Functional Constraints Added to an ICA Separating Algorithm: an Example on Magnetoencephalographic Signals

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Abstract. A constraint function expressing a priori information about the structure of data recorded in a MEG experiment is used to bias ICA towards a more realistic decomposition. To do so, a function measuring sensitivity to the stimulation considered is added to the usual contrast function to be optimized. Experiments show that the proposed algorithm effectively succeeds in separating physiologically significant activities that standard ICA fails to distinguish in half of the cases.

1 Introduction

Physiological activity in the brain can be evaluated by means of non-invasive techniques based on measurement of the electric or magnetic field generated by electrical neuronal currents (e.g. electroencephalogram - EEG, magnetoencephalogram - MEG). However, relevant signals, related to significant activity, are mixed and embedded in unstructured noise and in other physiological signals, non relevant to the desired observation. For this reason, extraction of information from such signals amounts to blind separation of sources in presence of noise, filtering, and interference, at least as long as we may assume all phenomena to be linear, as is usual and most often reasonable.

One of the most promising techniques to tackle such task is Independent Component Analysis (ICA) [1,2]. Several studies have proved its effectiveness in extracting relevant activations from MEG and EEG signals [3-6]. Nevertheless, in some cases signals are not effectively separated in single components, as they can remain partially mixed, or split into more than one component. Moreover, ICA may fail in presence of strong noise, showing very rapid degradation of performance under a certain SNR [7].

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ICA does not take other information into account than the statistics of the data. However, sometimes quite accurate information on some parameters of the signals we want to separate is known, and more often only general characteristics are known, such as regularities generally valid on a broad class of natural signals.

Some of the authors have developed a modified ICA algorithm that takes available general a priori information into account explicitly, and proved its effectiveness on artificial [8] and real fMRI [9] data. In this paper, such technique is applied to MEG recordings taken in experiments concerning individual finger stimulation. We show how addition of appropriate information to the separating algorithm allows to distinguish more satisfactorily activity from neural networks devoted to individual finger representation, with respect to standard ICA.

The paper is organized as follows. Section 2 describes the physiological background, and reviews the modified ICA technique employing additional information, and experimental methods. In section 3 we discuss results, and conclusions are drawn in section 4.

2 Physiological Background, Materials and Methods

2.1 EEG and MEG

Neurophysiological techniques (EEG and MEG), by allowing direct investigation of the electrical neuronal activity, obtain measures with the same time resolution as the cerebral processing itself. For this reason, EEG and MEG could be used to investigate cerebral connectivity as expressed in the inter- and intra-regional activity synchronization. The crucial problem is to gain access to the inner neural code, starting from the extra-cranial recorded EEG and MEG raw signals. The main approach has been, up to now, to solve the so-called 'inverse problem', i.e. to use Maxwell's equations to calculate spatial distribution of the intra-cerebral currents starting from the magnetic and/or electric field detected in a wide enough area of the scalp surface. Substantial theoretical and technical difficulties are present in solving the inverse problem [10].

A different approach has been recently considered, based on statistical properties of sources composed in the observed signals: ICA was applied by the EEG/MEG researchers not only as a computational technique able to remove artifacts, but also as a powerful tool in discriminating functionally different neural sources, possibly overlapping in time and space [11-13].

2.2 ICA with Prior Information

ICA applies to blind decomposition of a set of signals x that is assumed to be obtained as a linear combination (through an unknown mixing matrix A) of statistically independent non-Gaussian sources s:

$$x = As \, . \qquad (1)$$

Sources s are estimated (up to arbitrary scaling and permutation) by independent components (IC) y as

$$y = Wx ,$$

where unmixing matrix W is to be estimated along with the ICs.

ICA can be cast as an optimization process that maximizes independence as described indirectly by a suitable contrast function. As ICA only takes cumulative statistics of signals into account, other structural aspects remain irrelevant to the decomposition. For instance, temporal order of samples of a signal defined over time is indifferent.

Biomedical signals can often be assumed as generated through a linear mixing process as Eq. 1, where independent sources are supposed to model activities (of the brain in this case) that originate from separate causes, but coexist in adjacent and possibly overlapping volumes. In fact, strict independence of such sources is probably in many cases unrealistic, but using such hypothesis has proved very effective in many contexts, even if *a posteriori* we may observe that perfect independence is never achieved.

Often, however, we know more about such causes and signals. In particular, when a stimulation protocol is applied, we may make strong assumptions on the localization of response in time.

Some of the authors [8] have developed a modified ICA technique that explicitly uses such additional information to bias the decomposition procedure towards solutions that satisfy such assumptions, trading off some independence of the extracted signals. The method is based on optimizing a modified contrast function

$$F = J + \lambda H$$

where J is any function as normally used for ICA, while H accounts for the prior information we have on sources. Parameter λ is used to weigh the two parts of the contrast function. If λ is set to zero, maximization of F leads to pure independence.

