Reconstruction of cortical sources activities for online classification of electroencephalographic signals.

Joan Fruitet, Maureen Clerc

▶ To cite this version:

HAL Id: inria-00498768
https://hal.inria.fr/inria-00498768

Submitted on 8 Jul 2010

Reconstruction of cortical sources activities for online classification of electroencephalographic signals.

Joan Fruitet and Maureen Clerc

Abstract—**We compare the results given by different methods to reconstruct cortical sources activity in order to classify EEG in real time. Two motor imagery experiments were performed. The aim was to retrieve from 1-second windows of signal which motor imagery task the subjects were performing. The use of cortical activity reconstruction was compared to Laplacian filtering, which is often used in BCI. A recursive algorithm using Student's t-test was used to select relevant cortical sources. The Beamformer method led to an improvement of the classification for the first experiment, which included six motor imagery tasks. The weighted Minimum-Norm method required the use of a specific head model, extracted from the subject's MRI, to improve the classification. It then gave the best results on the second experiment, achieving a classification rate of 77% compared to 71% for direct use of electrode data and 75% for Laplacian filtering and Beamformer.**

I. INTRODUCTION

Numerous studies over the last two decades show that scalp recorded electroencephalography activity (EEG) can be used for non-muscular communication and control systems, commonly called brain-computer interfaces (BCI) [1-4]. One of the goals of these systems is to offer alternative methods of communication to people suffering from severe motor disabilities.

EEG is non-invasive, portable, relatively cheap, and has a very precise temporal resolution, which make it the most widely used recording method for human BCI. Unfortunately, because the signals are measured with electrodes on the surface of the scalp and have crossed the skull barrier, it is difficult to distinguish phenomena which have close origins within the brain. The solution we have focused on is to deconvolve the signals by reconstructing the cortical sources that are at the origin of the measurements on the scalp.

Although it has been shown that this approach can improve some BCI [5], it is as yet rarely used. On both of our experiments, using reconstructed cortical activity gives better results than directly using electrode data.

II. MATERIALS AND METHODS

A. The Experiment

The users were two right-handed male volunteers, both 25 years old and with no disabilities. They were sitting at 1,5m of a 23' LCD screen and were asked to stay motionless during the experiment. Scalp electrodes were recorded at a sampling rate of 2048Hz, on 64 channels of a TMSI amplifier, using electrode AFZ as ground electrode.

The experiment was composed of 5 to 8 blocks of 12 to 24 trials. Each trial started with the appearance of a fixation cross in the center of the screen, 0.5 seconds before the appearance of an image illustrating one out of six motor imagery tasks. The subject had to realize this task during 8 seconds while keeping his eyes on the fixation cross. A break of 1.5 seconds was observed before the next trial (Fig1).
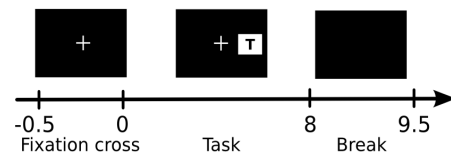

Fig 1. Time line of a trial, in seconds.

For subject one, the six motor imagery tasks were: playing the bass guitar (the subject's hobby), moving the right index, the right or the left hand and the right or the left foot (Fig. 2). For subject two, only three motor imagery tasks were proposed: moving the right or the left hand or both feet.
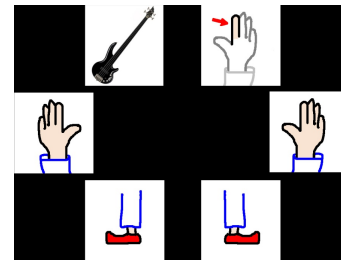

Fig. 2. The six motor imagery tasks proposed to the first subject: playing the bass guitar, moving the right index, the right or the left hand and the right or the left foot. The goal of the analysis was to recover which task the user was performing by analyzing 1-second windows of EEG signal.

B. Preprocessing, feature extraction and classification

To minimize the influence of noise, the signal was re-referenced on the mean of the electrodes and then filtered between 4 and 40Hz.

