

Discrimination Between Cognitive Tasks – a Comparative Study

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Abstract—In this paper we investigate the performance of using, within the EEG classification algorithm, feature extractors such phase synchrony and relative power spectral density indices calculated for seven frequency bands – delta (0.1–4 Hz), theta (4–7 Hz), alpha1 (7–10 Hz), alpha2 (10–13 Hz), beta1 (13–18 Hz), beta2 (18–30 Hz), gamma (30–70 Hz) –, that are believed to mostly reflect functionally different components of cognitive cortical activity. For classification of five mental tasks (baseline, count, letter, math and rotate) a Multi Layer Perceptron (MLP) neural network classifier was used. A standard principal component analysis (PCA) was applied here in order to reduce the high dimensionality of the input data. To quantitatively assess the performance of the extracted features a comparative study between their corresponding results and between them and some other EEG features is also provided.

I. INTRODUCTION

It is now largely recognized that the cognitive acts require the integration of numerous functional areas widely distributed over the brain and in constant interaction with each other [1]. Moreover, synchronization phenomena have been increasingly accepted as a key feature for the communication between different regions of the brain [2]. In neurophysiology the most common measures used to relieve synchronization proved to be correlation in the time domain and coherence in the frequency domain [3][4].

Recently, a new type of synchronization, called phase synchrony, was introduced [5]. This is more appropriate for the real signals analysis than the identical synchronization [6] or generalized synchronization [7] and it is defined as the appearance of a certain relation between the phases of the interacting systems while the amplitudes may remain uncorrelated. In particular, phase synchrony was frequently considered as possible subserving the overall integration of all dimensions of a cognitive act, including associative memory, emotional tone and motor planning [8]. Related to this new type of synchronization, coherence remains a measure that does not specifically quantify phase relationships. Moreover, being a measure of the linear co-variance between two spectra it can be applied only to stationary signals.

In this paper, the degree of phase synchrony was measured by two recently developed measures, statistical phase synchrony and mean phase coherence, both able to deal with nonlinear and non-stationary signals like the EEG one.

Another attribute of the cortical activity, the rhythmicity, has been extensively investigated so far in neuroscience. The rhythmic structure of EEG, revealed by the Fourier Transform, was capitalized to date in a large number of EEG features such

as: the absolute band power, the relation of power in different bands, spatial asymmetry of band power, overall mean frequency, band mean frequency, peak frequencies and so on. Here we revisit this EEG feature and evaluate the performance of a relative band power spectral density index within a brain-computer interface (BCI) application.

II. MATERIALS AND METHODS

A. EEG signals

Our EEG data comprise in a database freely provided by the Colorado State University, Department of Computer Science [9]. EEG data correspond to four subjects and to five mental tasks, each task being repeated twice. They were recorded simultaneously from 6 electrodes corresponding, in the International 10-20 system, to the C3, C4, P3, P4, O1 and O2 positions on the scalp. All channels were referred to the right mastoid A2. They were digitally sampled at 250 Hz and each recording lasted 10 s. The tasks were performed without vocalizing and with the eyes closed and they consisted of: *the baseline task*, for which the subject was asked to relax; *the letter task*, for which the subject was trained to mentally compose a letter to a friend; *the counting task*, for which the subject was asked to watch sequentially numbers written on an imaginary blackboard; *the math task*, for which the subject was instructed to perform a nontrivial multiplication and *the rotation task*, for which the subject was asked to imaginary rotate an object (previous presented) about an axis.

B. Phase Synchronization parameters

In EEG signals the identification of phase synchrony is one complicated by their main characteristics: chaotic behavior, noise and non-stationarity. First, it was shown that the properties of phase synchronization in coupled nonlinear chaotic systems are similar to those in periodic oscillators driven by noise [5], the general condition being:

$$\varphi_{m,n} = |m\phi_1 - n\phi_2| < \text{const.} \quad (1)$$

where: ϕ_1, ϕ_2 are the phases of the two different oscillators, $\varphi_{m,n}$ is their relative phase and n, m are some integers indicating the ratios of possible frequency locking. Because, in our case, the multivariate signals come from the same physiological system we considered the 1:1 ($m=n=1$) synchronization case. Additionally, in EEG signals the true synchronies, buried in a considerable background noise, can be detected only in a statistical sense. That is way the study of phase synchrony

requires two distinct steps: (1) to estimate instantaneous phase of each signal, and (2) to provide a statistical criteria to quantify the degree of phase locking. Both steps are equally provided by the two phase-synchronization indices computed here, statistical phase synchrony and mean phase coherence.