2.3 Experimental Setup

Magnetoencephalographic data were recorded from 16 healthy volunteers (8 female, mean age 31±2 years), during separate electrical stimulation of their right thumb or little finger. Ring electrodes were used to deliver the stimulus which consisted of 0.2-ms-long electric pulses (cathode proximal), with an inter-stimulus interval of 631 ms; stimulus intensities were set at about twice the subject's sensory threshold. The subjects had signed an informed consent and the experimental protocol followed the standard ethical directives of the declaration of Helsinki.

Brain magnetic fields were recorded from the left rolandic region, i.e., contralaterally to the stimulation, after positioning the central of the 28 sensors of the MEG system over the C3 site of the International 10–20 electroencephalographic system; a total area of about 180 cm^2 was covered. Data were filtered through a 0.16–250-Hz bandpass and gathered at 1000-Hz sampling rate. The noise spectral density of each magnetic sensor was 5–7 $fT/Hz^{1/2}$ at 1 Hz. About 280 single trials were recorded for each of the two stimulus conditions.

2.4 Functional Constraints

In order to identify neural networks devoted to individual finger central representation, the 'reactivity' to the stimuli was taken into account. It was defined as follows:

1) the evoked activity (EA) was computed separately for the two sensorial stimulations, by averaging signal epochs centered on the corresponding stimulus (EA_T, thumb; EA_L, little finger).
2) the reactivity coefficient (R) was computed as

$$R_X = \sum_{t=20}^{40} \left|\mathrm{EA}_\mathrm{X}(t)\right| - \sum_{t=-30}^{-10} \left|\mathrm{EA}_\mathrm{X}(t)\right|$$

with X = T, L, and t=0 corresponding to the stimulus arrival. The time interval ranging from 20 to 40 ms includes the maximum activation [14] and the baseline (no response) was computed in the pre-stimulus time interval (-30 to -10 ms).

3) The constraint function H_X was then chosen as

$$H_X = \varphi(R_X, k),$$

where

$$\varphi(R_X) = \begin{cases} R_X / k & \text{when } R_\mathrm{X} \le k \\ 1 & \text{else} \end{cases}$$

and k is a suitable parameter measuring the required minimum response.

In order to separate contributions generated by individual stimulations, we started by using constraint H_L, and extracted a single component. Then, after projecting residuals on the orthogonal space w.r.t. the extracted component, we repeated the procedure using H_T. From then on, we applied a composite $H = H_L + H_T$. This procedure was motivated by the fact that thumb representation is physiologically larger than little finger one. Therefore, by operating in this way we meant to favour extraction of the naturally weaker components first.

The same data were also analyzed by unconstrained ICA, using the popular fastICA algorithm [15]. Both algorithms were applied after the PCA whitening without dimensionality reduction.

For comparison, the positions of the known markers of signal arrival in the primary sensory cortex, occurring at around 20 ms from the stimulus (M20), were calculated by standard procedure of averaging original channel signals.

As a main criterion to evaluate the 'goodness' of extracted ICs in representing individual fingers, we observed their spatial position. To this aim, ICs representing thumb and little finger were separately retro-projected, so as to obtain their field distribution. A moving equivalent current dipole (ECD) model inside a homogeneous best-fitted sphere was used. ECD coordinates were expressed in a right-handed Cartesian coordinate system defined on the basis of three anatomical landmarks (x-axis passing through the two preauricolar points directed rightward, the positive y-axis passing through the nasion, the positive z-axis consequently). Only sources with a goodness-of-fit exceeding 80% and within a pre-defined physiological volume (a cube of 5 cm side, centred in x=-33, y=9, z=100, i.e. the

mean centre of hand cortical representation in a healthy population) [14] were accepted. It is to be noted that the field distribution obtained by retro-projecting only one IC, is time-invariant up to a scale factor. Consequently, the subtending current distribution (ECD position in our case) is time-independent.

Table 1. Average and s.d. across subjects (number of subjects, #) of IC_T and IC_L characteristics, fast_IC_T, fast_IC_L and fast_$IC_{T;L}$ (a unique IC responding best to both stimulations, found in 50% of the cases using fastICA): spatial position S_X (x, y, z) with their explained variance (e.v.); the evoked activity indexes (R_T and R_L). Mean $M20_T$ and $M20_L$ positions are reported.

