Advanced EEG Signal Processing

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***Abstract* – The study investigates the performance of some EEG signal processing methods in detecting the signal variations within the Event-Related Potential (ERP) and in extracting the EEG effective connectivity, and the obtained results are discussed. The advantage of applying the Independent Component Analysis (ICA) in EEG analysis is also considered. The EEG data are recorded in the framework of BCI 2005 competition, during a motor imager task, and includes segments of Event-Related (De)synchronization, revealed be the proposed signal processing methods: Event-Related Spectral Perturbation, , the Inter-Trial Phase Coherence, the Inter-Trial Linear Coherence and the Event Related Cross- Coherence. The effective connectivity is analyzed in time and frequency domain, by applying the Granger Causality Index (GCI) and the Partial-Directed Coherence (PDC) respectively, as time-variant or time-invariant methods.**

***Index Terms* – EEG, effective connectivity, ERP, ICA.**

I. INTRODUCTION

The brain behavior is still unknown and lately a lot of efforts are done to reveal i) its anatomical connectivity (AC), determined by the anatomical links, ii) its functional connectivity (FC) obtained when analyzing the statistical dependencies among the EEG signals, or iii) its effective brain connectivity (EC), which represents the instantaneous information flow within the brain [1]. The effective connectivity is to be extracted in time or in frequency domain, by using the Granger Causality Index or the Partial Directed Coherence. Both methods need a good EEG channel selection in order to have a high performance. The EEG channel selection is usually done after a deep channel analysis, in time and/or frequency domain, after investigating the functional connectivity. The current study shows a typical EEG signal processing when investigating the EEG effective connectivity.

II. DATA DESCRIPTION

The EEG dataset consist of EEG segments lasting for 7 s, recorded during a tongue motor imagery task. The first 2 s are used to extract the EEG characteristics corresponding to the resting state, before the stimuli are applied. A beep fixation cross makes the subjects concentrate on the EEG task; it lasts on the screen for 1 s. An arrow appears then, indicating the subjects to imagine the motor task, during a period of 4 s (Fig. 1) [2].

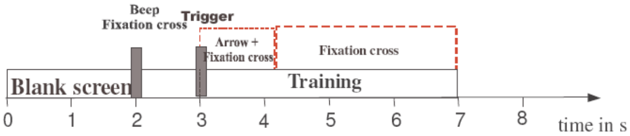


Fig. 1. Paradigm description

III. SIGNAL PROCESSING METHODS

Most of the EEG studies analyze the signal behavior in time or in frequency domain, when considering some particular stimuli that generate the Event-Related Potential (ERP). Since the non-stationary EEG signal has a low amplitude, decreasing exponentially with frequency, the time-domain analysis consists in averaging the corresponding EEG segments, which allows the localization of paradigms (i.e. P300, or P3 represents a positive peak in ERP).

The frequency-domain analysis usually investigates the variations of the spectral components, relatively to a period of relaxation, when the ERP is supposed not to be relevant (a short period before the stimulus application). The most applied frequency-domain methods are: the Event Related Spectral Perturbation, the Inter-Trial Phase Coherence, the Inter-Trial Linear Coherence and the Event Related Cross-Coherence.

Event Related Spectral Perturbation (ERSP)

The event related spectral perturbation allows scientist to observe when the spectral components are (much) reduced after a certain event, which is reported in literature as Event-Related Desynchronization (ERD) or to notice whether the neurons are getting synchronized, generating some additional frequency components, which is known as Event-Related Synchronization (ERS) [3].

The method performs an average over all the similar trials, in frequency-domain, to get the information relevant for the analyzed EEG task:

$$ERSP(f,t) = \frac{1}{n}\sum_{k=1}^{n}\left|F_k(f,t)\right|^2 \qquad (1)$$

where n represents the number of EEG segments, $F_k(f,t)$ is the spectral component at frequency f, computed at time t, for the k-th analyzed EEG segment. $F_k(f,t)$ can be computed by applying the Short-Time-Fourier Transform (STFT) and Wavelet Transform.

