ESANN 2019 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 24-26 April 2019, i6doc.com publ., ISBN 978-287-587-065-0. Available from http://www.i6doc.com/en/.

Tensor factorization to extract patterns in multimodal EEG data

Dounia Mulders[1,2], Cyril de Bodt[1], Nicolas Lejeune[2],
John A. Lee[1], André Mouraux[2] and Michel Verleysen[1] *

1- ICTEAM institute, Université catholique de Louvain
Place du Levant 3, 1348 Louvain-la-Neuve, Belgium

2- IONS institute, Université catholique de Louvain
Avenue Mounier 53, 1200 Woluwe-Saint-Lambert, Belgium

Abstract. Noisy multi-way data sets are ubiquitous in many domains. In neuroscience, electroencephalogram (EEG) data are recorded during periodic stimulation from different sensory modalities, leading to steady-state (SS) recordings with at least four ways: the channels, the time, the subjects and the modalities. Improving the signal-to-noise ratio (SNR) of the SS responses is crucial to enable their practical use. Supervised spatial filtering methods can be considered for this purpose to relevantly guide the extraction of specific activity patterns. Nevertheless, such approaches are difficult to validate with few subjects and can process at most two data ways simultaneously, the remaining ones being either averaged or considered independently despite their dependencies. This paper hence designs unsupervised tensor factorization models to enable identifying meaningful underlying structures characterized in all ways of multimodal SS data. We show on EEG recordings from 15 subjects that such factorizations faithfully reveal consistent spatial topographies, time courses with enhanced SNR and subject variations of the periodic brain activity.

1 Introduction

Noisy multi-way data sets are encountered in numerous machine learning and signal processing applications, including audio and image processing, biomedical studies, chemometrics and social sciences [1, 2]. In neuroscience in particular, neurophysiological recordings such as the electroencephalogram (EEG) naturally span more than two dimensions, including the channels, the time, the frequency and the subjects. The analysis of such data usually requires to isolate the underlying hidden patterns of interest from the noise activity [3]. For instance, to study the cortical processing of sensory stimuli, EEG can be recorded during periodic stimulation from different modalities (visual, auditory, etc.). This kind of stimulation can elicit periodic activity at the stimulation frequency in neuronal populations responding to the stimulus, referred to as a steady-state response (SSR). In this setting, guided (i.e. supervised) spatial filtering methods can be considered to uncover the temporal and spatial patterns of the SSR by maximizing the periodicity of the extracted components [4, 5, 6]. These approaches are particularly relevant when the hidden activity of interest has a specific structure,

*DM and CdB are FNRS Research Fellows. JAL is a Senior FNRS Research Associate.

ESANN 2019 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 24-26 April 2019, i6doc.com publ., ISBN 978-287-587-065-0. Available from http://www.i6doc.com/en/.

such as the periodicity, which can be directly optimized. Nevertheless, the structure optimization requires a careful validation of the obtained patterns, which is not straightforward, especially when the number of subjects is limited [6]. In addition, such approaches are defined on two-way arrays although the studied data usually are higher-order tensors, requiring to either average some results over the subjects or process pairs of ways independently. Finally, interpreting the underlying activity entails inverting the filters to obtain source patterns [7], which may lead to irrelevant patterns when few filters are computed.

On the other hand, unsupervised tensor factorization (TF) models circumvent the three aforementioned shortcomings of the supervised spatial filtering approaches to extract SSRs from noisy EEG. Indeed, their unsupervised nature eases their validation and they account for all data ways at once, without the need for any inversion. Surprisingly, despite numerous successful applications of TFs [1, 8, 9], including on EEG data mainly to identify space-time-frequency atoms of some waveforms [10, 11, 12, 13], higher-order tensors have not yet been considered for the SSR analysis. In this paper, we therefore analyze whether and how TF can enhance the SNR of the SSR observed on raw EEG. Using EEG data from 15 healthy subjects exposed to periodic stimuli from four modalities, we first create a tensor with three modes, namely the subjects, the channels and the time for all modalities, to capture common spatial and varying time patterns across modalities. Second, we employ the canonical polyadic (CP) model to factor this tensor, successfully enhancing the SNR of the SSR while preserving the specific temporal dynamics for each modality and extracting spatial and temporal patterns involved in all the subjects. Finally, a sensitivity analysis of the periodicity gain over the raw mean signals with respect to the number of tensor factors reveals significant improvements, even with as few as two factors.

