Application of Multi-way EEG Decomposition for Cognitive Workload Monitoring

[1, 2]Roman Rosipal [2]Leonard J. Trejo [2]Paul L. Nunez

[1]Department of Medical Cybernetics and Artificial Intelligence, Center for Brain Research,
Medical University Vienna, Vienna A-1010, Austria
E-mail: roman.rosipal@meduniwien.ac.at
[2] Pacific Development and Technology, LLC Palo Alto, CA 94303, USA
E-mail: ltrejo@pacdel.com

Abstract: This paper describes the use of multi-way decomposition methods to efficiently summarize electroencephalographic (EEG) data. A space-frequency-time atomic decomposition was applied to EEG data recorded while subjects performed tasks associated with varying levels of cognitive performance. The new atomic decomposition of cognitive workload data revealed alpha and theta EEG oscillations which agree with observations reported in the brain research literature. The temporal signature of the atoms discriminates between different levels of cognitive activity. The results and analysis confirm the utility of the multi-way decomposition method to construct new models and algorithms for monitoring cognitive status, which can supplement or overcome existing approaches based on conventional two-dimensional space-time or frequency-time data decomposition.
Keywords: multi-way decomposition, PARAFAC, cognitive workload

1 Introduction

Accurate and timely estimation and classification of operator functional state has important practical consequences in many safety-critical operational situations. Impairment of cognitive performance in subjects during a safety-critical task poses a high risk for procedural errors, often leading to severe consequences with high economic or life losses. Cognitive impairment has been documented in different operational situations, and attributed to several factors, including time on duty, sleep loss, extended time on single tasks, unusually high mental workload, psychosocial stress, exposure to neurotoxins and vestibular dysfunction.

Despite the extensive prior efforts to develop physiological methods for monitoring arousal and cognition, methods for monitoring mental workload are still unreliable. EEGs are considered to be the gold standard for objective detection of mental status and cognitive function and currently may be recorded and analyzed in almost any occupational setting. However, EEGs are usually recorded as a high-dimensional in time-space distributed data and many conventional 2-D decomposition techniques (for example, principal component analysis (PCA) or independent component analysis, Hyvärinen et al., 2001) may not be ideally suited to reveal the existing latent data structure, because unfolding 2-D decompositions can be done in several ways, and interactions of dimensions are not modeled

This research was sponsored by the Austrian Science Fund FWF, stand-alone project P19857 entitled “Multi-sensor sleep modeling based on contextual data fusion” and by a grant to Pacific Development and Technology, LLC from the U.S. Army Research Office, entitled, “Advanced Physiological Estimation of Cognitive Status.” This report does not necessarily reflect the position or the policy of the U.S. Government and no official endorsement should be inferred.

well in 2-D decompositions. Recently, promising results were achieved by applying multi-way decomposition models such as PARAFAC or TUCKER3 to EEG data (Estienne et al., 2001; Miwakeichi et al., 2004). Using these multi-way decomposition models we analyzed EEG data recorded from participants in a study of mental workload. To our knowledge this is the first time that multi-way decomposition models have been applied to the problem of mental workload analysis and monitoring.

2 Methods

2.1 Data acquisition and preprocessing

Two subjects were trained to stable performance on a simulated Unmanned Air Vehicle (UAV) task. The task consists of monitoring of the progress of four UAVs as they flew a preplanned mission. Each subject participated in three in time-separated sessions. Five channels of EEG (electrodes located at Fz, F7, Pz, T5 and O2 with a linked mastoid reference), ECG, vertical and horizontal EOG were recorded. In this study only the EEG data were used. The EEG data were sampled at 200 Hz and low-pass filtered with cutoff of 30 Hz. Next, the data were segmented into 2-s long windows with an overlap of 500 ms. For each segment the power spectral density (PSD) was computed using the Thomson multitaper method (Thomson, 1982). Frequencies in the range of 2.5 to 20 Hz were considered in this study. Initial analyses revealed a high level of power at frequencies below 4 Hz. Power at these frequencies often arose from motion artifacts and confounded the PARAFAC analyses of EEG. For this reason only frequencies from 5 to 20 Hz were considered for further analyses. This procedure was repeated for each EEG channel separately and a three-dimensional matrix $\mathbf{X}_{(I \times J \times K)}$ with I time segments, J electrodes and PSD estimates at K frequencies was constructed.

