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Space Time Frequency (STF) Code Tensor for the Characterization of the Epileptic Preictal Stage *

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***Abstract*— We evaluate the ability of multiway models to characterize the epileptic preictal period. The understanding of the characteristics of the period prior to the seizure onset is a decisive step towards the development of seizure prediction frameworks. Multiway models of EEG segments already demonstrated that hidden structures may be unveiled using tensor decomposition techniques. We propose a novel approach using a multiway model, Parallel Factor Analysis (PARAFAC), to identify spatial, temporal and spectral signatures of the preictal period. The results obtained, from a dataset of 4 patients, with a total of 30 seizures, suggest that a common structure may be involved in seizure generation. Furthermore, the spatial signature may be related to the ictal onset region and that determined frequency sub-bands may be more relevant in preictal stages.**

I. Introduction

Epilepsy affects approximately 1% of the world's population and represents the second most common brain disorder [1]. Epilepsy is characterized by the occurrence of spontaneous, and usually unforeseeable seizures. Seizures are due to excessive, abnormal activity of neuronal circuits in the brain, particularly in the cerebral cortex and may cause a temporary impairment in certain brain functions.

EEG has the ability to identify abnormal electrical activity (also known as epileptiform) and represents the main diagnostic tool in epilepsy [2]. The EEG from epileptic patients can be classified in different stages: the segment between the start and the end of a seizure is known as "ictal", the "preictal" stage is the data segment before the seizure and the "postictal" is the segment after the seizure. The segment between the "postictal" and the "preictal" of the next seizure is labeled as "interictal". To understand ictogenesis, the characterization of the preictal is a fundamental step [3].

One promising approach to enhance the interpretability of multichannel EEG signals is to apply blind source separation techniques, especially multiway arrays (also known as tensors) [4]. Multiway analysis dates back to 1920 and can be considered as an extension of traditional two-dimensional analysis. Tensors are higher-order generalizations of matrices that can be represented as $\underline{X} \in \mathbb{R}^{I_1 \times I_2 \times \cdots \times I_N}$, where the order of $\underline{X}$ is $N > 2$. Each dimension is called a mode (or way) and the number of variables in each mode is used to indicate its dimensionality [5].

Common two-way analysis methods applied to multichannel EEG data allow us to capture two dimensional patterns (e.g. space-time, time-frequency) [6]. However, matrix factorization methods may be insufficient to analyse large-volume segments of data encompassing many dimensions [4]. A more natural representation of the multi-dimensional structure may require the use of tensors that can retain more dimensions. EEG data for example, can be seen as a multidimensional problem: space (electrode position), time (samples), frequency (spectral decomposition), condition or state (label of each sample), etc.. The neurophisiological interpretation of the decomposition of this structure may reveal patterns hidden in a common two dimensional analysis [7], [8]. Promising results were presented recently modelling the epileptic seizure structure [9].

We present a novel approach to characterize the preictal period using multiway analysis. According to [10] there is a decrease of power in the delta frequency band in the preictal period in comparison to the interictal period, also accompanied by an increase in the remaining bands. We hypothesize that the space-time-frequency code tensor presents this structure, and variations in the preictal state are identifiable. To do so, we rearranged EEG segments with the duration of three hours (two hours prior to the seizure onset and 1 hour after). Then, using a PARAFAC model with non-negativity constraints [11], we computed spatial, temporal and spectral patterns underlying the tensor structure. After the third-order tensor decomposition we correlated the temporal mode of the extracted components with the target proposed. The target is a binary vector with '1' in the preictal period (we considered a 20 minutes interval) and '0' in the rest samples. After determining the factor presenting the best correlation coefficient we analysed the spatial and frequency signature.

The paper is structured as follows. The dataset and methods are presented in section II. Section III details the results obtained using the PARAFAC model. Finally, the conclusion is reported in section IV.

II. Methods

A. Dataset

The data are from four patients affected by refractory epilepsy. The patients were monitored using long term multi-

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TABLE I

DATASET DESCRIPTION.

Patient ID	Epileptic focus (ictal onset)	Num. of seiz.	Num. of channels	Samp. Freq. Hz
A	P4, O2, P8, PZ	6	27	256
B	F3, C3, P3, O1, F7, T7, P7, F8, T8, P8, FZ, CZ, PZ	9	19	256
C	FP1, FP2, F3, F4, C4, P3, P4, O1, F7, F8, T7, T8, P8, CZ	7	19	256
D	F3, C3, P3, F7, F8, T7, T8, P7	8	19	256

channel EEG scalp electrodes placed according to the 10-20 system. The seizures were annotated by trained technicians and reviewed by a neurologist. The data modelled using PARAFAC model consists, for each seizure, in a two hours segment before the seizure onset plus a one hour segment containing ictal and postictal data. An overview of the data is presented in table 1. The dataset is part of the database developed by the EPILEPSIAE project [12].

