Identification of Signal Components in Multi-Channel EEG Signals via Closed-Form PARAFAC Analysis and Appropriate Preprocessing

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Abstract — **It is a major task in EEG analysis to identify signal components based on time-frequency distributions. The main objective is to decompose a multichannel EEG into time-frequency-space atoms. A lot of work was done in the field of subspace estimation with two of the aforementioned three dimensions, e.g., by using an SVD, PCA or ICA as well as space-time filtering or beam-forming. A more powerful approach is the use of tensor decompositions. For example, PARAFAC (Parallel Factor) analysis decomposes a tensor into rank-one components and thereby represents a multidimensional extension of the SVD. This renders it an attractive approach for EEG signal analysis. The selection of an appropriate time-frequency preprocessing scheme improves the results of the PARAFAC analysis. In a first study, we have investigated several time-frequency preprocessing techniques to create a tensor in time, frequency, and space for multi-channel EEG signals. The common approach in PARAFAC analysis is the use of a wavelet transformation based on the MORLET wavelet as a preprocessing step. In this paper, we show that preprocessing based on the Wigner distribution leads to much better results than a wavelet analysis. First results have been obtained by the use of EEG signals of evoked potentials.**

Keywords — **PARAFAC analysis, MORLET Wavelet, Wigner-Ville Distribution, RID kernel, EEG Preprocessing.**

I. INTRODUCTION

Finding the components of activity in the brain from recorded EEG signals is a great challenge in the field of biomedical signal analysis. This knowledge can be used to detect and localize sources of epileptic seizures as well as sources of cognitive processing like speech or auditory handling. Unfortunately, the solutions to these types of inverse problems may not be unique: Different sources in the brain can produce the same EEG pattern on the scalp.

Therefore, different approaches to find a suitable approximation have been developed. For example, LORETA is one out of a class of methods which resolve the ambiguity by assuming that neighboring neurons are active synchronously [1]. This guarantees that a set of bipolar sources exists over the whole cortical surface.

Another approach is based on the dipole model. It is assumed that there exist a limited number of dipoles as point sources in the brain. Dipole fitting methods estimate the location of these dipoles by iterative calculations. It has to be defined how many dipoles have to estimated, where they can be and how they interact in time. To improve the estimation process, preprocessing of the signal in the form of a subspace decomposition can be applied. There exist several contributions in the field of EEG processing for applying techniques such as PCA, ICA, SVD (which ignore the spatial information) or beam-forming strategies (which exploit the spatial information) [2]. However, not all the assumptions for these methods are fulfilled in the case of EEG signals. Moreover, not all dimensions (time, frequency, space) are integrated in the analysis.

Tensor-based methods are a more natural approach to handle signals that vary in more than two dimensions (e.g., time, space, and frequency). The well-known PARAFAC decomposition (also known as CANDECOMP) is a powerful approach to decompose a tensor into components. In the last few years a lot of work was done in applying PARAFAC for EEG signal analysis, e.g., for estimating the sources of cognitive processing using a Wavelet decomposition [3], for ERP analysis [4] or for epileptic seizure localization [5]. It is well known that Wavelet analysis is not always a suitable time-frequency decomposition because it may not provide adequate time and frequency resolution. Due to this problem we compare the results of a Wavelet decomposition in an ERP analysis with a Wigner distribution. In this contribution, both methods are applied as preprocessing steps for a new closed-form PARAFAC solution [12,13].

II. MATERIAL AND METHODS

A. Signal Component Analysis

Preprocessing

The first step in the signal component analysis is applying preprocessing in the form of an appropriate time-frequency decomposition (TFD). That means that the measured time signal from each channel is transformed into a time-frequency representation in order to resolve both, the

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temporal evolution as well as the frequency content of the measured signal.

There exist a large number of methods to perform this task. An approach that is very often used is some form of wavelet analysis. In particular, the continuous wavelet transform (CWT) can be applied to decompose a signal into its time and frequency content [6]. The CWT at scale a and time t of a signal $x(t)$ is defined as

$$C(a,\tau) = \int_{-\infty}^{+\infty} x(t)\varphi(a,t,\tau)dt \qquad (1)$$

where φ represents the chosen wavelet. Common choices include the class of biorthogonal wavelets, Debauchy wavelets, and the MORLET wavelets. The disadvantage of CWT-based time-frequency preprocessing is the limited resolution, especially in the low-frequency region, which is very important in EEG signal analysis.