Inter-Trial Phase Coherence (ITPC)

The Inter-Trial Phase Coherence (ITPC) reveals the phase synchronization, relatively to the resting state, when considering different trials:

$$ITPC(f,t) = \frac{1}{n}\sum_{k=1}^{n}\frac{F_k(f,t)}{\left|F_k(f,t)\right|} \qquad (2)$$

When the phase coherence is determined based on the spectrum averaging, normalized by the averaged spectrum, we get the Inter-Trial Linear Coherence:

$$ITLC(f,t) = \frac{\sum_{k=1}^{n} F_k(f,t)}{\sqrt{n \sum_{k=1}^{n} |F_k(f,t)|^2}} \quad (3)$$

Event Related Cross- Coherence (ERCOH)

Event Related Phase Cross-Coherence (ERCOH) determines the relation between two different event types, by analyzing the phase of the corresponding computed spectra.

$$ERPCOH^{a,b}(f,t) = \frac{1}{n} \sum_{k=1}^{n} \frac{F_k^a(f,t) F_k^b(f,t)^*}{\left| F_k^a(f,t) F_k^b(f,t) \right|} \quad (4)$$

When the averaging doesn't include the normalization, which extracts only the phase, the Event Related Linear Cross-Coherence (ERLCOH) is computed:

$$ERLCOH^{a,b}(f,t) = \frac{\sum_{k=1}^{n} F_k^a(f,t) F_k^b(f,t)^*}{\sqrt{\sum_{k=1}^{n} |F_k^a(f,t)|^2} \sqrt{\sum_{k=1}^{n} |F_k^b(f,t)|^2}} \quad (5)$$

Independent Component Analysis (ICA)

ICA extracts the components that are not only decorrelated but also independent. It considers the computation of higher order moments (3rd and 4th moment) and is suitable for signals that have no more than one Gaussian component [4]. The algorithm is briefly described in the figure bellow:

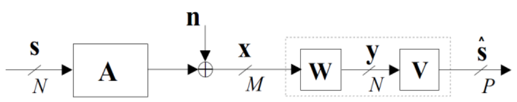


Fig. 2. ICA model - BSS extraction of *p* signals

ICA extracts the signal sources by applying the matrix inverse:

$$\mathbf{s} = \mathbf{A}^{-1}\mathbf{x} \quad (6)$$

Two of the most representative ICA algorithms reported in the literature are: i) the one developed by J. F. Cardoso and Antoine Souloumiac, JADE (joint approximate diagonalization of eigen-matrices) (Cardoso & Souloumiac, 1993); ii) FastICA, developed by Hyvärinen; it is based on a fixed-point iteration scheme maximizing non-Gaussianity as a measure of statistical independence. The idea of ICA is to extract the vector sources, **s,** with q components, from the recorded vector **x**, including p channels:

$$\mathbf{x} = \mathbf{A}\mathbf{s} + \mathbf{n} \quad (7)$$

A is the mixing matrix, **n** represents the additive noise. The following assumptions must be met in order to apply ICA:

1. **A** has linear independent columns (satisfied for real signals usually)
2. **x** contains independent variables
3. **n** and **x** are independent**.**

Under these assumptions the mixing matrix can be estimated and the sources are extracted:

$$\mathbf{s} \approx \hat{\mathbf{s}} = \hat{\mathbf{A}}^{-1}\mathbf{x} \quad (8)$$

ICA (JADE)

It is the most applied ICA algorithm and uses the fourth cumulant to compute the kurtosis. The steps of the algorithm are:

1. Initialization (data whitening):

$$\hat{\mathbf{W}} = diag\left(\left(\lambda_1 - \hat{\sigma}^2\right)^{-1/2}, \cdots, \left(\lambda q - \hat{\sigma}^2\right)^{-1/2}, 0, \cdots, 0 \right) \mathbf{V}^T$$

with $\hat{\mathbf{y}} = \hat{\mathbf{W}}\mathbf{x}$ and,

$$\hat{\sigma}^2 = \frac{1}{p-q} \cdot \sum_{j=p+1}^{q} \lambda_j$$

with $q < p$.

