Reconstructing the cortical functional network during imagery tasks for boosting asynchronous BCI

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RECONSTRUCTING THE CORTICAL FUNCTIONAL NETWORK DURING IMAGERY TASKS FOR BOOSTING ASYNCHRONOUS BCI

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ABSTRACT

Brain-Machine Interfaces are aimed at providing a new communication channel to link the human brain to external world without using the usual nervous and muscular pathways. The work undertaken in our lab is focused on the study and development of an asynchronous BMI: the user communicates trough self-paced imagined motor or cognitive tasks which are not triggered by an external stimulation system. The system is based on the real time analysis of electroencephalographic (EEG) recordings from scalp electrodes in a human subject. For this application, efficient quantification of EEG signals is required to identify the performed mental tasks. Currently used features are spectral power and coherence of respectively each sensors and each couple of sensors. In this paper, we propose to improve the spatial resolution of EEG data by using a preliminary reconstruction of the cortical activity. Power and coherence features are then computed at the cortical level to feed a Support Vector Machine classifier. We applied this new approach to BCI data recorded in our lab on 5 subjects. Our results show that reconstructing the underlying neuronal network dynamics improves the performance of the device compared to a usual sensor level approach.

KEYWORDS

Brain computer interfaces and neural Prosthesis, Brain imaging, Data analysis.

1 Introduction

Brain computer interfacing (BCI) is a challenging application aiming at providing a communication channel for completely paralyzed patients through the real time analysis of their cerebral functional imaging data during specific mental tasks. This analysis is usually performed in two steps: 1) quantification of cerebral imaging signals to extract informative characteristics of cerebral activity, 2) classification of the quantified data to estimate the mental task being performed.

For this application, functional brain signals can be acquired either invasively or non invasively. Invasive BCI use mainly microelectrode arrays to record the activity a very specific neural assembly. Such devices have led to impressive results in decoding the motor cortex both in non human and human primates. However, these systems require surgery and cause tissue damage. An alternative is to use non invasive brain imaging techniques such as Electroencephalography (EEG), Magnetoencephalograhy (MEG) or functional Magnetic Resonance Imaging (fMRI). The most promising non-invasive BCI devices are based on electro-encephalographic (EEG) signals because of the high temporal resolution and portability of the recording system. Nevertheless, the information transfer is limited by a low spatial resolution, as the signal on each EEG sensor can originate from several brain regions and is blurred by diffusion. To overcome that, source reconstruction methods, which enable to estimate the electrical activity of the populations of cortical neurons from EEG measurements, are currently focusing interest from the BCI community [1, 2, 3, 4, 5]. As a matter of fact, these methods can lead to a better dissociation of the activities of many task-specific neural networks at this "source level" compared to the "sensor level".

Among them, distributed linear inverse solutions such as minimum norm estimate (MNE) [6] are advantageous because computationally tractable in the real time context of BCI. These methods enable to estimate simultaneously the amplitude of many current elements uniformly distributed over the cortex using a linear transform of the instantaneous EEG signals. One shortcoming of this approach is the large amount of dipoles in the model, generating a high number of variables in the quantification step of the BCI device. To reduce the number of quantification variables, a priori selection of brain regions (such as motor areas) or variable selection techniques have been used to select the most useful cortical features to feed the classification algorithm [2, 3].

In this paper, we propose to apply source reconstruction to an asynchronous BCI experiment based on motor and non motor imagery tasks. As the imagery tasks are complex cognitive processes requiring the cooperation of many functional areas, the task related cortical activities can be widespread on the cortex and communication between distant brain areas is likely to happen. We thus propose to reconstruct the whole cortical network by quantifying both the local activities of each cortical source and the long distance interactions between areas without variable selection. We show that this new cortical level approach can be rapidly computed for on line classification and leads to a more accurate classification of mental tasks on real data compared to a usual sensor level approach.

2 Overview of the method

The proposed approach is aimed at classifying in real time mental states from EEG for an asynchronous BCI. In this device, EEG signals are acquired and processed on sliding time windows in 3 steps:

1. Source reconstruction: Let $\boldsymbol{M}$ be the (n,T) matrix of the measured EEG signal recorded during a time window of T samples. The corresponding amplitude of N (≈ 10000) cortical sources, stored in the matrix $\boldsymbol{J}$ of size (N,T), is reconstructed using MNE. In addition, these cortical sources are partitioned in K (≈ 90) regions according to a template of Brodmann areas.

2. Quantification of source activities: for each cortical source, activity is quantified by spectral power in 5 frequency bands. Moreover, interaction between brain regions is also quantified by computing coherence between each couple of Brodmann areas. The quantification variables are concatenated and stored in a feature vector $\boldsymbol{x}$ of size $(5N + 5 \times K \times (K-1)/2, 1)$.