This paper is organized as follows. Section 2 introduces the studied EEG data. The TF model is detailed in Sect. 3 and the obtained results are commented in Sect. 4. Section 5 concludes the work and sketches perspectives.

2 Electroencephalogram (EEG) Data

To study the perception of long-lasting periodic thermal stimuli, we recorded scalp EEG on $N = 15$ healthy subjects to whom we applied, with a thermode, sinusoidal stimulation from $M = 4$ modalities: warm and cool, each applied on a variable or fixed skin surface along the stimulation cycles, respectively denoted by w1, w2, c1 and c2. The EEG was sampled at $f_s = 1000$ Hz and recorded using $C = 64$ electrodes (i.e. channels). The subjects received each kind of stimulus with a frequency $f_\star = 0.2$ Hz and a duration of 75 seconds ($15/f_\star$). Additional data descriptions are provided in [4]. The EEG time courses and their Fourier transforms are illustrated in Sect. 4 with some tensor factors.

The activity of interest in these data is the SSR reflecting the stimulus processing in the brain, which is assumed to be periodic, with fundamental frequency $f_\star$. To assess and compare further results, we hence quantify the periodicity of

ESANN 2019 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 24-26 April 2019, i6doc.com publ., ISBN 978-287-587-065-0. Available from http://www.i6doc.com/en/.

a unidimensional signal $y(t)$, whose frequency transform is denoted by $Y(f)$, as

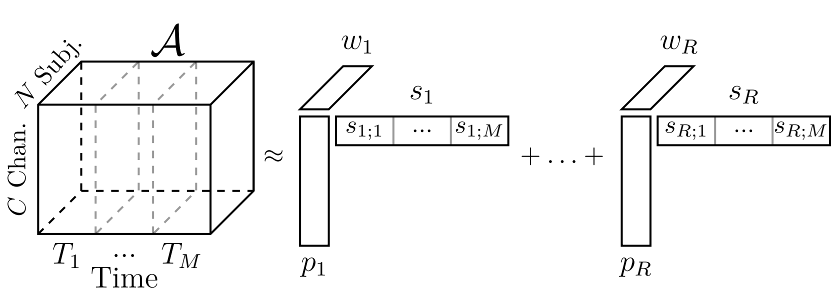
$$M_\pi(y) = 100 \cdot \frac{\sum_{k=1}^{10} Y_{NS}(k \cdot f_\star)}{\sum_f |Y(f)|}, \tag{1}$$

with $Y_{NS}(f)$ the *noise-subtracted* frequency amplitude at frequency f, obtained by subtracting the average amplitude at 10 neighboring frequencies (5 higher and 5 lower) from $|Y(f)|$ [4]. If y is (resp. not) periodic, $M_\pi(y)$ will be positive (resp. tend towards 0). According to one-sample t-tests with 5% confidence, M_π indicates a significant periodicity, on average over the subjects, for the raw signals of the conditions w1, w2 and c1, at the fronto-central electrode named FCZ, where the periodicity is the highest. In condition c2, neither M_π nor $Y_{NS}(k \cdot f_\star)$ for any k are significantly greater than 0 at FCZ.

3 Methods

This section aims to construct a tensor containing the data described in Sect. 2 and whose factorization emphasizes the SSR. In the following, vectors are written in lower-case and tensors, with at least three dimensions, in calligraphic letters. Since the stimuli from all four conditions activate the spinothalamic system, they are expected to elicit brain activities with similar spatial topographies, but with possibly distinct time courses, at least partly due to the different conduction velocities of the activated afferent fibers. In addition, the identified SSR should be common to (almost) all subjects, possibly in distinct proportions.