2.2 The PARAFAC model

A three-way PARAFAC model was applied to data. PARAFAC can be seen as a generalization of PCA for dealing with multi-dimensional data (Bro, 1997). Three loading matrices, **A**, **B**, and **C** with elements a_{if}, b_{jf}, and c_{kf} defines the model that can be mathematically described as

$$x_{ijk} = \sum_{f=1}^{F} a_{if} b_{jf} c_{kf} + \varepsilon_{ijk}$$

where ε_{ijk} are the residual elements or errors and F stands for number of components or *atoms* that are considered. The loadings elements are then found by minimizing the sum of squares of the residuals ε_{ijk} (Bro, 1997), that is

$$\min_{a_{if} b_{jf} c_{kf}} \| x_{ijk} - \sum_{f=1}^{F} a_{if} b_{jf} c_{kf} \|^2$$

For the analyses reported here we used proprietary m-codes developed by Pacific Development and Technology, LLC, and subroutines from the *N*-way toolbox for Matlab® (Andersson and Bro, 2000).

3 Results

A three-atom PARAFAC model was observed to provide acceptable and physiologically interpretable results for EEG recordings of both subjects, for which *core consistency diagnostic* values, which index the stability of the decompositions, reached 87% and 97%, respectively (Bro and Kiers, 2003; Andersson and Bro, 2000).

Three distinct spectral signature atoms (components) were observed in the first subject (Figure 1, right). Atom 1 exhibits a typical background EEG spectrum with relatively high power in the bands 5-7 Hz and 9-12 Hz. Atom 2 is somewhat concentrated in the alpha band (7.5-11 Hz). Atom 3 forms a contrast between the theta (5-7 Hz) and alpha (10-12 Hz) bands. These two rhythms have been shown to be key indicators of cognitive processes, such as attention, executive control, and working memory (Klimesch, 1999). These spectral atoms are not simply measures of spectral power because they can have both positive and negative loading values. This is in accordance with the physiological results where coupled increases in alpha band power and decreases in theta band power, and vice-versa, are often be observed during cognitive and memory performance tasks (Klimesch, 1999).

Inspection of the spatial atoms (not plotted here) showed high loadings corresponding to Atoms 1 across electrodes Oz, Pz, and Fz. Atom 2 loadings showed a clear maximum at Pz, indicating an association with the alpha rhythm. Atom 3 loadings were maximal at Fz and Pz, indicating an association with the theta rhythm. The loadings for the remaining two electrodes (T5, F7) were small for all three atoms suggesting a weak influence of these brain regions on EEG variance on this task. The temporal signatures of the three atoms (Figure 1, left) and the sum of Atoms 2 and 3 are also plotted in Figure 1. These temporal signatures of the EEG decomposition reflect the EEG variance in mental workload as indexed by task demands and complexity. The NASA TLX scales (Hart and Staveland, 1988) were used to define three levels of workload. Peaks in the sum of the time loadings clearly reflect the highest (dark gray areas) and lower (light gray areas) mental workload states. Although the loadings fluctuated over time, rest periods were often followed by marked increases of the loadings in tandem with the low-and high workload conditions.