To be compatible with real time experiments, each 8-second trial was divided into 1-second windows with 0.25-second overlap, leading to 29 windows per trial. The goal of the analysis was to recover from each 1-second window the mental task performed by the subject.

We used as classification features the power of the signal recorded at each electrode in 21 frequency bands between 6 and 36Hz. When considering cortical activity, after solving an inverse problem, the same features were used, but on cortical activity instead of electrode data.

A linear support vector machine (SVM) was then used for classification [6]. The different methods were evaluated by cross validation, while the parameters were automatically adjusted by a second level of cross validation on the training data sets (see [12] for more details).

C. Different methods for extracting cortical activity in real time.

Several methods exist for cortical source activity estimation from EEG recordings. They are generally used on signals that have been averaged over many trials to improve the signal to noise ratio. The challenge to be addressed here is to analyze online data, in which the part of the signal related to the task is very weak.

Our purpose is to use cortical source activity to enhance classification for BCI, so we have used solutions that can be applied on single trials and that are compatible with real-time computation.

The results obtained with these methods were compared to the use of Laplacian filtering which is frequent BCI [7].

1) Surface Minimum-Norm

Cortical sources are represented by a large number of dipoles (around 1800) distributed over a surface that models the cortical gray matter. Each dipole represents a cortical macro-column, and the amplitude of the dipole models the bulk activity of the column.

The first stage consists of modeling and solving the forward problem, i.e., computing the lead field matrix L relating the cortical source activity to the electrode measurements. The relationship between the measurements M and the cortical activity S is modeled by

$$M(t) = LS(t) + N(t) \quad (1)$$

where N represents an Gaussian, centered white noise.

The second stage consists of solving the inverse problem. The Minimum-Norm method selects the source activity S that minimizes the difference between the measurements M(t) and the ideal measurements LS(t):

$$min_S(\|M - LS\|_2^2) \quad (2)$$

Because the number of cortical sources is much greater than the number of electrodes, the minimizer is not unique. One method to obtain a unique minimum is to use a Tikhonov regularization (3) whose unique solution is given by (4)

$$min_S(\|M - LS\|_2^2 + \lambda\|S\|_2^2) \quad (3)$$
$$S_\lambda(t) = A_\lambda M(t) \text{ with } A_\lambda = L^t(LL^t + \lambda I)^{-1} \quad (4)$$

The benefit of this method is that the matrix A can be computed offline; the reconstruction of the cortical activity S can then be obtained in real time through a single matrix multiplication.

Source localization by Minimum-Norm looks for the distribution of source activity with the smallest norm that best explains the measurements. One inconvenience of this method is that the measurement noise can be projected onto the cortical sources. The adjustment of the regularization parameter λ is intended to limit this effect.

Another drawback is that the L2 norm for the regularization tends to produce very smooth cortical activity. An L1 norm can give solutions with greater spatial accuracy;

unfortunately it can no longer be computed linearly, which is a problem as we are working in real-time.

In this paper we have tested a variant of the Minimum-Norm method called the weighted Minimum-Norm. A weighting matrix W, calculated from the lead field matrix L, is applied to the source distribution in the regularization term, so that the sources more distant from the electrodes are not penalized [8]:

$$min_S(\|M - LS\|_2^2 + \lambda\|WS\|_2^2) \quad (5)$$

2) Beamformer

The second method which we have tested for cortical activity reconstruction is the minimum-variance distortion-free beamformer originally developed in the field of array signal processing [9]. This method constructs a spatial filter that extracts from the measured signals the activity coming from a specific position in the brain. It relies on the hypothesis that cortical sources that are spatially distinct are not correlated and that the noise is not correlated with the sources.

Like the Minimum-Norm, the Beamformer first requires to model and solve the forward problem to compute the lead field vector $l(x_0)$ associated to the position x_0 in the cortex.

