when the phase-locking values are calculated using the whole time series. We also perform a time-frequency analysis and examine the stability of phase synchrony. We can conclude that phase synchrony was able to reveal dependencies between different EEG channels, which can be mapped to functional interactions between the underlying brain regions. Moreover, by comparing the performance of the phase synchrony measure and GMA, we conclude that GMA behaves better when a high time resolution is of interest. Although it has been shown that the used phase synchrony measure is indeed able to quantify and discriminate the two conditions, this comes at the expense of sacrificing the time resolution. As future work, it would be interesting to infer more information about the interdependencies between the recorded time series by computing phase locking values for all pairwise channels. Another approach would be to validate the current methodology on more subjects to solidify the above conclusions.

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