3. Classification of brain state: We focus on the case of binary classification corresponding to a subject switching between two mental tasks labeled $y = 1$ for task 1 and $y = -1$ for task 2. The ongoing mental task is then estimated by $\hat{y}$ from the feature vector using a discriminant function $f(\boldsymbol{x})$ such that $\hat{y} = \text{sign}(f(\boldsymbol{x}))$.

Each step of this processing is described in the following parts.

3 Source reconstruction

Our estimate of cortical source activities rests on a forward model accounting for instantaneous EEG data formation by equivalent current dipoles whose locations and orientations are constrained to a surface tessellation of the subject's cortical mantle (surfacic model). This leads to the equation:

$$\boldsymbol{M} = \boldsymbol{G}\boldsymbol{J} + \boldsymbol{\epsilon}$$

where $\boldsymbol{M}$ is the matrix of n EEG measurements on the electrode cap; $\boldsymbol{J}$ is a matrix of N elementary source amplitudes in the model; $\boldsymbol{G}$ is the gain that contains the unitary contributions of all elementary sources sampled at each electrode; $\boldsymbol{\epsilon}$ is an additive noise term. As N is very large (≈ 10000) compared to n, computing an estimate $\hat{\boldsymbol{J}}$ of $\boldsymbol{J}$ from $\boldsymbol{M}$ is an ill posed inverse problem that requires additional constraints to get a unique solution. We used the Minimum Norm Estimate (MNE) [6] approach whose solution minimizes the objective

$$||\boldsymbol{M} - \boldsymbol{G}\boldsymbol{J}||^2 + \alpha||\boldsymbol{J}||^2$$

where alpha is a regularization parameter. The solution can then be expressed explicitly by

$$\hat{\boldsymbol{J}} = \boldsymbol{G}^T(\boldsymbol{G}\boldsymbol{G}^T + \alpha\boldsymbol{I}_n)^{-1}\boldsymbol{M} = \boldsymbol{W}\boldsymbol{M}$$

As the matrix $\boldsymbol{W}$ is only a function of the subjects' anatomy, this approach allows fast computation of source amplitude from EEG measurements. In our settings, according to an heuristic, alpha is set to 10% of the first eigenvalue of $\boldsymbol{G}\boldsymbol{G}^T$.

4 Quantification

The spectral power and coherence in 5 frequency bands (4-8Hz, 8-12Hz, 15-20Hz, 20-30Hz et 30-40Hz) is computed respectively for each cortical source and each couple of Brodmann area using Welch's periodogram. This is done through the computation of the cross spectral matrix $\boldsymbol{\Gamma}$ for the EEG sensors in each frequency band.

$$\boldsymbol{\Gamma}(f) = \mathbb{E}\left[\tilde{\boldsymbol{M}}\tilde{\boldsymbol{M}}^H\right] \text{ with } \tilde{\boldsymbol{M}} \text{ FFT of signal } \boldsymbol{M}$$

The spectral power at frequency f for source i is then computed with the equation:

$$P(i, f) = \boldsymbol{W}_i\boldsymbol{\Gamma}(f)\boldsymbol{W}_i^T$$

Where $\boldsymbol{W}_i$ is the i-th line of $\boldsymbol{W}$. This approach requires the computations of n Fourier transforms instead of N and is thus less computationally demanding. A fast computation of cortical coherence between Brodmann areas is also used with the following equation:

$$C(A1, A2, f) = \frac{|\boldsymbol{S}_{A1}^H\boldsymbol{W}_{A1}\boldsymbol{\Gamma}(\boldsymbol{f})\boldsymbol{W}_{A2}^T\boldsymbol{S}_{A2}|}{\sqrt{P(A1, f)P(A2, f)}}$$

with S_{Aj} the first singular vector of the spectral matrix of area Aj: $(\boldsymbol{W}_{Aj}\boldsymbol{\Gamma}(\boldsymbol{f})\boldsymbol{W}_{Aj}^T)$.

All these features (P and C) are computed for each time window and stored in a feature vector $\boldsymbol{x}$ to feed the classification algorithm.

5 Classification

5.1 Basic principles

Standard classification methods can be broadly described as a two-step procedure:

- First, using a learning set $\{(\boldsymbol{x}_i, y_i)\}_{i \in I}$ consisting of feature vectors $\boldsymbol{x}_i$ and their associated class label y_i, a discriminant function $f(\boldsymbol{x})$ is optimized in order give the better prediction of the class label using the equation $\hat{y} = \text{sign}(f(\boldsymbol{x}))$: this is the training phase.

- Then the resulting discriminant function can be used to estimate class labels corresponding to new feature vectors. This is the testing phase, where the classifier accuracy is quantified by the percentage of correct estimations of the class label.