Consequently, let us first define a three-way array $\mathcal{A} \in \mathbb{R}^{C \times T \times N}$, where $T := \sum_{i=1}^{M} T_i$ and T_i is the number of time samples for condition i, $i \in \{1, \ldots, M\}$. The time samples for the M modalities are hence stacked along the second dimension of $\mathcal{A}$. We then consider the canonical polyadic (CP, also known as CANDECOMP or PARAFAC) model to factorize $\mathcal{A}$ [13]. For a given number of factors R, it computes the sum of R rank-1 tensors which best approximates $\mathcal{A}$ in the least squares sense [14]. The factorization can be expressed as $\mathcal{A} \approx \sum_{r=1}^{R} p_r \circ s_r \circ w_r$, where $\circ$ denotes the vector outer product, $p_r \in \mathbb{R}^C$ the spatial patterns, $s_r \in \mathbb{R}^T$ the factor time courses (i.e. temporal patterns) and $w_r \in \mathbb{R}^N$ the subject weightings. This decomposition can be illustrated as



, (2)

where the segment $s_{r;i}$ is the time course for the modality i in the r^{th} factor. All ways of the data set can hence be analyzed in a single factorization with shared

ESANN 2019 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 24-26 April 2019, i6doc.com publ., ISBN 978-287-587-065-0.
Available from http://www.i6doc.com/en/.

spatial and distinct temporal patterns for all modalities. Each w_r (i.e. mode-3 fiber) indicates the between-subject variations. Indeed, in accordance with the above intuition, each frontal slice (i.e. matrix for a fixed third index) in (2) is defined through the same spatial and temporal patterns pairs, but with different proportions according to the mode-3 fibers (i.e. weightings across subjects). As the periodicity of the time courses drives our interest in the factors of this decomposition, they are sorted in decreasing order of the value $\max_i M_\pi(s_{r;i})$, such that s_1 contains the most periodic time course from one modality.

The fast and scalable algorithm CP-OPT, using the L-BFGS optimization method, is employed to compute the CP models for various R values [14]. It is implemented in the open-source Tensor Toolbox [15].

4 Results

This section presents how model (2) can extract periodic time courses as a function of the number R of factors and illustrates the three-way patterns obtained on the EEG data set described in Sect. 2. The factor time courses $s_{r;i}$, and their periodicity in particular, are compared to the raw EEG recordings at electrode FCZ, since they depict the highest periodicity and would hence be the analyzed signals if no factorization was employed [6]. The significance level of the statistical tests is set to 5%.

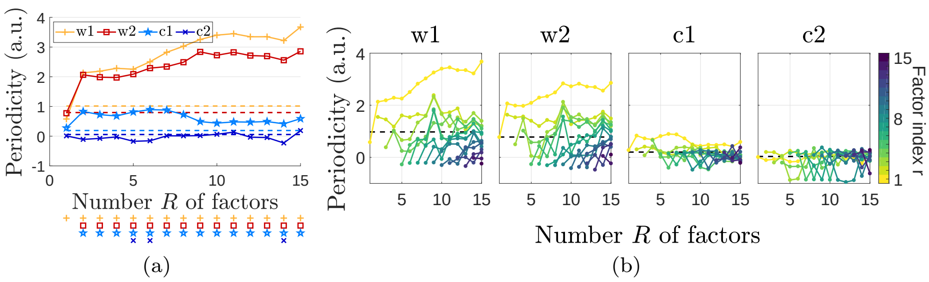


Fig. 1: Periodicity measure M_π of (a) the first temporal patterns $s_{1;i}$ and of (b) all patterns $s_{r;i}$ as a function of the number R of factors. The dotted horizontal lines indicate the periodicity at FCZ, averaged over the subjects for each condition. In (a), a marker below the plot for a given R indicates that the periodicity of the pattern represented with the same marker is significantly different from the mean periodicity at FCZ (one-sample t-tests, Holm-Bonferroni corrected).