B. Feature Extraction

In order to estimate the relative frequency power for different sub-bands of each channel, we used a five seconds non-overlapping sliding window. For the purpose of seizure prediction we considered that a five seconds interval is suitable to represent the variations of the EEG data. Moreover, it represents a good compromise between the stationarity assumption (long windows) and low frequency resolution (short window). The preprocessing of the EEG data consisted in a 50Hz notch filter to remove possible artifacts related to the power line. In each window we computed the relative power using the Fast Fourier Transform in the five different sub-bands: Delta (0.1Hz-4Hz), Theta (4Hz-8Hz), Alpha (8Hz-15Hz), Beta (15Hz-30z) and Gamma (30Hz-Nyquist frequency). The relative power is the average of the squared coefficients of the Fast Fourier Transform [13].

C. Multilinear model

To perform the analysis of the multiway arrays, we used the N-way toolbox for MATLAB [14]. The toolbox contains a comprehensive set of tools to model, decompose and analyse multiway datasets.

A N^{th}-order rank-one tensor is described as the outer product of N vectors. Mathematically can be defined as:

$$\underline{Y} = a \circ b \circ c \text{ if and only if } y_{ijk} = a_i b_j c_k, \qquad (1)$$

where a, b and c are column vectors of size $I \times 1$, $J \times 1$ and $K \times 1$; $\underline{Y}$ is a tensor with size $I \times J \times K$.

A PARAFAC model can be represented as the decomposition of a tensor as a linear combination of rank-one tensors (Fig. 1). It is possible to define the number of decomposition components R. In this study we used three rank-one

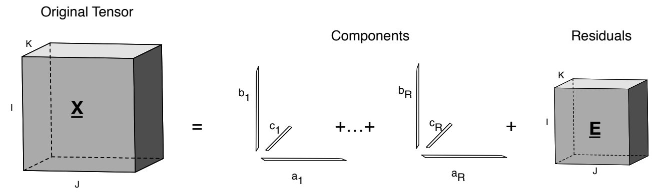

Fig. 1. The PARAFAC model, a three-way array $\underline{X}$ is expressed as the sum of R rank-one tensors and $\underline{E}$, the three-way tensor containing the residuals.

tensors to model the data (according to previous studies it represents an appropriate number of components [9]). The R-component model can be expressed as the following vector outer product sum:

$$\underline{X} = \sum_{r=1}^{R} a_r \circ b_r \circ c_r + \underline{E}, \qquad (2)$$

where $\underline{E} \in \mathbb{R}^{I \times J \times K}$ is a three-way array containing the residuals.

In the PARAFAC model we extract the same number of components from each mode. Therefore, the model obtains a single solution such that the rank-one tensors can be arbitrarily reordered (unique up to a permutation). When one of the three components considered is identified as descriptor of an event (using one of the modes), that particular component presents the signature of that event in the other modes. Let us consider a correlation in the temporal mode of a particular component with an event, the spatial and spectral modes of that particular component are particularly related to the event.

Other models were proposed to decompose multiway arrays, such as the Tucker-3 model [5], [9]. However, the linear combination of rank-one tensor used by the simpler PARAFAC model makes the interpretability of the solution much easier than using other alternatives.

The algorithm used to decompose the PARAFAC model is the alternating least squares (ALS). The ALS algorithm finds the solution using an iterative method, successively estimating the unknown set of parameters of a determined mode, assuming the parameters of the remaining modes as known [5].

D. Component analysis

A three-component PARAFAC model, extracts three components defined in the space, time, and frequency domains. According to the correlation of the temporal mode of each component with the target proposed we determine the 'best' component. We determined the value ρ representing the correlation coefficient and the p-value that represents the probability of rejecting the Null-Hypothesis (in other words, the hypothesis of no correlation). A test rejected with a significance level of 0.05 corresponds to 95% of confidence that the observed statistic, i.e., the correlation ρ, is significant. In this case, we can state that an observed value of a high ρ correlation does not occur by random chance when the true correlation is zero.