2. Computation of the Kurtosis for $\hat{\mathbf{y}}$; the set of the fourth cumulants, $\{Q_i^y\}$, is obtained.
3. Optimize an orthogonal contrast: the matrix V has to be estimated so that the contrast function is minimized:

$$\phi^{JADE} = \sum_{ijkl \neq ijkl} Q_{ijkl}^y = \sum_i off\left(\mathbf{V}^T \mathbf{Q}_i^y \mathbf{V}\right)$$

where $off(\mathbf{A})$ are the nondiagonal elements:

$$off(\mathbf{A}) = \sum_{i \neq j} a_{ij}$$

The matrix **V** is computed using the Jacobian.

4. Mixing matrix estimation:

$$\hat{\mathbf{A}} = \mathbf{W}^T \mathbf{V}$$

5. The extraction of the independent components:

$$\mathbf{s} \approx \hat{\mathbf{s}} = \mathbf{V}^T \mathbf{y} = \mathbf{V}^T \mathbf{W} \mathbf{x}$$

IV. EFFECTIVE CONNECTIVITY DETECTION

The effective connectivity can be estimated based on the linear multivariate auto-regressive model. When the model parameters are time-varying, the Granger Causality Index and the Partial Directed Coherence are time-variant; otherwise, they are computed as time-invariant measures of effective connectivity.

Granger Causality Index

Let us consider the full MVAR(p) model with regard to y with time-dependent parameters and with the prediction error:

$$\mathbf{y}(n) = \sum_{k=1}^{p} \mathbf{A}_k(n) \cdot \mathbf{y}(n-k) + \boldsymbol{\varepsilon}_y(n), \quad \mathbf{A}_k(n), \boldsymbol{\varepsilon}_y(n) \in \Re^N \quad (9)$$

The reduced MVAR(p) model is so:

$$\mathbf{v}_i(n) = \sum_{k=1}^{p} B_k(n) \mathbf{v}_i(n-k) + \boldsymbol{\varepsilon}_{v_i}(n), \quad \mathbf{B}_k(n), \boldsymbol{\varepsilon}_{v_i}(n) \in \Re^{N-1}, \quad (10)$$

with:

$$\mathbf{v}_i = \left(y_1, \ldots y_{i-1}, y_{i+1}, \ldots, y_M\right)^T$$

Multivariate Time-variant Granger Causality (MVAR tvGCI) from i to j is defined by:

$$\gamma(i \to j)(n) = \log\left(\frac{\mathrm{var}_j(\varepsilon_{v_i}(n))}{\mathrm{var}_j(\varepsilon_y(n))} \right) \quad (11)$$

When only pairs of signals are considered, we have the Bivariate Time-Variant Granger Causality Index (BIV tvGCI).

Partial Directed Coherence

The PDS is evaluated by:

$$\pi_{ij}(\omega) = \frac{\overline{A}_{ij}(\omega)}{\sqrt{\overline{\mathbf{a}}_j^H(\omega)\Sigma^{-1}\overline{\mathbf{a}}_j(\omega)}} \qquad (12)$$

where:

$$\overline{\mathbf{A}}(\omega) = 1 - \mathbf{A}(\omega) = \\ = [\overline{\mathbf{a}}_1(\omega) \quad \overline{\mathbf{a}}_2(\omega) \quad \cdots \quad \overline{\mathbf{a}}_M(\omega)]$$

and

$$A_{kl}(\omega) = \delta_{kl} - \sum_{r=1}^{p} \hat{a}_{kl,r} e^{-i\omega r}$$

The performance in EC estimation depends mainly on improving the parameter estimation for the group EC analysis.

V. RESULTS AND DISCUSSIONS

Figure 3 shows the ERD starting at 1.5 s after the stimulus application, in the beta frequency band. An ERS appears just after the stimuli application, at about 0.5 s, in alpha band. The ITC has no relevant information for the analyzed motor imagery task. Even when the ICA is applied, the ITC is not relevant for the study (see Fig. 4). Contrary, ICA improves the EEG analysis in frequency domain, when considering the ERSP (see Fig. 5).