A more powerful approach to time-frequency analysis is given by the family of Wigner-Ville distribution functions, based on the seminal work by Wigner in 1932 and Ville in 1948. The distribution is based on the temporal correlation function (TCF) $q_x(t,\tau)$ of the complex signal $x(t)$

$$q_x(t,\tau) = x\left(t+\frac{\tau}{2}\right)x^*\left(t-\frac{\tau}{2}\right). \qquad (2)$$

The Fourier Transform (FT) of the TCF with respect to the lag parameter τ leads to the Wigner-Ville Distribution (WVD) of $x(t)$

$$W_x(t,f) = \int_{-\infty}^{+\infty} q_x(t,\tau)\, e^{-j2\pi f\tau} d\tau\,. \qquad (3)$$

The main drawback of the TCF is that it produces cross terms in the WVD and in the Ambiguity Function (AF), which is the FT of TCF with respect to *t*. On the other hand, its advantage is that time and frequency resolution can be adjusted separately. Cohen introduced a class of TFDs based on the WVD which allow the use of kernel functions for reducing cross terms [7]. There exist a great variety of TFDs for a large number of applications.

To apply the Pseudo WVD (PWD), the WVD has to be filtered with a one-dimensional filter as a sliding window function. This leads to a spectral leakage but has no effect on the cross terms in time-frequency plane.

One way to reduce the influence of these cross terms is the construction of a cross-shaped low-pass filter which allows high time and frequency resolution and has a large time and frequency support. This method is the Reduced Interference Distribution (RID) which can be combined with several window functions [8].

Three-Way PARAFAC

After the time-frequency analysis the overall signal comprises three dimensions: For every channel, the signal is represented by a time-frequency matrix.

Therefore, the signal can be expressed as a three-dimensional tensor

$$\boldsymbol{X} \in \mathbb{R}^{N_T \times N_F \times N_C} \qquad (4)$$

where N_T and N_F represent the number of samples in time and frequency and N_C the number of channels, respectively. In order to separate signal components in this tensor, three-dimensional extensions of the singular value decomposition can be used. The SVD has a long standing history in signal component analysis in the form of PCA.

In the tensor case, the PARAFAC decomposition is known as a multi-dimensional extension of the SVD that decomposes a tensor into a minimal sum of rank-one tensors. The underlying model can be represented in the following fashion

$$\boldsymbol{X}_{i,j,k} = \sum_{n=1}^{d} u_n(t_i)\cdot v_n(f_j)\cdot w_n(k), \qquad (5)$$
$$i = 1,2,\ldots N_T,\ j = 1,2,\ldots N_F,\ k = 1,2,\ldots N_C$$

Here, $u_n(t_i)$ and $v_n(f_j)$ represent the sampled time and frequency responses of the n-th component at time instant t_i and frequency bin f_j, respectively. Also, $w_n(k)$ represents the strength of the n-th component in the k-th channel. Moreover, d represents the number of signal components (i.e., the model order) of the signal. In practice, the measured tensor does not obey the model exactly for a number of reasons:

- There is noise in the system. For EEG data this noise is in general not Gaussian distributed and also not spatially uncorrelated.
- The individual components are not necessarily rank-one, each of them may have a higher rank.
- The superposition of components is not ideally linear, nonlinear couplings have been observed and are in general included in the models.
- The observed process is not stationary. This issue can be partially taken care of by dividing the original signal into smaller time intervals and analyzing each interval on its own.

Therefore, we require an algorithm to compute an approximate fit of a measured tensor to a PARAFAC model. Also, we need an algorithm that is numerically stable to cope with the non-ideal conditions in practical data.