The signal $M(t)$ is filtered with a spatial filter $w(x_0)$ to recover the activity of the source at x_0.

$$s(x_0, t) = w^t(x_0) M(t) \quad (6)$$

The weight vector $w(x_0)$ is derived by minimizing $w^t(x_0) C_M w(x_0)$ under the constraint $l^t(x_0)w(x_0) = 1$ which leads to:

$$w(x_0) = \frac{C_M^{-1} l(x_0)}{l^t(x_0)C_M^{-1}l(x_0)} \quad (7)$$

where C_M is the covariance matrix of the measurements and $l(x_0)$ is the lead field vector corresponding to the position x_0.

The main difference with the Minimum-Norm method is that the Beamformer does not try to explain the whole signal by an activation of the sources, but tries to filter the signal to extract what originates from a specific position within the brain. The noise that is present in the measurements and that is not correlated with the sources (ambient noise, ocular and muscular activities...) is better filtered out than with the Minimum-Norm method and supposedly will not be projected on the sources.

The main drawback is that the fidelity of the cortical source reconstruction depends on the quality of the covariance matrix of the measurements. Several tens of minutes of recording can be necessary to obtain a good covariance matrix. The Beamformer can nevertheless be applied online, provided an imprecise covariance matrix is used at the beginning of the experiment.

D. Head model

The reconstruction of cortical activity is an inverse problem whose first step, as explained above, consists of modeling and solving a forward problem to compute the lead field matrix L.

We have used for each subject a three-layer head model composed of the scalp, the skull and the brain (around 600 points per interface). The source space was composed of around 600 sources with no fixed orientation (which is represented by 1800 dipoles with fixed orientation).

For subject one, a generic head model was used. For subject two, a specific head model was built from the subject's anatomical MRI with ASA[1].

The lead field matrix L was computed with Open-MEEG using the Symmetric Boundary Element Method (BEM) [10].

E. Feature selection

There are two different approaches for feature selection: the *filtering approach*, which consists of eliminating the irrelevant features (or selecting the useful ones) before applying a classification algorithm, and the *Wrapper approach,* which on the contrary tests the classification on different subsets of features to determine the optimal one. The Wrapper approach can provide better feature selection [11], at a higher computational cost. Due to the large amount of features, we have chosen the filtering approach and a recursive selection algorithm described in [12] that relies on Student's t-test [8].

The first selected feature is the one with the highest t-test:

$$F(v) = \frac{|\bar{v}_1 - \bar{v}_2|}{\sqrt{\frac{d_1 + d_2}{n}}} \qquad (8)$$

where $\bar{v}_k$ and d_k are the mean and variance of the feature on the class k.

It is most likely that the features extracted from cortical sources close to the first selected feature will be similar. They will then have a very high t-test score but will not bring new information for the classification. Our objective is to select other features that may have lower t-test score but contain different information.

We define a scalar product on the space of the features (9) and use it to project the remaining features orthogonally to the first one selected (10).

$$\langle u|v \rangle = \sum_{i \in E} u(i)v(i) \qquad (9)$$

$$\tilde{v} = v - \frac{\langle v|v^* \rangle}{\|v^*\|^2} v^* \qquad (10)$$

where u(i) is the value of the feature u for the ith trial, E is the ensemble of all the trials and $\tilde{v}$ is the projection of v orthogonally to the first selected feature v^*.

The next feature selected is the one whose projection has the highest t-test score, the other features are projected orthogonally to this newly selected feature and the selection continues recursively.

As shown in figure 3, this feature selection algorithm leads to better classification and with fewer features than selecting directly the features having a high t-test. Although this procedure is designed to maximize the information yield out of a limited number of features, it also improves their discriminative power.
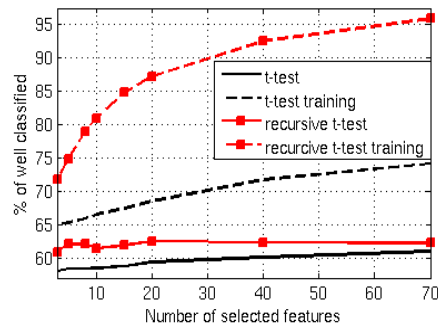
Fig. 3. Result on the training data set (dashed lines) and testing data set (full lines) as a function of the number of selected features. In black (no markers): the N features with the highest t-test score are selected. In red (square markers): results for the recursive feature selection algorithm. The recursive selection algorithm leads to better results with less features.

