PARAFAC on ERP data from a visual detection task during simultaneous fMRI acquisition

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Abstract— **The combination of EEG and fMRI has gained substantial interest in the past years because of the complementary spatial and temporal resolution of both modalities. Among the numerous EEG-fMRI integration approaches, many are based on blind source separation techniques like ICA. These decompositions, however, can only be achieved by imposing constraints on the sources, which do not necessarily hold for the given data.**

For this reason, this paper investigates the possibilities of PARAFAC, a technique allowing a unique data decomposition without any additional assumptions. PARAFAC can be performed on three- or higher dimensional data and is therefore especially suitable for the decomposition of ERP data, allowing subject, task or trial information to be included in the model. As a first aspect, the robustness of the PARAFAC decomposition is evaluated for *channels x time x subjects* arrays, acquired both simultaneously with fMRI and outside the scanner. An attempt is made to interpret the obtained components in relation to the task and the environment. Further, also single-subject arrays with dimensions *channels x time x trials* are decomposed. We conclude that PARAFAC can be performed on data from simultaneous measurements, but that more investigation is needed for the interpretation of the obtained components.

Index Terms—**ERP, fMRI, PARAFAC, visual detection task**

I. Introduction

The combination of electroencephalography (EEG) and functional magnetic resonance imaging (fMRI) constitutes a promising tool towards a better understanding of cerebral dynamics. Their complementary temporal and spatial properties not only motivated researchers to optimize the quality of their simultaneous acquisition, but also led to the development of a variety of integration approaches. A part of these approaches are based on decomposing the data with blind source separation techniques. These decompositions, however, are usually based on one or several assumptions. One of the approaches is e.g. to use independent component analysis (ICA) [1], thereby assuming the components to be statistically independent.

Parallel factor analysis (PARAFAC) by contrast, can be used to decompose data in a unique way without imposing additional constraints. Moreover, it has the advantage of taking more than two data dimensions into account. This latter property is particularly interesting for event-related potentials (ERPs), since apart from their temporal course and spatial localization, their specific behavior over subjects, trials, conditions, etc. can be investigated. PARAFAC has already shown its value in different EEG applications, as e.g. in the localization of time-varying neonatal seizures [2]. It has also already been applied to ERPs in several studies (e.g. [3]), but to our knowledge it has not found its way yet to ERP data measured simultaneously with fMRI.

This study therefore explores the possibility of extracting meaningful components with PARAFAC from ERP data recorded during a visual detection task. The ERP data were collected both inside the scanner (with and without simultaneous fMRI acquisition) and outside the scanner in a control room. As such, the robustness of the PARAFAC decomposition on data subject to different levels of scanner-related contamination could be investigated. Subsequently, we focused on the interpretation of the resulting components and their specific advantages over other (more standard) methods. The latter was done both for ERP data averaged per subject and arranged in *channels x time x subjects* arrays as well as for single-trial ERP data per subject, resulting in *channels x time x trials* arrays. In addition, for all PARAFAC decompositions, also the need for preprocessing, the optimal number of components and the advantage of imposing orthogonality constraints were investigated.

II. Materials & Methods

A. Data acquisition

Fifteen healthy subjects (10 male and 5 female, aged 21-33) with no history of neurological or cardiological disorders participated in this study. They performed a visual detection paradigm consisting of segments of circular black-and-white checkerboard stimuli presented one at a time to one of the four quadrants of the visual field and a large circular black-and-

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white checkerboard presented centrally [4]. Subjects were asked to press a button upon detection of each of the stimuli and performed 4 runs of the task. This simple detection task was selected as it is known to evoke robust P1 and N1 components. The P1 component is a positive deflection in the ERP around 100 ms after the stimulus onset and the N1 component is the negative deflection following this P1.
The EEG data were collected from 62 standard scalp sites using the BrainAmp MR+ system (BrainProducts, Munich, Germany) with a sampling rate of 5 kHz. Two additional electrodes were placed below the left eye and on the back to monitor eye blinks and electrocardiograms (ECGs), respectively. All 64 channels were recorded with a central electrode as reference (Cz or FCz) and an occipital electrode as ground (Iz or POz). Electrode impedances were kept below 10 kΩ.
For validation purposes, EEG data were measured under different circumstances. For 14 of the subjects, EEG data were acquired simultaneously with fMRI data in a Philips 3T Intera whole-body scanner. For 10 subjects, the same measurement was repeated in a Siemens 3T Allegra scanner. In addition, from 6 out of these 10 subjects EEG data were acquired in the scanner without simultaneous fMRI acquisition and also outside the scanner room. The distinction between these different conditions is essential to separate the effects of the two major scanner-related artifacts, ballistocardiogram (BCG) artifacts caused by the constant magnetic field of the scanner and gradient artifacts caused by switching magnetic fields during fMRI acquisition.