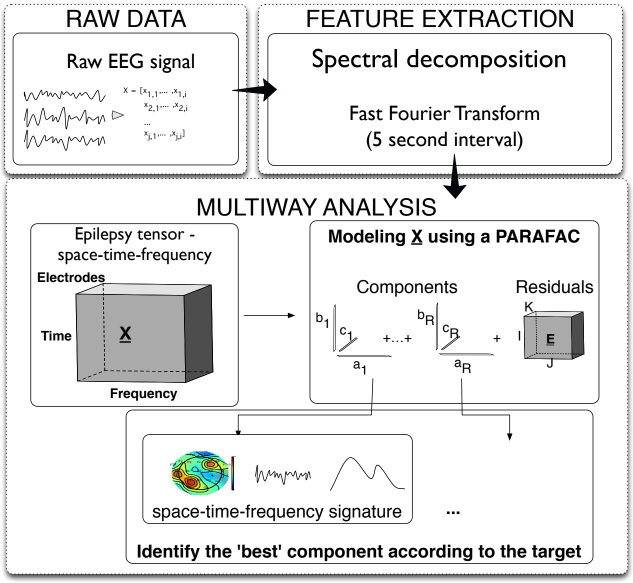

Fig. 2. Overview of the method proposed.

After determining the component with higher correlation and its statistical significance, we analysed the spatial and frequency modes and compared the signatures among the seizures of each patient (Fig. 2).

III. Results

The tensor $\underline{X}$ structure for each event is composed by the original three modes. The spatial mode corresponds to the number of electrodes available for each patient (table 1), the temporal mode has 2160 samples corresponding to three hours of data (two hours before the seizure onset and one hour after), and the frequency mode presents five samples (one for each frequency sub-band considered). Each element of the tensor $\underline{X}$ can be denoted by x_{ijk} and represents the relative frequency power at the i^{th} time sample for the j^{th} sub-band at k^{th} electrode.

We scale the tensor within the spatial mode before we proceed to the decomposition of the tensors. Different approaches were proposed to determine the initialization values of the model [14], however none of the methods guarantees convergence. We used random initialization values and performed three runs to confirm convergence to the global minimum. We also imposed nonnegative constraints (NTF) in the temporal mode [15].

Once the STF code tensor, is constructed, we model $\underline{X}$ using a three-component PARAFAC model, mathematically:

$$\underline{X} = a_1 \circ b_1 \circ c_1 + a_2 \circ b_2 \circ c_2 + a_3 \circ b_3 \circ c_3 + \underline{E} \quad (3)$$

Our objective is to identify spatial, temporal and spectral signatures of the preictal period for each event. Also important is to find common properties among events.

Patient A: The components that presented the best correlation coefficient for the 6 seizures analysed were statistically significant. The analysis of the spatial signatures of the most correlated component present relevant extrema in the parietal region, in most cases in the right hemisphere. These spatial distributions can be related to prior knowledge about the ictal onset. According to the electrographical review of the EEG data, the ictal onset area was located in the right parietal and occipital region (electrodes P4, P8, PZ, O2), and early propagation patterns presented bilateral electrodes in temporal and parietal lobes. The spectral signature also presented similar patterns among events suggesting that lower frequency sub-bands are more important. **Patient B:** The patient presented 9 seizures. According to the statistical evaluation of the correlation of the temporal components most correlated components were statistically significant. The electrographical review of the ictal onset of the events revealed that different regions are involved in the ictogenesis processes. The spatial signatures of these components presented two different patterns, that can, to some extent, be related to ictal onset (a good example is presented in Fig. 3, patient B seizure number 8). The spectral signature also presents two different patterns. **Patient C:** The electrodes identified by the neurologist in the ictal onset varied among the 7 seizures analysed. Such as with the previous patients, all the tensors analysed presented one component with significant correlation to the target. The spatial and spectral components presented variations among seizures. The analysis of the first seizures emphasized the importance of left fronto-temporal regions. Other seizures presented different patterns (electrode C4 has a major importance in the spatial signature of almost all seizures - associated to the ictal onset in some of the seizures), but the onset area and the spatial signature observed do not suggest any association. **Patient D:** For this patient, the ictal onset zone defined by the electrographical review of the data was defined bilaterally in the fronto-temporal regions. Reviewing the spatial signatures of the most correlated temporal modes of the tensors, we observed that the spatial distributions were very stable among seizures. Extreme occurred in temporal (T7 and T8) and parietal electrodes (P3 and P4). Low frequency bands (Delta) are consistently presented in the spectral signature of the components. Only one tensor did not present a statistically significant correlation to the target.

IV. Discussion

We presented an approach based on multiway arrays for the characterization of the epileptic preictal period. A three-way PARAFAC model using non-negative constraints (NTF) was used to fit three-dimensional datasets. We analyzed 30 seizures from four patients and found common patterns among seizures and evidences that these similarities occur for each patient. Only one seizure did not present a significant correlation to the target proposed.