The ERP is presented in Fig. 6, for all the analyzed trials.

The spectral maps for different spectral components are shown in Fig. 7.

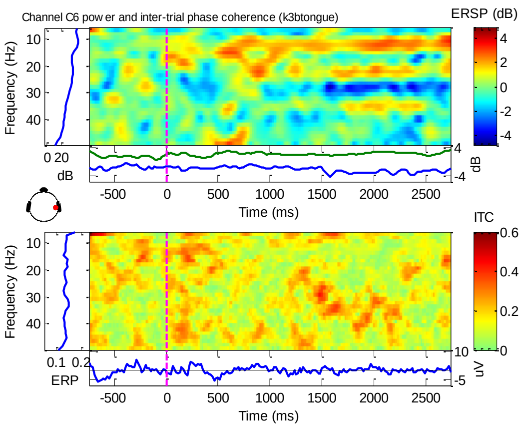


Fig. 3. ERSP (up) and ITC (down), for channel C6, analyzed during the tongue motor imagery task. The ERD/ERS is to be noticed at about 30 Hz/ 10 Hz.

Figure 8 presents the variation of the EEG maps in time.

The effective connectivity, shown in Fig. 9, reveals an effective connection from channel 5 to the others, by applying the tvGCI. When the signal is assumed to be stationary (the time-invariant PDC), which is not correctly describing the analyzed EEG signal, no connection is identified.

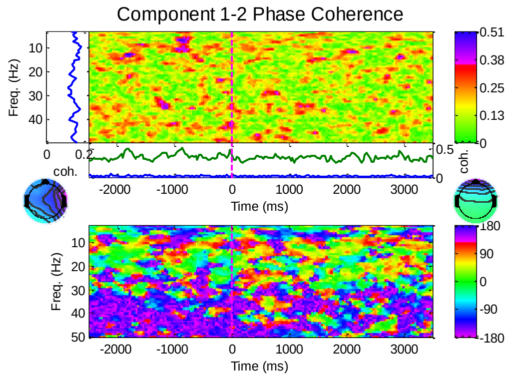


Fig. 4. ERPCOH for the 1st and 2nd ICA components.

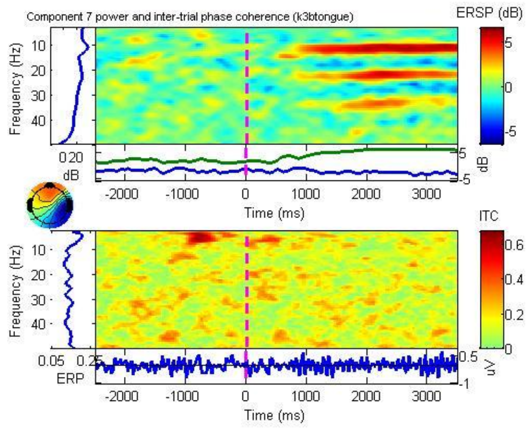


Fig. 5. ERSP and ITC of the 6th and 7th ICA components, when considering the tongue motor imagery task

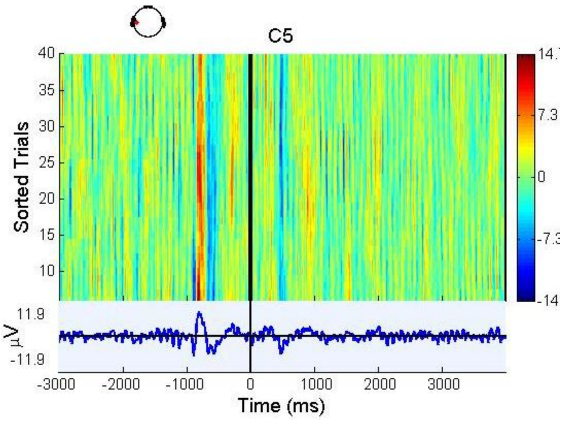


Fig. 6. ERP for all trials (Channel 28 – C5)