5.2 Support Vector Machine

We used a linear Support Vector Machine (SVM) [7], which is a state of the art classification algorithm optimizing a linear discriminant function of equation $f^*(\boldsymbol{x}) = \boldsymbol{\omega}^*\boldsymbol{x} + b$ such that

$$(\boldsymbol{\omega}^*, b^*) = \arg\min_{\boldsymbol{\omega},b} \|\boldsymbol{\omega}\|^2$$

under the constraints

$$\forall i, y_i(\langle \boldsymbol{\omega}, \boldsymbol{x}_i \rangle + b) \geq 1$$

The classifier coefficients are computed by solving a dual problem in $\mathbb{R}^q$, with q the number of elements in the learning set.

$$\hat{\boldsymbol{\alpha}} = \arg\max_{\boldsymbol{\alpha}} \sum_i \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j \langle \boldsymbol{x}_i, \boldsymbol{x}_j \rangle$$

Finally the solution writes $\boldsymbol{w}^* = \sum \hat{\alpha}_i \boldsymbol{x}_i$. This dual solution is a crucial property of SVM: since only scalar products of feature vectors appear in the objective, the computational complexity of the problem does not depend on the number of features, which is very high in our case.

6 Asynchronous BCI experiment

This methodology is applied off-line to an asynchronous BCI experiment performed in our lab on 5 subjects. The subjects were asked to perform continuously a mental task indicated on a screen during consecutive 20s epochs. Successive tasks were separated by a resting period of 3 seconds. There were six different mental tasks, including three motor imagery tasks (grasping an object with the right hand, moving the right finger, moving the tongue) and three non-motor tasks (visuo-spatial navigation, imagined music, calculation). These tasks appeared successively in random order on the screen. For each subject, we recorded 4 to 6 sessions of 6 min each per day during 3 days. The EEG data were recorded using a 60 electrodes BrainCap. Data were amplified using a BrainAmps (Brain Products, Inc) 64 channels system sampled to 500Hz. These data are quantified on 2s time windows with an overlap of .5 s.

7 Results

To evaluate the accuracy of the system, we performed a cross validation across the sessions of the same day by leaving out one session, training the classifier on the remaining sessions on testing on the previously drown out

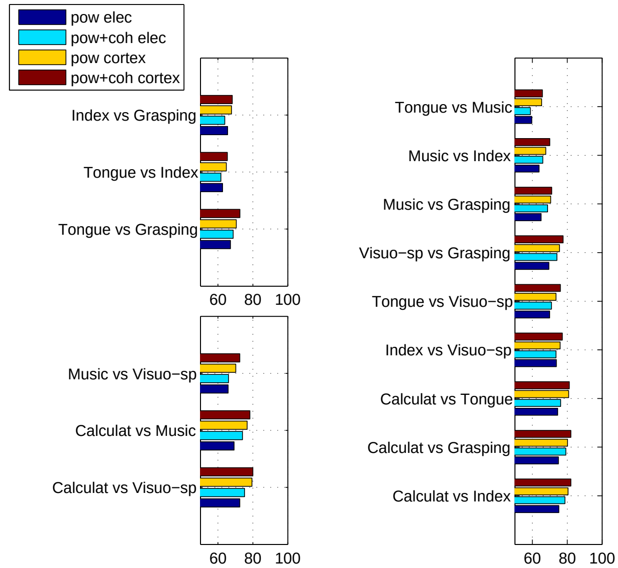

Figure 1. Average accuracy for each possible discrimination.

session. In order to evaluate the improvements of source level quantification versus sensor level quantification, the proposed approach has been compared using directly the spectral powers and coherences computed on EEG sensors in the same 5 frequency bands. Moreover, at each level, classification accuracy has been computed with and without coherence features to quantify their additional information content compared to spectral power features. The accuracies of these 4 approaches are reported for each binary classification between 2 cognitive tasks on Fig. 1., averaged across the subjects. A gradual improvement of classification accuracy appears both when switching from sensor level to source level, and from spectral power features to power+coherence. This figure also shows that many couples involving non motor cognitive tasks give good classification results, which supports the interest of using these tasks for BCI. The most discriminant cortical features across subjects for the best couple of tasks (Grasping versus Calculation) are depicted on Fig. 2 on an average cortex. The discriminant cortical network clearly involves the motor area contralateral to the grasping hand in the classical mu band, but coherence features also shows the presence of centro-parietal network in the same frequency range, possibly revealing communication between motor and spatial processing modules required for the planing of the grasping task. Finally, a temporo-parietal network is also visible in the lower frequency that may be associated to calculation.

