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ScienceDirect
International Journal of Psychophysiology 67 (2008) 200–211
INTERNATIONAL JOURNAL OF PSYCHOPHYSIOLOGY
www.elsevier.com/locate/ijpsycho

# Decomposition of working memory-related scalp ERPs: Crossvalidation of fMRI-constrained source analysis and ICA

Michael Wibral [a,*], Georg Turi [b], David E.J. Linden [c], Jochen Kaiser [d], Christoph Bledowski [d]

[a] MEG Unit, Brain Imaging Center, Johann-Wolfgang-Goethe University, Haus 93B, Heinrich-Hoffmann Strasse 10, 60528 Frankfurt am Main, Germany
[b] Max Planck Institute for Brain Research, Deutschordenstrasse 46, 60528 Frankfurt am Main, Germany
[c] School of Psychology, University of Wales Bangor, Penrallt Road, Bangor LL57 2AS, United Kingdom
[d] Institute of Medical Psychology, Johann-Wolfgang-Goethe University, Haus 93C, Heinrich-Hoffmann Strasse 10, 60528 Frankfurt am Main, Germany

Received 28 February 2007; accepted 11 June 2007
Available online 10 August 2007

**Abstract**

Both functional magnetic resonance imaging (fMRI)-constrained source analysis and independent component analysis (ICA) claim to estimate the neuronal sources of electroencephalographic (EEG) scalp signals. In fMRI-constrained source analysis, event-related potential (ERP) generator locations are defined by fMRI activation patterns, and their contribution to the scalp ERP signal is probed. In contrast, ICA assumes that networks of cortical generators can be separated on the basis of their statistical independence. While good arguments can be put forward to justify both approaches, it is unclear how results from both methods compare. A clarification of these issues is of utmost importance to reconcile findings made using identical paradigms but these two complementary analysis methods. As both methods share the concept of spatially static sources a natural space to compare both methods and to crossvalidate the respective findings is at the level of source activity in the form of dipole source waves and independent component time courses and their corresponding maps. We used fMRI-constrained source analysis and ICA followed by clustering using the Kuhn–Munkres algorithm to analyze data from a working memory experiment. We demonstrate that crossvalidation is indeed possible using an appropriate statistical test. However, the sensitivity of this crossvalidation approach is ultimately limited by the low number of dimensions that contribute significant variance to the *grand average* scalp ERP. We conclude that testing at the single-subject level is preferable for crossvalidation purposes if the signal-to-noise ratio of the data allows for this approach.


*Keywords:* ICA; EEG; FMRI; Source analysis; Working memory

## 1. Introduction

The goal of the cognitive neuroscience is to understand the neuronal activity underlying cognitive processes. Event-related potentials (ERPs) provide a measure of these neuronal processes with an excellent temporal resolution helping to investigate the *timing* of cognitive processes in question. However, the spatial resolution of ERPs is limited because of volume conduction; hence several neuronal processes can strongly overlap at the scalp level making their attribution to specific brain regions very difficult. The existence of a signal mixture at the scalp level also limits the usefulness of high temporal resolution as peaks at a given electrode can result from temporally overlapping neuronal source processes.

Several approaches have been proposed to solve this problem. One class of approaches draws on physical information in combination with physiologically plausible constraints to solve the ill-posed electromagnetic inverse problem. Another class of solutions tries to blindly decompose the neuronal source processes by their differing statistical signatures.

The first class of approaches tries to invert the well-defined equations of scalp signal generation from known sources in a known conductor configuration (head model). This inversion is mathematically impossible without additional constraints as described for electro- and magnetoencephalography (EEG and

* Corresponding author. Tel.: +49 69 6301 83193; fax: +49 69 6301 83231.
*E-mail addresses:* wibral@bic.uni-frankfurt.de (M. Wibral), gturi@gmx.de (G. Turi), d.linden@bangor.ac.uk (D.E.J. Linden), j.kaiser@med.uni-frankfurt.de (J. Kaiser), bledowski@em.uni-frankfurt.de (C. Bledowski).