The number R of factors considered in the CP approximation needs to be determined. Intuitively, too small R would not enable separating the noise from the periodic activity of interest (e.g. if $R = 1$, the whole EEG activity needs to be approximated in the sole factor), whereas too large R could tend to spread this activity among several factors. The periodicity of the temporal patterns $s_{1;i}$ are reported in Fig. 1a, with one color and marker for each modality i. For all $R \geq 2$, the periodicity of the extracted pattern is significantly larger than the

ESANN 2019 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 24-26 April 2019, i6doc.com publ., ISBN 978-287-587-065-0.
Available from http://www.i6doc.com/en/.

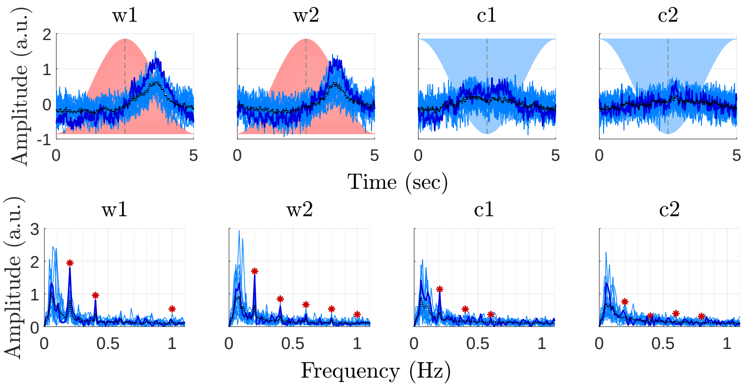


Fig. 2: Time courses averaged over the cycles and frequency transforms of the first factors $s_{1;i}$ when $R = 6$ (dark blue lines), and of the EEG at FCZ (subject-level curves in blue and mean curves over the subjects in black and dotted). The stimulation temperatures are shaded and a star indicates a significant difference between the amplitudes at FCZ and of $s_{1;i}$ at $k \cdot f_\star$ (one-sample t-tests).

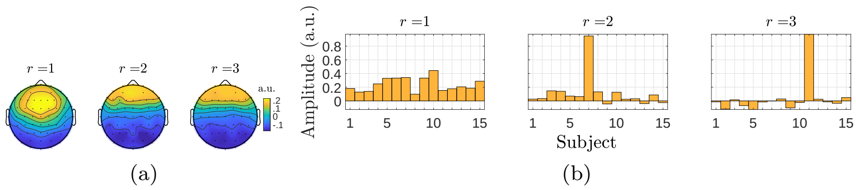


Fig. 3: First three (a) spatial patterns p_1, p_2 and p_3 and (b) between-subject weightings w_1, w_2 and w_3, when $R = 6$ (r being the factor index).

one of the signal at FCZ for all conditions except c2. The absence of periodicity gain for all R for condition c2 suggests that there is indeed no periodic response for this condition, as the periodicity at FCZ was not significant in Sect. 2. Also, Fig. 1b indicates the periodicity of $s_{r;i}$ for all $r = 1, \ldots, R$, the factors being ordered in decreasing order of $\max_i M_\pi(s_{r;i})$. It can be noted that the first time course $s_{1;i}$ is the most periodic for all three first conditions i and all R, suggesting that employing shared spatial patterns for the conditions is indeed relevant.

Fig. 2 illustrates $s_{1;i}$ extracted when $R = 6$ compared to the signals at the single electrode FCZ. One can observe that considering all the channels and subjects at once in the CP model improves the SNR of the periodic components, while preserving their temporal dynamics, especially the latencies of the peaks.

Finally, Fig. 3 depicts the first spatial patterns $\{p_i\}_{i=1}^3$ and subject weightings $\{w_i\}_{i=1}^3$ obtained when $R = 6$. The first extracted topography is consistent with the nature of the considered stimuli [4] and w_1 indicates that the first spatio-temporal factor is reflected in all subjects with well-balanced proportions, whereas the second and third factors appear to be more subject-specific.