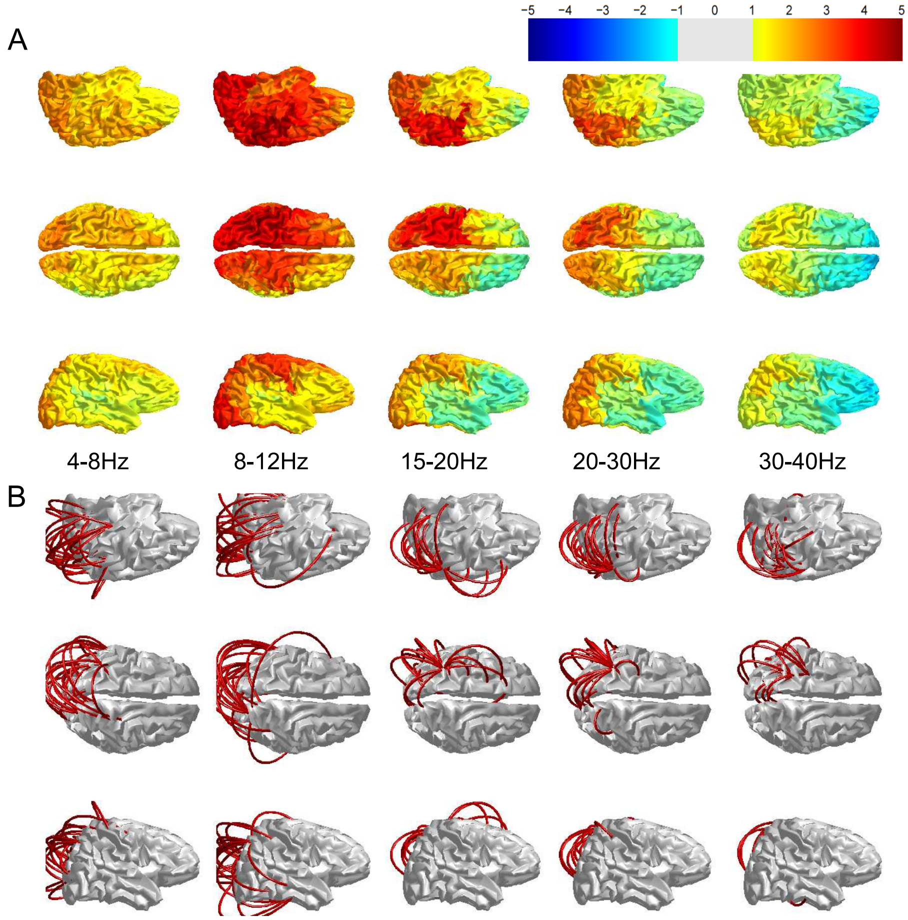

Figure 2. Discriminant variables in each frequency band for the couple *Grasping vs Calculation* (average across subjects). A) maximum T-test for spectral power in each Brodmann area.B) 20 most discriminant cortical interactions.

8 Conclusion

According to these results, source reconstruction methods can improve the separability of tasks related cortical networks. Moreover , the resulting discriminant reconstructed brain network is in accordance with the literature on the considered cognitive tasks. Therefore, cortical network reconstruction is also an efficient tool to improve our knowledge about self-paced cognitive tasks that can be used to drive a BCI. This approach could be used as a preliminary investigation before the implantation of an invasive BCI in the most relevant brain areas.

References

[1] Q. Noirhomme, R. I. Kitney, and B. Macq. Single-trial eeg source reconstruction for brain-computer interface. *IEEE Trans. Biomed. Eng.*, 55:1592–1601, 2008.

[2] M. Congedo, F. Lotte, and A. Lécuyer. Classification of movement intention by spatially filtered electromagnetic inverse solutions. *Phys. Med. Biol.*, 51:1971–1989, 2006.

[3] R Grave de Peralta Menendez, S Gonzalez Andino, L Lucas Perez, P Ferrez, and J del R. Millan. Non-invasive estimation of local field potentials for neuroprosthesis control. *Cogn Process*, 6:59–64, 2005.

[4] L Qin, L Ding, and B He. Motor imagery classification by means of source analysis for brain-computer interface applications. *J. Neural Eng.*, 1:135–141, 2004.

[5] F. Lotte, A. Lécuyer, and B. Arnaldi. FuRIA: A novel feature extraction algorithm for brain-computer interfaces using inverse models and fuzzy region of interest. *Proc. of the 3rd IEEE-EMBS international Conference on Neural Engineering*, pages 175–178, 2007.

[6] S. Baillet, J.C. Mosher, and R.M. Leahy. Electromagnetic brain mapping. *IEEE Signal. Proc Mag*, 18:14–30, 2001.

[7] V. Vapnik. *Statistical Learning Theory*. Wiley-Interscience, New York, 1998.