0167-8760/$ - see front matter 
doi:10.1016/j.ijpsycho.2007.06.009

MEG) by Hamalainen (Hamalainen and Ilmoniemi, 1994). If the number of possible generators is known *a priori* and sufficiently small, the ill-posed inverse problem is transformed into an over-determined one that has a unique solution in the least squares sense. In this case orientation and location of the sources can simply be calculated (usually referred to as dipole fitting). A special case of this approach is to assume only one or two dominant sources at any given time interval and then fitting these sequentially over the whole ERP, adding one source after another (for example Di Russo et al., 2002). Another approach would be to obtain the information on the number of sources from an independent measurement, preferably using an identical experimental paradigm. Functional magnetic resonance imaging (fMRI) provides task-related cortical activation maps of the human brain with high spatial resolution. fMRI-constrained source analysis, as described in this study tries to supply the necessary information on the number of sources by interpreting BOLD fMRI activations from an identical paradigm as the potential source locations of the scalp EEG (Bledowski et al., 2004; Scherg and Berg, 1996). Subsequent source analysis then models the activity time-courses of the identified brain regions in the millisecond range using the identified *physical* inverse model. In contrast to sequential dipole fitting, this approach does not require that only very few sources are active at a given moment in time. It is therefore preferable for cognitive tasks where a larger number of concurrent processes are involved. Due to the imperfect correspondence of BOLD fMRI activations and ERP signal generators certain precautions have to be taken. A detailed discussion is found in Bledowski et al. (2006).

The second class of approaches to the decomposition of scalp ERP signals into the underlying source processes relies on statistical signal properties. Decomposition of scalp EEG data into potential generating processes *via* independent component analysis (ICA) draws on the central limit theorem stating that mixtures of signals (random variables) are more Gaussian in their distribution than their unmixed components and searches for independent components (ICs) that are as non-gaussian as possible. The performance of ICA in separating brain-related components in the scalp EEG from artificially introduced artifactual ones (Jung et al., 2000) can be taken as indirect evidence for its potential to unmix the independent generators of the scalp EEG.

Both fMRI-constrained source analysis and ICA suffer from a range of difficult problems. In fMRI-constrained source analysis the number of sources may be over- or underestimated from the fMRI data. Similarly the number of ICs that is desired after decomposition must be passed to the algorithm *a priori* although their true number may not be known precisely. Moreover, after successful ICA of scalp data in several subjects, the researcher is faced with the task to align the obtained components for group analysis, not knowing whether a specific component is present in all datasets (Onton et al., 2006). The necessary clustering of components is a field of ongoing research, and several algorithms have been proposed for neurophysiological data (k-means (MacQueen, 1967), self organizing hierarchical clustering (Himberg et al., 2004), Kuhn–Munkres algorithm (Tichavsky and Koldovsky, 2004)). In addition ICA *per se* does not provide information on the localization of the generators of the ICs. In the best case the corresponding scalp map of an IC allows to assume a dipolar source as the generator. This source can then be fitted using dipole fitting. Recently the use of ICs as regressors for concurrently obtained BOLD-fMRI has been proposed (Debener et al., 2005b; Feige et al., 2005). As this method relies on single trial fluctuations in the observed ICs, a high signal-to-noise ratio and a robust decomposition into artifacts and brain signals are prerequisites. Moreover, for group analysis the problem of aligning components from different decompositions persists.

Given that localization is one of the strengths of fMRI-constrained source analysis while estimating the *independent* neuronal processes is the main goal of the ICA, a crossvalidation using results from both approaches seems possible, at least for generators that are both well localized and independent. Therefore one important goal of the present study was to explore to what extend a dual analysis using fMRI-constrained source analysis and ICA can serve such a crossvalidation.

Here we used data from a previous combined ERP/fMRI experiment (Bledowski et al., 2006) where we decomposed the ERP signal into several dipolar sources showing distinct time courses (dipole source waves) during working memory retrieval. Using ICA at the single-subject level with subsequent clustering and averaging across subjects, we calculated grand average ERP equivalents for IC time-courses (termed gaICERPs hereafter). To solve the clustering problem posed by multiple ICAs we applied the graph-theoretical Kuhn–Munkres algorithm (Tichavsky and Koldovsky, 2004). Using temporal correlation we identified corresponding pairs of decomposed waves, *i.e.* dipole source wave and gaICERP. To address the question of crossvalidation we developed a statistical test procedure to identify pairs of decomposed waves that had a higher correlation coefficient than expected by randomly decomposing the data into source waves. We discuss the potential of this approach to cross-validate findings from both methods.

## 2. Methods

### 2.1. Subjects and task

We used data from 18 healthy participants from a previous visual working memory experiment. The paradigm had two conditions, load 1 and load 3 (with 80 trials each per participant), and we analyzed the ERP to the test stimulus (retrieval period) for correct trials only, using a pre-stimulus baseline of 200 ms and a post-stimulus averaging epoch of 1000 ms. For a full description of the paradigm and data acquisition see Bledowski et al. (2006).

### 2.2. FMRI-constrained source analysis

In order to create a grand averaged data set across subjects, the individual ERP waves (62 electrodes and an additional reference electrode at FCz) were interpolated to a standardized 81 electrode configuration using spherical spline interpolation. Prior to the ERP analysis the data were transformed to an average reference montage. A discrete multiple source model