The existing algorithms to compute approximate PARAFAC model fits can coarsely be divided into three categories. The first category includes the iterative algorithms. These are based on the alternating least squares (ALS) idea [9]: In each iteration, two of the three factors are fixed and the third factor is computed via a least squares fit. Then, this factor is fixed and the next one is optimized for in a similar fashion. This iterative procedure is repeated until convergence is detected. While it can be shown that ALS converges monotonically, it is not guaranteed that it reaches the global optimum. Also, the number of iterations may be too big for practical purposes. A large amount of research was dedicated to making ALS faster either through smart initializations or optimized update rules. A fast implementation of ALS is given by the PARAFAC-algorithm [10], which is available in the N-way toolbox.

The second class of algorithms are suboptimal solutions that enable a closed-form solution through coarse approximations. Well-known methods in this category include the Generalized Rank Annihilation Method (GRAM) and the Direct Trilinear Decomposition (DTLD) [11]. While these methods are very fast, the obtained fit is usually not very satisfactory.

Finally, the third class of algorithms for approximate PARAFAC model fitting is based on a framework introduced in [12, 13], which shows a class of closed-form solutions that can achieve a very good performance without the necessity of ALS iterations. The approach is based on the Higher-Order SVD [14] and simultaneous matrix diagonalizations. The authors demonstrate the enhanced robustness of the Closed-Form PARAFAC scheme which renders it an attractive approach for the non-ideal EEG signals.

B. EEG Recording

The EEG signal is recorded from a 23 year old woman, healthy and right-handed. The position of the 64 EEG electrodes is based on the international 10-10-system with earlobe reference [(A1+A2)/2]. The sampling frequency is chosen to 1000 sps. For preprocessing of the raw signal, several filters are applied: a 7 Hz high-pass, a 135 Hz low-pass and a band-stop filter between 45 and 55 Hz.

Because of the investigation of effects in the field of evoked potentials we use data taken from a visual stimulus. The subject is sitting in front of a hemispherical perimeter. The stimulus is set by a 20 ms central flash with white LED here realized for the right eye. The experiment is repeated 1600 times. The triggered EEG answers are averaged over all 1600 trials for all channels (see Fig.1).

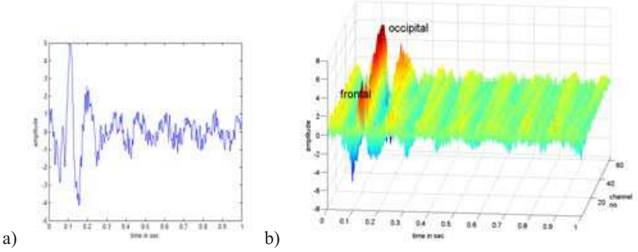

Fig. 1: a) Time course of ERP from an occipital EEG channel b) Time course for all 64 channels – occipital channels show the response earlier than frontal ones

III. Results

We have applied the signal component analysis scheme to the measured EEG data. For the results shown here, the Closed-Form PARAFAC algorithm is applied together with three preprocessing methods: a CWT with Morlet Wavelets, the PWD, and the RID. The analysis is carried out on the windowed EEG signal. The window length is 80 ms with an overlap of 20 ms between adjacent windows. Hence, 47 windows are analyzed for the whole one second signal. As it was stated before the number of components has to be determined by hand. For the results shown here, three components are used.

Fig. 2 shows the six windows with Morlet preprocessing as time-frequency plot and component strength for all three

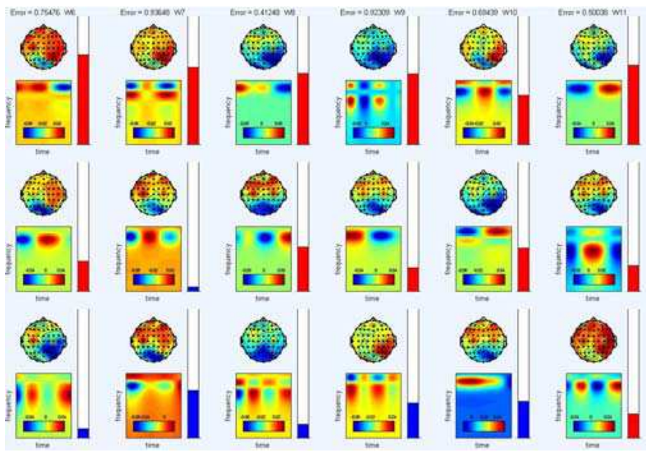

Fig. 2: We display the three components for six adjacent time windows (from left to right) from 101 to 280 ms with Morlet as preprocessing step. For each component in each window the spatial distribution is indicated by a topographical plot, the time-frequency signature by the image below and the bar visualizes the strength of the component.