B. Data preprocessing

All EEG analyses are performed in MATLAB making use of the MATLAB toolbox EEGLAB [5]. As explained above, EEG data acquired simultaneously with fMRI data suffer from serious data distortion by gradient artifacts, with amplitudes 10-100 times larger than those of the EEG data of interest. Therefore, from all datasets acquired under these conditions, first these gradient artifacts need to be removed. This is achieved making use of a template subtraction approach [6] as implemented in the Bergen EEG-fMRI EEGLAB plug-in [7]. Subsequently all datasets (regardless of their condition) are filtered with a low-pass filter at 30 Hz and downsampled to 250 Hz. After this, datasets measured inside the scanner (both with and without simultaneous fMRI acquisition) are still contaminated by the BCG artifact, which is removed with the Optimal Basis Set (OBS) method as proposed in [4,8].
For each condition, the 4 blocks per subject are then merged together and re-referenced to the average of TP9 and TP10 (the closest electrodes to the mastoids in the present electrode setup). They are segmented around the stimulus onset for each stimulus and baseline removal was performed. The resulting ERP signals are used for the PARAFAC analyses, which will be discussed next.

C. Parallel Factor Analysis

PARAFAC is a multidimensional decomposition technique that can decompose three- or higher dimensional signals into a series of distinct atoms [9]. Every atom is characterized by a certain distribution or course in each of the modes and ideally represents a distinct brain source. For the three-dimensional case, the data is presented by the sum of these atoms as follows:

$$S_{dft} = \sum_{k=1}^{N_k} a_{dk} \cdot b_{fk} \cdot c_{tk} + E \qquad (1)$$

with N_k the number of atoms, a_{dk}, b_{fk} and c_{tk} the signatures of every atom in each of the modes and E the model error.

In this study, only three-dimensional data arrays are considered and they are built up as follows. In the first analysis average ERPs for each of the stimuli and for all subjects and channels are created, by averaging the segments obtained during preprocessing. Data arrays are then composed of these average ERPs on 5 left or 5 right occipital channels and for all subjects, resulting in arrays with dimensions *channels x time x subjects* (5 channels, 1000 ms and the number of subjects depending on the chosen situation).
For another type of analysis, data arrays are created per subject, by arranging single trials in the third dimension. The first dimension is again composed of only left or right occipital electrodes, since the task-related ERP components are most pronounced there.

D. Preprocessing and validation aspects of PARAFAC

When it comes to the application of PARAFAC, it has clearly been discussed in [3] and [9] that a careful selection of preprocessing and decomposition parameters is essential. Data arrays can be rescaled or centered before performing the PARAFAC analysis and also the number of components needs to be chosen beforehand. In addition, a problem sometimes encountered with PARAFAC solutions is degeneracy, yielding redundant sources which are often unstable and unreliable [9]. This can be avoided by imposing orthogonal constraints but also this requires additional optimization.
To be able to distinguish between the different cases, it is therefore necessary to assess the quality of the obtained decomposition. Next to a visual inspection of the components, different quantitative measures are available for this purpose. First of all, we checked for every solution whether it was degenerate or not, according to the definition given in [3]. Second, the Core Consistency Diagnostic (corcondia) was used to evaluate the appropriateness of the trilinear structure of the PARAFAC model for the given data. Third, a relative mean squared error (MSE) was computed following [3], evaluating the goodness of fit of the obtained decomposition.

III. Results

Preprocessing-wise, our results confirm the findings in [3], meaning that preprocessing steps and other PARAFAC choices should be optimized for each dataset individually. However, in general we found that two components gave the best compromise between the corcondia and the relative MSE

and that centering and rescaling only worsened the results. In most cases imposing orthogonality was necessary to avoid degeneracy, preferably on the subject or trial mode.

When performing PARAFAC on *channels x time x subjects* arrays (restricting the channel dimension to five left or right occipital channels), our results revealed that the grand average ERP could indeed be identified as one specific component in the PARAFAC decomposition. This was the case both inside and outside the scanner, with or without fMRI acquisition and in both the Philips and Siemens scanner. This is illustrated in figure 1, where for all situations the temporal modes of the ERP-related components are shown (for the central stimulus). The PARAFAC analysis used for this figure was performed on the left occipital channels, with orthogonality imposed in the subject mode. Corcondia and relative MSE are also indicated for each case above the subfigures.