III. RESULTS

A. First subject: Results with a generic head model and six different tasks

The idea behind this experiment was to try different tasks to see which ones led to the best performances and whether recovering the cortical source activity could improve the results [13]. The performances for all pairs of tasks were computed and the average for each method is given in table 1.

The results vary greatly depending on the tasks (not presented in the table). For example it is possible to differentiate "playing the bass guitar" from "moving the right index" with more than 80% accuracy. On the contrary it was not possible to discriminate "moving the left foot" from "moving the right one". The difficulty of separating between the two feet is due to the proximity of the right and left foot motor areas in the central region.

The only method that significantly increases the result is the Beamformer.

Method	Average result
Preprocessing only	59.9%
Spatial Laplacian	60.9%
Weighted Minimum-Norm	60.7%
Beamformer	62.0%

Table 1. Results for the first subject with different cortical sources reconstructions. The values are the percentage of 1-second windows from which a mental task out of two could be determined.

B. Second subject: Results with a specific head model and three different tasks

For the second subject only three tasks were proposed: right hand, left hand or both feet. The results are given in table 2 for each method.

The best results are obtained with the weighted Minimum-Norm. This benefit is maximal when differentiating right hand from left hand imagery.

method	right/left	right/feet	left/feet	average
Preprocesing only	68%	75%	71%	70,9%
Spatial Laplacian	69%	81%	75%	75,1%
Minimum-Norm	76%	82%	72%	76,6%
Weighted Minimum-Norm	77%	81%	74%	77,2%
Beamformer	75%	75%	74%	74,7%

Table 2. Results for the second subject with different cortical source reconstruction methods. The values are the percentage of 1-second windows from which a mental task out of two could be determined. The mental tasks were motor imagery of the right hand, left hand or both feet.

C. Localization of cortical sources

Figure 4 shows the localization of the most discriminative cortical sources for the Beamformer compared to the weighted Minimum-Norm and to the electrode data. The Beamformer method leads to slightly higher t-test scores but the discriminative sources are less focal. With the weighted Minimum-Norm method some discriminative sources appear on the left hemisphere, while only electrodes over the right motor cortex are discriminant.
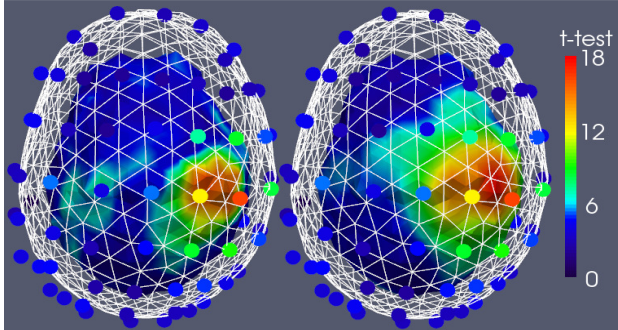

Fig. 4. Localization of the discriminant features with a t-test to differentiate right hand movement imagination from left hand for the second subject. Cortical source reconstruction with weighted Minimum-Norm (on the left) and Beamformer (on the right). The positions of the electrodes and associated t-test values are superimposed on both figures.

IV. DISCUSSION AND PERSPECTIVES

Another type of method, called dipole fitting, is often used for source localization in EEG (MUSIC, RAP-MUSIC,... [14]). It consists of finding a small number of dipoles (1 to 10) that best explain the measurements. In our opinion, it is more appropriate for BCI to reconstruct a distributed activity (constituted of thousands of dipoles) and then select the few dipoles that maximize the discrimination between the different tasks.

For the first subject, source localization with Minimum-Norm did not lead to a significant improvement of the results, whereas for the second subject, for whom a specific head model was used, the best results were obtained with the weighted Minimum-Norm. A good inverse solution really relies on a good forward model, and so precise source localization needs a precise head model which is subject specific.