A method that does not require the signal to be stationary, namely the analytic concept of Hilbert transform, was used to estimate the instantaneous phase. For this, the analytic signal, $X(t)$, obtained with the formula:

$$X(t) = x(t) + ix_h(t) = x(t) + i \frac{1}{\pi} \int_{-\infty}^{+\infty} \frac{x(\tau)}{t-\tau} d\tau \quad (2)$$

and corresponding to the analyzed signal $x(t)$ (with its Hilbert transform, $x_h(t)$, and the integration performed in the sense of the Cauchy principal value) was further decomposed as $X(t) = a(t)e^{i\phi(t)}$; here, $a(t)$ represents the instantaneous amplitude and $\phi(t)$ is the phase we are looking for.

1) *Statistical phase synchrony*: Statistical phase synchrony index, characterizing the strength of phase synchrony between two signals, was computed as follows: first, the relative phase was calculated as $\varphi(t) = |\phi_1(t) - \phi_2(t)|$; here $\{\phi_{i,2}(t)\}$ are the instantaneous phases obtained with eq. (2). Then, the distribution function for $\{\varphi \bmod 2\pi\}$ was computed and its deviation from the uniform distribution was statistically assessed with the index given by eq. (3) and based on Shannon entropy [10]:

$$\rho = \frac{H_{max} - H}{H_{max}} \quad (3)$$

The value for maximum entropy (H_{max}) was computed as $\ln M$, where M – the optimum number of bins used to obtain the distribution function $\{\varphi \bmod 2\pi\}$ –, was set $e^{0.626+0.4\ln(L-1)}$ [11]; L parameter is the number of data points and the entropy H of the distribution was simply calculated as:

$$H = - \sum_{i=1}^M p_i \ln p_i \quad (4)$$

with p_i representing the probability of finding the relative phase $\phi(t)$ within the i -th bin.

2) *Mean phase coherence*: Another phase synchrony index, mean phase coherence [12], was computed based on the same instantaneous phases $\{\phi_{i,2}(t)\}$ calculated above but, this time, restricted to the interval $[0, 2\pi]$. The relative phase, $\varphi(t) = \phi_1(t) - \phi_2(t)$, was used to determine the phase locking value as the average value:

$$R = \left| \frac{1}{L} \sum_{i=1}^L e^{i\varphi(i\delta t)} \right| \quad (5)$$

where δt represents the sampling period. Indices ρ and R take values between 0 (no synchrony) and 1 (perfect synchrony).

C. Features Extraction

Prior to the estimation of phase synchrony measures and power spectral densities, each set of data was de-trended by using a polynomial 2nd order for removing slow drifts introduced by the EEG acquisition systems (associated, for example, with gradual changes in the quality of electrode contact to the skin).

1) *Relative band power indices*: Relative band power was estimated for seven frequency bands – δ (0.1–4 Hz), θ (4–7Hz), $\alpha 1$ (7–10 Hz), $\alpha 2$ (10–13 Hz), $\beta 1$ (13–18 Hz), $\beta 2$ (18–30 Hz) and γ (30–70 Hz) –, within all 2.048 s successive sliding windows (512 points) (overlapped by 0.256 s) of all 6 acquiring channels. The sliding step duration of only few hundreds of milliseconds ensures an appropriate tracking of the temporal cortical activations corresponding to the sequence of cognitive processes while the assumption of time invariant properties of the EEG signal was supported by the signal breakdown into short time slide windows [13].

Relative power contribution ratio at each frequency band was expressed as a percentage of the EEG power in the 0–125 Hz band:

$$RP_b = \frac{\sum_{i=k_1}^{k_2} P_i}{\sum_{j=1}^{window/2} P_j} \quad (6)$$

where: b is the frequency band, $k_{1,2}$ are the limits of the band range divided by the spectral resolution, df ($df = \text{sampling frequency} / \text{window size}$) and P_l represents the power of the l -th component of the frequency spectrum. Thus, a feature vector of 42 components (6 channels * 7 frequency bands) and 32 such vectors per each recording (1280 vectors in all) were obtained.