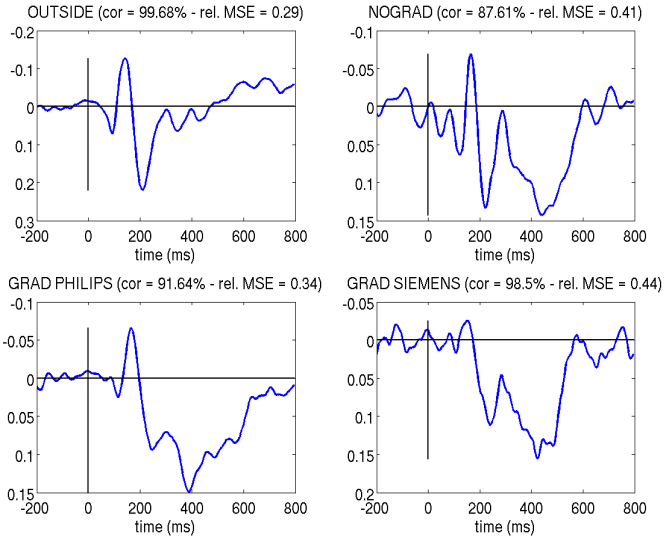


Fig. 1. Temporal modes of ERP-related components of PARAFAC decompositions on *channels x time x subjects* arrays, indicating that for each situation a component related to the grand average ERP can be found, showing the expected P1 and N1 deflections. GRAD indicates that the EEG data was acquired simultaneously with fMRI data, NOGRAD means that the data was acquired inside the MR scanner but without simultaneous fMRI. For every case also the corcondia (cor) and relative MSE (rel. MSE) are indicated above the subfigures. Note that the shown amplitudes are not the actual ERP amplitudes. To obtain the latter, the components need to be reconstructed to the signal space.

Further exploring the possibilities of PARAFAC for these data, an interesting property was found when subjects show distinct ERP latencies. This was e.g. the case for the upper right stimulus in the data measured simultaneously with fMRI in the Philips scanner. Figure 2 shows the ERP created by averaging the segmented data over all subjects and trials and over five left occipital channels (solid blue line). It can clearly be seen that the P1 component shown here seems to be composed of two parts. When looking at the temporal courses of the two PARAFAC components (reconstructed to the signal space to have comparable amplitudes, shown in dashed red and dot-dashed green), each component seems to represent an ERP with a different latency. This hypothesis was confirmed by the fact that the subject modes of these components showed similar patterns as the graphs obtained by plotting the latencies of the P1, N1 and also P3 for all individual subject ERPs.

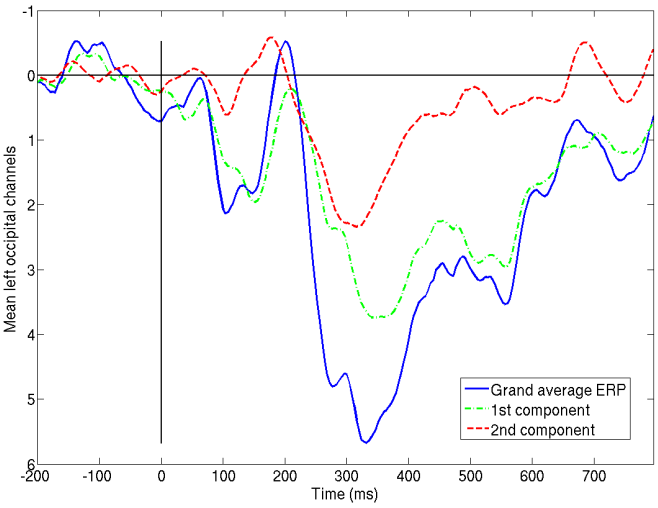


Fig. 2. Illustration of PARAFAC separating ERPs with different latencies in different components. The blue solid curve shows the average ERP on 5 left occipital channels from the upper right stimulus in the data acquired simultaneously with fMRI in the Philips scanner. Red dashed and green dot-dashed lines represent temporal modes of the two components obtained when performing PARAFAC on the same data.

It is also interesting to have a look at the PARAFAC components obtained when all the channels are included in the analysis. In figure 3 this is illustrated with the data measured inside the scanner without simultaneous fMRI acquisition. Two components are obtained, again without any preprocessing and with imposing the additional orthogonality constraints on the subject mode.