In the first experiment, which was difficult because some of the tasks were similar, the Beamformer method led to an increase of the classification accuracy. This supports the idea that source reconstruction can increase discrimination between tasks whose activities are closely located on the cortex. In the second experiment, the increase due to source reconstruction was maximal for the right hand/left hand discrimination, which was the most difficult one when using preprocessing only or Laplacian filtering.

Although the gain reported here from using cortical activity rather than Laplacian filtering is rather small, reconstruction of the cortical activity has other benefits for EEG classification that need to be explored. One of them is

that its output, meaning the activation of the sources, is coherent with the physiology of the subject. This can be use to check if the results are valid but also to incorporate neurophysiological knowledge that can be useful for the classification.

An other point that needs to be studied is the impact of source reconstruction on the training of BCI users. It is likely that using cortical activity instead of electrode measurements will facilitate the user training and may lead to a level of control otherwise not possible.

When using source localization, the position of the electrodes over the scalp are measured and registered to the head model. If the electrodes are not set in the exact same position during different sessions, the forward model can be recomputed. An expected advantage of using cortical source activity rather than Laplacian filtering is session to session stability.

One of our objectives is to develop feature selection and classification methods that take into account the spatial coherence of the cortical sources from which the features are extracted. These algorithms could better exploit the advantages of source reconstruction.

REFERENCES

[1] L. A. Farwell & E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials" Electroencephalogr. Clin. Neurophysiol. 70 510-523, 1988

[2] G. Pfurtscheller, D. Flotzinger & J. Kalcher, "Brain-computer interface - a new communication device for handicapped persons" J. Microcomp. Applic. 16 293-299, 1993

[3] J.R. Wolpaw, D.J. McFarland, G.W. Neat & A.C. Forneris "An EEG-based brain-computer interface for cursor control" Electroencephalogr. Clin. Neurophysiol. 78 252-259, 1991

[4] N. Birbaumer, N. Ghanayim, T. Hinterberger, I. Iversen, B. Kotchoubey, A. Kubler, J. Perlmouter, E. Taub & H.Flor, "A spelling device for the paralyzed" Nature 398 297-298, 1999

[5] M. Besserve "Analyse de la dynamique neuronale pour les Interfaces Cerveau-Machines : un retour aux sources" Thèse, 2007

[6] V. Vapnik "The nature of statistical learning theory" Springer-Verlag: New York, 1995

[7] D.J. McFarland, L.M. McCane, S.V. David & J.R. Wolpaw, «Spatial filter selection for EEG-based communication" Electroencephalography and Clinical Neurophysiology 103:386-394, 1997

[8] F.-H. Lin, T. Witzel, S. P. Ahlfors, S.M. Stufflebeam, J. W. Belliveau & M.S. Hämäläinen "Assessing and improving the spatial accuracy in MEG source localization by depth-weighted minimum-norm estimates" NeuroImage 31 2006

[9] J. Capon, "High-resolution frequency wavenumber spectrum analysis", Proc. IEEE, vol. 57, 1408-1419, 1969.

[10] J. Kybic, M. Clerc, T. Abboud, O. Faugeras, R. Keriven, T. Papadopoulo "A common formalism for the integral formulations of the forward EEG Problem", IEEE Trans Med Imag, vol. 24, no.1, 2005.

[11] R. Kohavi & G.H. John, "Wrappers for feature subset selection" Artificial Intelligence 97:273-324, 1995

[12] J. Fruitet , D.J. McFarland & J.R. Wolpaw, "A Comparison of Regression Techniques for a Two-Dimensional Sensorimotor Rhythm-Based Brain Computer Interface" J. Neural Eng. 7, 2010

[13] J. Le Pavec & M. Clerc, "Adaptive classification of mental states for asynchronous brain computer interfaces" Proceedings of NeuroComp, 2008.

[14] S. Baillet, J.C. Mosher & R.M. Leahy, "Electromagnetic brain mapping" IEEE Signal Processing Magazine, 2001