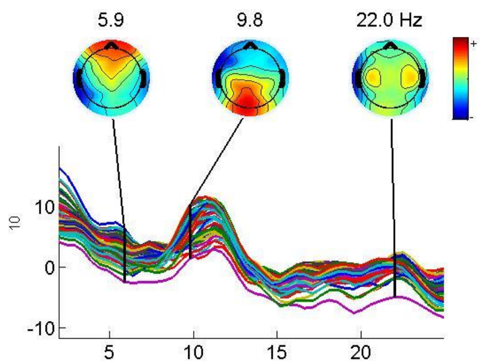
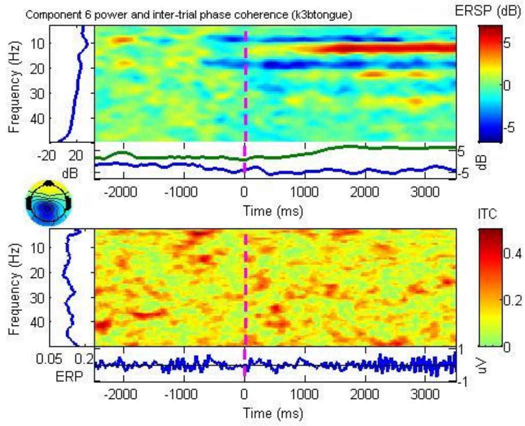


Fig. 7. Pseudocolor spectral maps for different frequency bands.



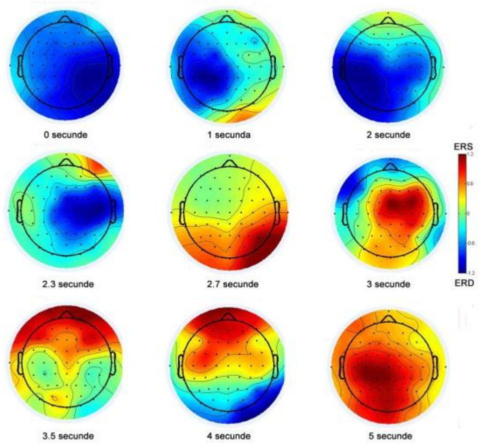
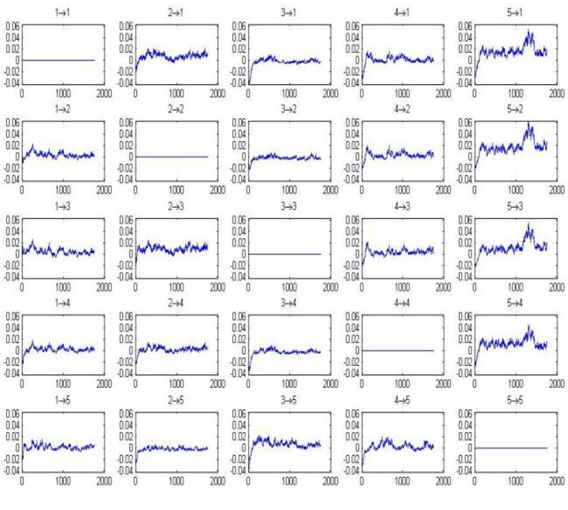
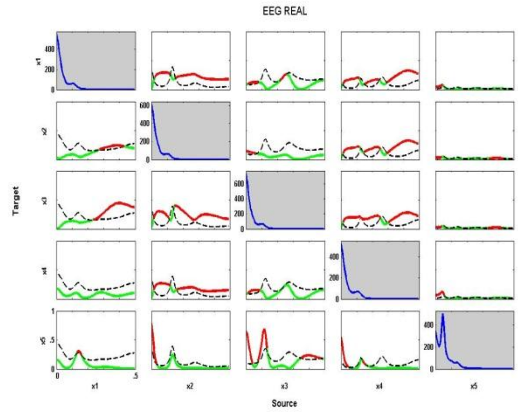


Fig. 8. The variation of pseudocolor spectrum maps in time (tongue motor imagery task)



a)



b)

Fig. 9. Estimation of EEG effective connectivity: a) tv-GCI; b) PDC

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