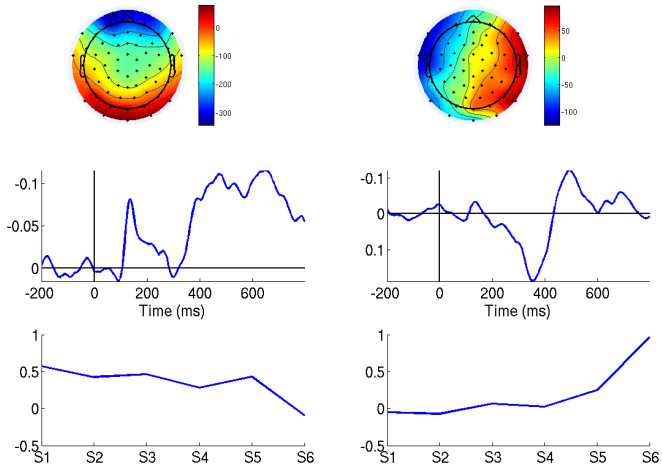


Fig. 3. PARAFAC components retrieved by performing PARAFAC on data measured inside the scanner without simultaneous fMRI acquisition. The first component is shown on the left, the second on the right and from top to bottom respectively their spatial distribution, temporal course and distribution over subjects can be found (subjects are named S1 to S6). Note that the shown amplitudes are again not the actual ERP amplitudes.

Although the grand average ERP (first component) was expected to be less obvious as not only occipital electrodes were taken into account, it is still visible. Moreover, the topography of the second component points in the direction of

the BCG artifact, as it corresponds to the well-known opposite polarity of this artifact [10]. This idea is further confirmed by the fact that this component is most pronounced in the subject with the highest amount of residual BCG artifact (subject 6).

Besides looking at the application of PARAFAC to averaged data of all the subjects together, it is also interesting to apply it to single-trial data per subject, so as to have arrays with dimensions *channels x time x trials*. An illustration for one subject and five left occipital channels is given in figure 4 (ERPs created with the central stimulus). Also here two components were extracted and orthogonality was imposed in the trial dimension.

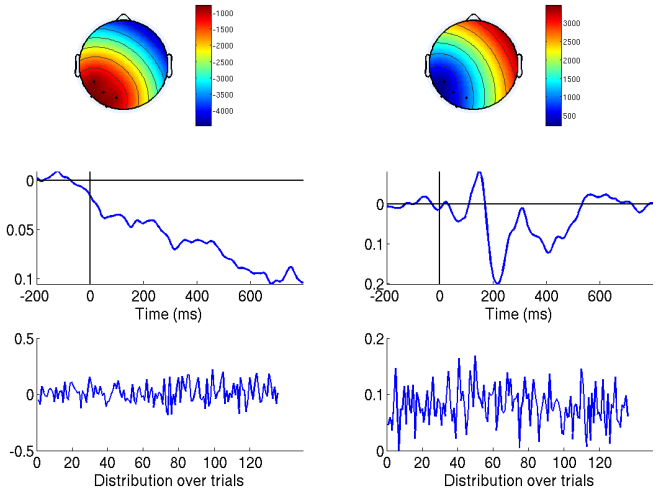


Fig. 4. PARAFAC decomposition on data measured outside the scanner from one subject (left occipital channels, central stimulus), arranged in an array with dimensions *channels x time x trials*. Each column represents one component, with from top to bottom respectively their spatial, temporal and trial signatures. Note that the spatial distribution is only exactly known in the chosen left occipital channels, the rest of the distribution is obtained with extrapolation. The shown amplitudes are again not the actual ERP amplitudes.

It can be seen that it is possible to retrieve the average single-subject ERP as one of the components in the decomposition. Further analyses need to be performed to assess their value in more detail.

IV. Conclusion

PARAFAC has obvious advantages over two-dimensional blind source separation techniques like ICA, in the sense that it does not require any additional assumptions and that it can take three or more data dimensions into account. This latter property is exploited when applying PARAFAC to ERP data, since higher dimensions are inherently present, resulting from collecting different subjects, tasks, trials, etc.

This study provides explorative results of the performance of PARAFAC applied to data measured simultaneously with fMRI. Since these data are typically contaminated with serious artifacts, it was necessary to verify whether its quality after artifact removal was still sufficient for further PARAFAC processing. In the obtained components, ERPs with different latencies could be distinguished and the presence of residual BCG artifacts could be assessed. Also single-subject data arranged in *channels x time x trials* arrays allow a trilinear decomposition but in that case sufficient data quality is even more crucial. We conclude that PARAFAC can be used for decomposing ERP data possibly allowing finding ERP properties that could not be found with simple averaging. However, more research is needed to fully understand the meaning of the components and their advantages compared to more traditional methods.

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