			S_X (mm)				
	#	**e.v.**	**x**	**y**	**z**	**R_T**	**R_L**
IC_T	16	0.95±0.05	-41±9	9±12	88±11	11.6±4.1	1.2±1
IC_L	16	0.94±0.05	-35±11	5±12	100±14	7.2±5.5	13.3±5.3
fast_IC_T	8	0.94±0.05	-44±13	10±38	83±19	8.5±5.1	1.9±3.5
fast_IC_L	7	0.97±0.04	-38±13	6±22	98±11	4.3±4.7	9.2±7
fast_$IC_{T;L}$	8	0.94±0.08	-38±14	9±6	96±13	7.9±5.2	8.4±3.6
$M20_T$	16	0.96±0.18	-42±8	11±11	91±10		
$M20_L$	16	0.94±0.06	-33±10	6±13	100±10		

3 Experimental Results

The activity of the source representing a finger is compared when stimulating the finger itself with respect to when an other finger is stimulated. To do this, the defined indexes R_T and R_L, describing respectively the responsiveness to thumb and little finger stimulations, were both tested for each of the two functional sources IC_L and IC_T . The evoked activity of the two extracted sources (IC_T and IC_L), resulted significantly higher when the finger that source represents was stimulated (Table 1, $R_T > R_L$ for thumb source (IC_T), $p < .0001$; $R_L > R_T$ for little finger source (IC_L), $p = .001$).

Components obtained by fastICA failed in half of cases (8 out of 16) to separate thumb and little finger response: in those cases a unique IC was selected that responded best to both stimulations (fast_$IC_{T;L}$) . Moreover, in one subject out of the eight showing the thumb source (fast_IC_T), the little finger one lacked. Therefore, in the fastICA case, R_L and R_T were tested for the three types of sources obtained, including for each test only those subjects for whom the components considered were indeed found. Results were positive for two out of the three comparisons (Bonferroni post-hoc comparisons): $R_L > R_T$ for fast_IC_L ($p=0.02$) and for fast_$IC_{T;L}$ versus fast_IC_T ($p=0.04$), but not significantly difference was found between fast_IC_L and fast_$IC_{T;L}$ ($p=0.95$). R_T did not result significantly different for any contrast between pairs of obtained sources.

As shown in Table 1, dipole coordinates (x,y,z) were computed from the two retro-projected components IC_T and IC_L in our 16 subjects group. We have to note that for 4 subjects, localization of the retro-projected IC_T was not possible (variance explained

< 0.8, dipole not accepted). The same retro-projection was performed for the fastICA sources.

A General Linear Model (GLM) for repeated measures was estimated to test for differences in source localization: as dependent variables the 3-dimensional coordinates vectors obtained for each subject were used, with the two levels Finger (Thumb, Little) as within-subjects factor. Factor Finger resulted significant ($F(3,9)=16.512$, $p=0.001$), corresponding to S_T (position of retro-projected IC_T) significantly lateral, anterior and lower with respect to S_L (position of retro-projected IC_L). This was in agreement with M20 ECD positions when stimulating respectively thumb and little finger (Table 1).

Testing the seven subjects for whom thumb and little finger response was separated, for the position of retro-projected ICs (fast_S_T and fast_S_L resp.), factor Finger resulted not significant at the standard threshold *p* value of 0.05 ($F(3,4)=4.37$, $p=0.09$; x and y axes not significantly different, z axis at $p=0.06$). Moreover, dipole coordinates of fast_$S_{T;L}$ (retro-projected fast_$IC_{T;L}$) with respect to fast_S_T and fast_S_L resulted not significantly different (Kruskal-Wallis test, $p>0.05$).

It can be noted that the first two functionally-constrained components (IC_T and IC_L), well positioned in agreement with homuncular distribution, were characterized by non-Gaussian kurtosis values: normalized kurtosis median=0.84; interquartile range=[0.36-1.02]. The remaining components, having excluded the artifactual abnormally peaked ones [5], tended to Gaussianity, confirming that the main ICA criteria work properly: normalized kurtosis median=0.11; interquartile range=[0.05-0.23]. This difference was found statistically significant (Mann-Whitney p-value<0.0001).

Kurtosis differences in the fastICA components resulted less evident between task-related and non task-related components: fast_IC_T, fast_IC_L and fast_$IC_{T;L}$ had normalized kurtosis median=1.5; interquartile range=[0.88-1.99]. The remaining components had normalized kurtosis median=0.91; interquartile range=[0.43-1.5], Mann-Whitney p-value=0.06.

4 Conclusions

The proposed procedure proved able to extract somatotopically consistent sources. A specific added value of the ICA approach lies in detecting the complete time course of the estimated sources, trial by trial, instead of describing the activations by averaging all sensors channels and only in specific instants, as usually done in the standard procedures.

On the other hand, standard ICA failed in half of the examined subjects to separate the two sources, producing in that cases a "mixed finger" source, both in spatial position and in task reactivity.

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