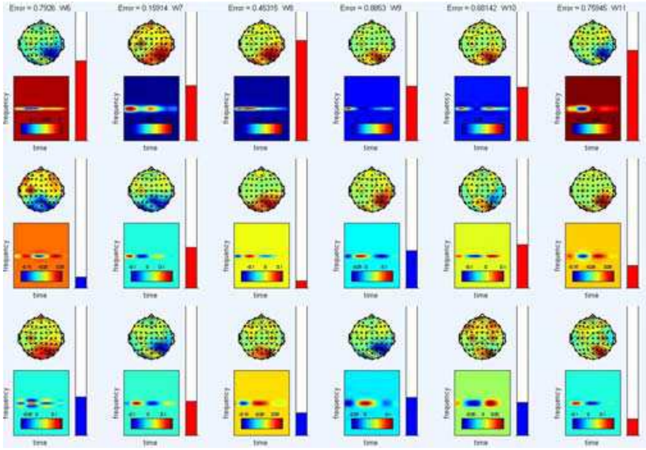

Fig. 3: We display the three components for six adjacent time windows (from left to right) from 101 to 280 ms with preprocessing by Pseudo Wigner Ville Distribution.

components. It is expected that there is a strong component in the right hemisphere right from the beginning of the signal. This was already observed from the potential mapping in a previous study. Because of the bad time resolution for low frequencies and the bad frequency resolution for high frequencies, the CWT cannot exactly localize the signal sources. Much better results are achieved with a WVD.

Fig. 3 shows the results of the PWD. The localization is much more accurate than using the MORLET analysis. Cross terms are not reduced in this kind of analysis and hence spectral leakage occurs. The use of RID leads to a reduction of the cross terms, which can be seen in Fig. 4. However, for RID there is a leakage in time and frequency which influences the spatial localization of the sources.

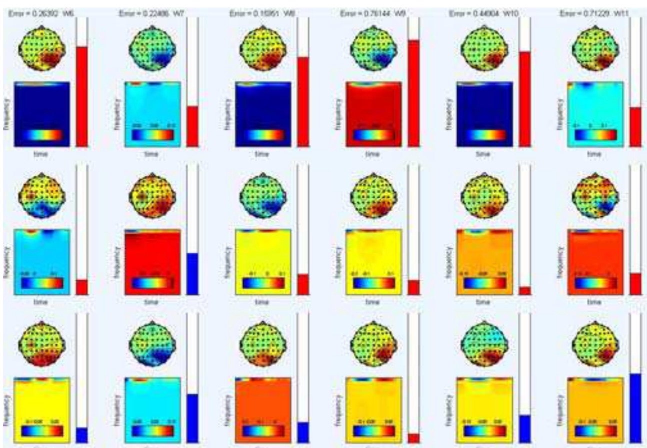

Fig. 4: We display the three components for six adjacent time windows (from left to right) from 101 to 280 ms with preprocessing by Reduced Interference Distribution.

The Closed-form PARAFAC solution offers new possibilities in the dipole fitting estimation. The next studies will show whether it is possible to take into account the non-stationary nature of EEG signals even better. This can be achieved by a sliding window for example. Furthermore we have to develop a procedure to track the components in their temporal evolution. At the moment, components are ordered by their power, which may however vary over time.

IV. CONCLUSIONS

The choice of an appropriate preprocessing scheme is an important factor for the success of the entire EEG signal analysis process. We have observed that WVD based methods enhance the spatial localization of components compared to Wavelet based methods since they have a better time and frequency resolution compared to Wavelet or STFT analysis. We have shown that RID based preprocessing can be useful to reduce the cross terms, however, it also introduces unwanted leakage effects. Optimizing the cross term suppression is hence an issue of future studies.

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