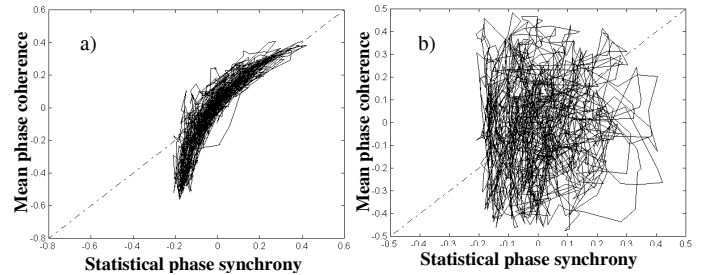


Figure 1: Mean phase coherence versus Statistical phase synchrony obtained a) for the same pair channels and b) for different pair channels

2) *Phase synchrony indices*: In order to estimate phase synchrony indices, that are meaningless for a signal with broadband or a multimodal spectrum, we first pre-filtered the EEG signals. We applied to each channel seven linear band-pass filters corresponding to the seven frequency bands also used for the relative power estimation. This resulted in seven signals for each acquisition point and the measures ρ and R were, then, calculated for all two-channels combinations (C3C4, C3P4, C3O2, C3P3, C3O1, P3C4, P3P4, P3O2, P3O1, O1C4, O1P4, O1O2, C4P4, C4O2, P4O2) and only for pairs of filtered signals representing equivalent frequency band. Each phase-locking value was calculated for sliding windows of 512

data points, overlapped by 64 data points. Finally, a feature vector of 105 components (15 pair channels*7 frequency bands) and 32 such vectors were obtained per each recording, totaling 1280 feature vectors per each synchrony measure (ρ and R) and for all subjects. For both synchronization parameters we achieved the same qualitatively results.

Two reasons made us to further keep only the *statistical phase synchrony* parameter for the classification part: 1) ρ and R showed the same tendency (see Figure 1) and 2) the *mean phase coherence* (R) can underestimate phase synchronizations when the distribution of $\varphi(t)$ has more than one peak [14].

D. Features selection and classification

Five neural networks (*NNs*) of the multilayer perceptron (MLP) structure have been used as classifiers. The first *NN* had as inputs the relative band power spectral densities (input vectors of 42 components, 7 bands*6 channels) estimated for sliding windows of 512 samples (overlapped by 64 samples), for all subjects and for all tasks and it had as outputs five classes corresponding to the five tasks. The 2nd and the 3rd *NNs* are similar to the first *NN*; what differs here is the window size used for spectral estimate: 256 samples and, respectively, 128 samples. The 4th *NN* had as inputs feature vectors consisting of 45 principal components corresponding to the 105-feature vectors represented by the *statistical phase synchrony* parameters. The features selection was done using PCA. Thus, for each of the seven bands the PCA was applied to the 15 R corresponding parameters and it produced the first principal components contributing at least 90% of the total data variance. As a result, for each of the δ , θ , α_1 , α_2 and β_1 bands the PCA produced seven values, for β_2 -band we obtained 6 values and for γ -band only 4 principal components were chosen. In this way, a simpler topology of the neural network and a reduction of the dimension of layers were achieved. The last *NN* was a network of the third *NN* type, with the input vectors obtained by concatenating only the first three principal components corresponding to each of the seven bands. Thus, we got feature vectors of 21 components (3 principal components * 7 frequency bands). For all networks the same five classes corresponding to the five mental tasks represented the outputs. The nucleus of classification, based on feedforward neural networks with two hidden layers (of 10 and, respectively, 6 processing elements), was trained with the backpropagation algorithm [15] using the L_2 mean-square-error criterion. The cross-validation data set used for both, the training stop criteria and the performance evaluation of correct classification rate, was randomly chosen as 10% (128 samples) from the entire data set; the others 1152 samples formed the training data set.

III. RESULTS

The mental tasks classification results obtained with the five *NNs* are all summarized in Table 1.