5 Conclusion

This paper shows that tensor approximations can be employed to enhance the SNR of some EEG responses. In particular, we found a relevant spatial pattern shared by four modalities and associated with modality-specific periodic time courses, reflecting the SSR of all subjects. Employing unsupervised tensor factorizations enables (1) avoiding overfitting a given criterion, (2) highlighting temporal activity patterns from all subjects with a higher SNR than the raw mean signals and (3) considering all the modes of a multi-way data set at once, without requiring further averaging nor data selection. These encouraging results motivate further works to study the model fitting and its robustness as a function of both the model and the sample sizes and to enlarge its application.

References

[1] A. Cichocki, D. Mandic, L. De Lathauwer, G. Zhou, Q. Zhao, C. Caiafa, and H. A. Phan. Tensor decompositions for signal processing applications: From two-way to multiway component analysis. *IEEE Signal Processing Magazine*, 32(2):145–163, 2015.

[2] E. Acar, D. M. Dunlavy, T. G. Kolda, and M. Mørup. Scalable tensor factorizations with missing data. In *Proceedings of the 2010 SIAM international conference on data mining*, pages 701–712. SIAM, 2010.

[3] A. Hyvärinen. Independent component analysis: recent advances. *Phil. Trans. R. Soc. A*, 371(1984):20110534, 2013.

[4] D. Mulders, C. de Bodt, N. Lejeune, A. Mouraux, and M. Verleysen. Spatial filtering of EEG signals to identify periodic brain activity patterns. In *LVA-ICA*, pages 524–533. Springer, 2018.

[5] R. Sameni, C. Jutten, and M. B. Shamsollahi. Multichannel electrocardiogram decomposition using periodic component analysis. *IEEE transactions on biomedical engineering*, 55(8):1935–1940, 2008.

[6] M. Cohen and R. Gulbinaite. Rhythmic entrainment source separation: Optimizing analyses of neural responses to rhythmic sensory stimulation. *NeuroImage*, 147:43–56, 2017.

[7] B. Blankertz, S. Lemm, M. Treder, S. Haufe, and K.-R. Müller. Single-trial analysis and classification of ERP components – a tutorial. *NeuroImage*, 56(2):814–825, 2011.

[8] N. Sidiropoulos, L. De Lathauwer, X. Fu, K. Huang, E. Papalexakis, and C. Faloutsos. Tensor decomposition for signal processing and machine learning. *IEEE Transactions on Signal Processing*, 65(13):3551–3582, 2017.

[9] T. G. Kolda and B. W. Bader. Tensor decompositions and applications. *SIAM review*, 51(3):455–500, 2009.

[10] F. Miwakeichi, E. Martınez-Montes, P. A. Valdés-Sosa, N. Nishiyama, H. Mizuhara, and Y. Yamaguchi. Decomposing EEG data into space–time–frequency components using parallel factor analysis. *NeuroImage*, 22(3):1035–1045, 2004.

[11] M. Mørup, L. K. Hansen, and S. M. Arnfred. ERPWAVELAB: A toolbox for multichannel analysis of time–frequency transformed event related potentials. *Journal of neuroscience methods*, 161(2):361–368, 2007.

[12] E. Acar, C. Aykut-Bingol, H. Bingol, R. Bro, and B. Yener. Multiway analysis of epilepsy tensors. *Bioinformatics*, 23(13):i10–i18, 2007.

[13] F. Cong, Q.-H. Lin, L.-D. Kuang, X.-F. Gong, P. Astikainen, and T. Ristaniemi. Tensor decomposition of EEG signals: a brief review. *Journal of neuroscience methods*, 248:59–69, 2015.

[14] E. Acar, D. M. Dunlavy, and T. G. Kolda. A scalable optimization approach for fitting canonical tensor decompositions. *Journal of Chemometrics*, 25(2):67–86, 2011.

[15] B. W. Bader, T. G. Kolda, et al. Matlab tensor toolbox version 2.6. Available online, February 2015.