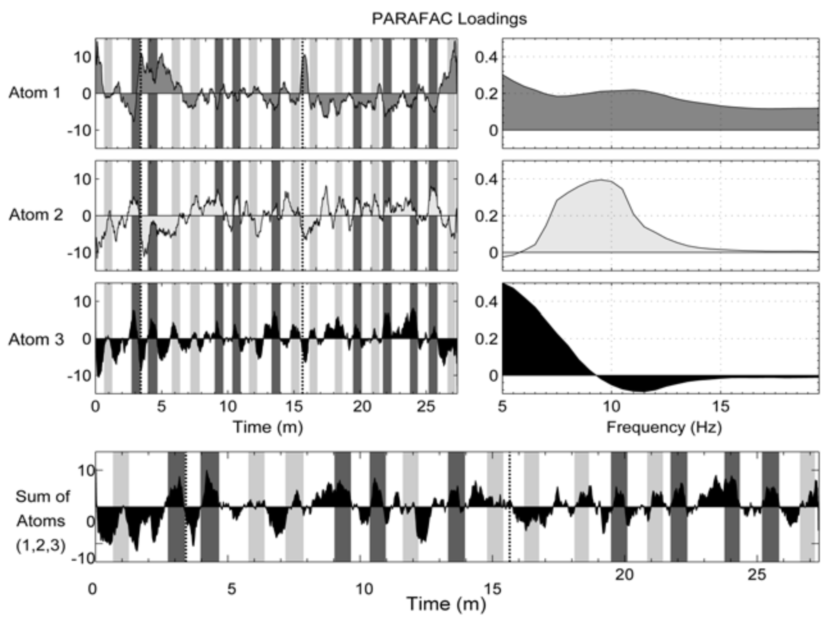

Figure 1 Loadings of the three PARAFAC atoms extracted from EEG recordings of Subject 1. Left panel: Temporal signatures of the EEG atoms. Light bars mark periods of low mental workload; dark gray barks mark periods of high workload conditions, as defined by task demands. Vertical dotted lines separate three distinct experimental sessions. Bottom panel: The summed temporal loadings of Atoms 1, 2, 3. Right panel: Spectral signatures corresponding to the atoms numbered in the left panel.

Three distinct atoms were also extracted from the matrix of EEG recordings of the second subject. As for the first subject, the spectral loadings for Atom 1 reflected background EEG power with high loadings in the bands 5-5.5 Hz and 9.5-14 Hz (Figure 2). Unlike the results for Subject 1 no clear alpha-like atom appears in the results for Subject 2. There is a slight concentration of high loadings between 10 and 14 Hz for Atom 1, which could include the variance of the alpha rhythm. The range of high loadings for Atom 1 decays too smoothly to serve as an indicator of any specific rhythm or band, and most likely reflects background EEG. Atom 2 shows a concentration of high loadings for frequencies in the theta band. Loadings for Atom 3 were maximal in the band 5-9.5 Hz. The spatial loadings of Atom 1 were the same as for Subject 1 (Fz, Pz, Oz), whereas those of Atom 2 were maximal at Fz, indicating an association with theta rhythm. The spatial loadings of Atom 3 were maximal at Fz and Pz, also indicating association with theta and low alpha rhythms. The temporal loadings of Atoms 1 and 2 did not show a marked relationship to workload conditions; however, the temporal loadings of Atom 3 tracked closely with the various mental workload conditions and rest periods.

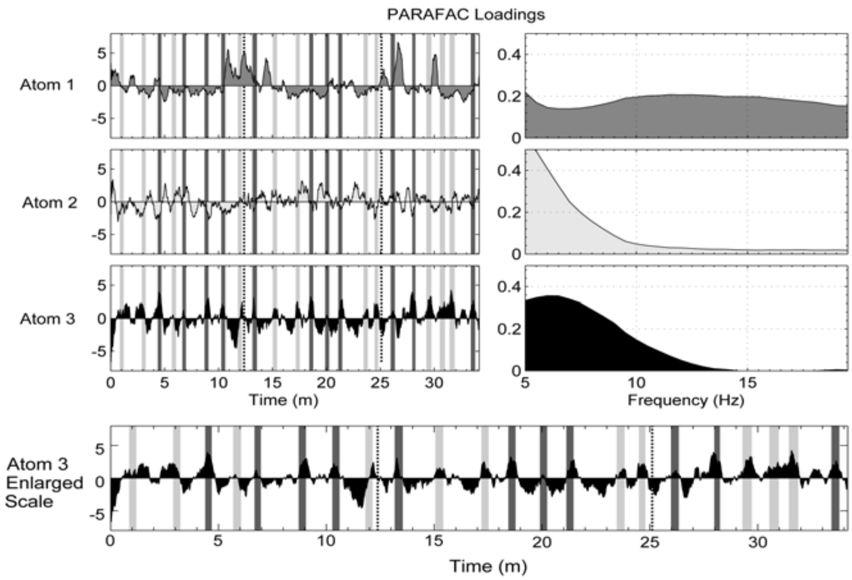

Figure 2 Subject 2. Left panel: Temporal signatures of the EEG decomposition. Light gray areas mark lower mental workload states while the higher workload states are marked by the dark gray areas. Vertical dotted lines separate three in time distinct experimental sessions. Bottom panel: The third temporal atom alone. Right panel: Spectral signatures corresponding to temporal atoms plotted in the left panel.