Because there is a body of literature dedicated to the BCI subject and because there are papers discussing the same five mental tasks discrimination, we further relate our results to part of these ones. Thus, in [16] Anderson *et al.* used the autoregressive (AR) models for all six EEG channels and the

classification accuracy obtained for the subject who better performed all the tasks was in the range 31%÷54%. Moreover, by averaging the output of the best performing network over 20 consecutive overlapping time windows, which amounted to 5 s of actual EEG data, they improved the performance to 70% for two of four subjects tested, and near to 40% for the other two. In [17], Anderson *et al.* evaluated, only for two tasks (baseline and math), four different EEG representations and found that the frequency-band representation yielded the best results: 73.9% classification accuracy. The five cognitive tasks classification for only one subject was then revisited in [18]. Here, a frequency-band representation was used to represent the sources computed by independent component analysis (ICA). The best classification results obtained for three tasks (baseline, letter, math) and for two tasks (rotation and math) were 86% and, respectively, 94% correct classification rate. Compared to these results, the correct classification rate – obtained in our case for all subjects and for all tasks using the relative band power descriptors –, is a better one. One reason for this performance could be a more appropriate selection for the frequency bands. Being generally believed that frequencies above 40 Hz convey little information related to mental state, most frequency-based BCIs have been focused only on the α - and/or β -rhythms [17][18][19]. Most recently, oscillations at higher frequencies (γ band) have been found to be actually a signature of cognitive processes [20] such as active memory, percept formation, and/or object representation. In particular, functional correlates of γ -activity were reported during mental arithmetic [21], language processing [22] and, respectively, mental rotation [23] – all with respect to the rest condition. Moreover, recent studies have indicated that the standard 8-13 Hz α -band actually may be comprised of a lower α -band (aprox. 8-10 Hz), usually found over prefrontal and parietal scalp locations and considered to be sensitive to working memory load and of a higher α -band (aprox. 11-13 Hz), usually found over parietal and occipital scalp locations and believed to be sensitive to visuospatial components of a task [24], as well as to semantic task [25]. Unlike the previous works we used these sub-bands for features extraction considering that they would provide a better tasks representation.

TABLE 1: THE CORRECT CLASSIFICATION RATE

<i>NNs</i> \ <i>Tasks</i>	Baseline	Count	Letter	Math	Rotate
1st <i>NN</i>	90.62±3.61	90.70±6.45	87.00±4.55	94.55±6.85	92.28±4.86
2nd <i>NN</i>	72.61±7.46	52.61±7.46	63.66±6.69	68.64±9.27	63.21±8.06
3rd <i>NN</i>	30.83±9.49	20.68±7.65	41.36±7.87	39±16.81	54.89±9.91
4th <i>NN</i>	76.54±7.79	75.73±8.14	83.88±6.00	85.00±3.46	87.96±6.90
5th <i>NN</i>	70.36±17.51	75.53±7.60	72.78±11.21	72.18±11.90	70.88±10.89

Another point of improvement is related to the EEG quasi-stable epochs considered for spectral estimations. The first three *NNs* point out that, for the same step (256 ms), we obtain better performance for increasing window length. Thus, for a window of 2.048 s we got the best results. Most of the BCIs consider shorter time periods (0.5 s in [16][18], 1 s in [19] and even less) overlapped by aprox. 250 ms but there are also

papers that use a 2 s window [26].

Regarding the *statistical phase synchrony* parameter, it provided a relative good classification rate in both cases, with 4th NN and with 5th NN. The last network performed a little worse than the 4th NN due to the supplementary constraints imposed. The first use of this descriptor in the BCI applications was reported in [19]. The results were in the range of the accuracies reported in the other studies (aprox. 60%). Some reasons for this lack of improvements could be: 1) the index was computed in the frequency band 8-30 Hz comprising together two EEG bands (α and β) and 2) many averages of this index were done over different groups of scalp locations, thus diluting the very localized activities and hemispheric asymmetries assumed by the five mental tasks.

From the presented EEG descriptors, the *relative band power spectral density* calculated for 2.048 s sliding windows gave the better results. Moreover, both descriptors outperform the results reported in the literature.

IV. CONCLUSIONS

A present-day interest for research is the relative importance of EEG oscillations versus EEG frequency-band synchrony between pairs of recording sites. Our results suggest that the relative energy within standard frequency bands is more useful in discriminating the five mental tasks than are the AR parameters or the EEG phase synchronization indices. Nevertheless, the results obtained in the classification task using only the phase synchrony parameter promote it as valuable complementary information to the relative band power one.

Moreover, oscillations at higher frequencies (γ -band) in the human brain as also the EEG α - and β sub-bands may be related to a variety of controllable mental states, indicating its possible utility in BCIs.

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