4 Conclusions

The results of this study show that mental workload may be tracked by EEG components isolated using parallel factor analysis or PARAFAC. Components or atoms of the PARAFAC decomposition had high loadings in the frequency spectrum and across electrodes, which reflected alpha, theta, and broad-band EEG processes. Unlike other approaches to isolate EEG factors related to mental workload, our application of PARAFAC begins with a truly three-dimensional model of EEG variance observed during performance of a cognitive task. This model is fit to the EEG simultaneously in frequency, space, and time. The time dimension in the present study reflects imposed task demands that produced calibrated states of low-or high mental workload.

For an unsupervised method of decomposition, these PARAFAC results are remarkable. Using a small number of electrodes, the loadings of several PARAFAC atoms in time, co-varied with task demands and mental workload. Admittedly, these results are based on a small sample of two subjects. However, the task performances were long, providing about 30 minutes of EEG recordings for analysis. In our extensive experience with similar experiments, the discovery of EEG atoms that track workload and have meaningful spectral and spatial propertied from recordings of these durations is not likely to arise from chance.

We are extending our research in two directions. First we are increasing the number of tasks and subjects in which we are applying the PARAFAC method. Two additional studies are in process, including a cognitive fatigue study and a warfare simulation task. Second, we are now testing a fourth dimension in the PARAFAC model: coherence of EEG sources. Short-and long range coherence of alpha and theta sources are expected to increase with cognitive effort, based on theoretical studies of EEG dynamics and considerable experimental data (Nunez and Srinivasan, 2005). We expect models that can encompass the direction, bandwidth, and extent of EEG coherence will help to further define neural sources that interact in cognition.

References

[1] Andersson C.A., Bro R. (2000) The *N*-way Toolbox for MATLAB, *Chemometrics and Intelligent Laboratory Systems*, 52, 1-4.

[2] Bro R. (1997) PARAFAC. Tutorial and applications, *Chemometrics and Intelligent Laboratory Systems*, 38, 149-171.

[3] Bro R., Kiers H.A.L. (2003) A new efficient method for determining the number of components in PARAFAC models, *Journal of Chemometrics*, 17, 274-286.

[4] Estienne F., Matthijs N., Massart D.L., Ricoux P., Leibovici D. (2001) Multi-way modelling of high-dimensional electroencephalographic data, *Chemometrics and Intelligent Laboratory Systems*, 58, 59-72.

[5] Hart S.G., Steveland L.E. (1998) Development of NASA-TLX (Task Load Index) : Results of empirical and theoretical research, in: *Human Mental Workload*, Hancock P.A. & Meshkati N. (Eds.), North Holland Press.

[6] Hyvärinen A., Karhunen J., Oja E. (2001) *Independent Component Analysis.* Wiley, New York.

[7] Klimesch W. (1999) EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis, *Brain Research Reviews*, 29, 169-195.

[8] Miwakeichi F., Martínez-Montes E., Valdés-Sosa P.A., Nishiyama N., Mizuhara H., Yamaguchi Y. (2004) Decomposing EEG data into space-time-frequency components using Parallel Factor Analysis, *NeuroImage*, 22, 1035-1045.

[9] Nunez P.L, Srinivasan R. (2005) *Electric Fields of the Brain*. Oxford University Press, New York.

[10] Thomson D.J. (1982) Spectrum estimation and harmonic analysis. in: *Proceedings of the IEEE*, 70, 1055-1096.

[11] Smilde A., Bro R., Geladi P. (2004) *Multi-way Analysis: Applications in the Chemical Sciences.* Wiley.