Patient A and B demonstrated a strong spatial relationship between the ictal onset region and the spatial signature of the best correlated component. In the example (patient B) showed in Fig. 3, the only seizure with right temporo-parietal ictal onset presented an extreme in the same region. The frequency mode suggest that the Delta (Patient A and B)

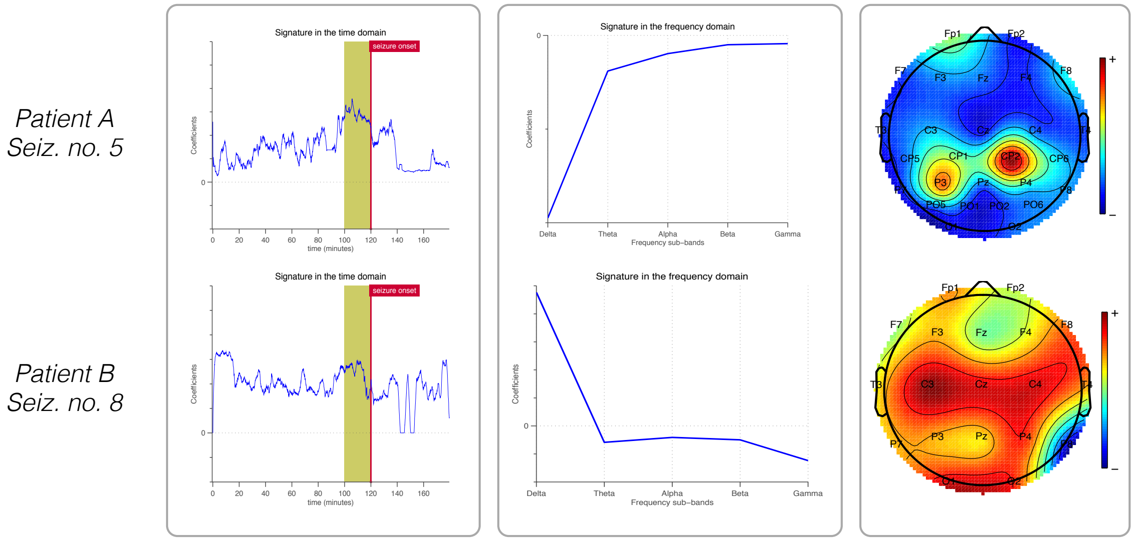

Fig. 3. A 3-component PARAFAC model with nonnegative constraints in the temporal mode for different seizures is displayed. The component represented has the best correlation coefficient between the target proposed and the temporal mode. The rows represent the temporal (the yellow region represent the preictal stage and the red line highlights the ictal onset sample), spectral and spatial modes of the components. The bottom row illustrates the spatial signature of the 8^{th} seizure of patient B.

and Gamma (patient B) sub-bands play an important role. The variability presented in the results of Patient C are confirmed by neurologist evaluation. Patient D presented a very stable spatial signature among seizures, with multiple areas highlighted in the topographic map among the seizures.

The results suggest that the spatial signature of the components analysed may be related to the ictal onset zone. However, the other regions highlighted should also be carefully analysed. The variability presented in some cases shows that different regions may be involved in the seizure generation processes. Spectral signature demonstrates the importance of low frequency sub-bands.

Different research directions will be addressed as future work. Add an additional mode (for example the class of each point, either interictal, preictal) or concatenate the several seizures trying to find a single model for each patient may help to understand the structure of the data. Another alternative approach is the analysis of dynamic tensors. The decomposition of dynamic streams (sequence) of tensors can be an important step towards the development of real-time algorithms to predict seizures.

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REFERENCES

[1] J. S. Duncan, J. W. Sander, S. M. Sisodiya, and M. C. Walker, "Adult epilepsy," *Lancet*, vol. 367, pp. 1087–1100, 2006.

[2] F. H. Lopes da Silva, "The Impact of EEG/MEG Signal Processing and Modeling in the Diagnostic and Management of Epilepsy," *IEEE Reviews in Biomedical Engineering*, vol. 1, pp. 143–156, 2008.

[3] N. Mammone, J. C. Principe, F. C. Morabito, D.-S. Shiau, and J. C. Sackellares, "Visualization and modelling of STLmax topographic brain activity maps.," *Journal of Neuroscience Methods*, vol. 189, no. 2, pp. 281–294, 2010.

[4] A. Cichocki, Y. Washizawa, T. Rutkowski, H. Bakardjian, and A.-H. Phan, "Noninvasive BCIs: Multiway Signal-Processing Array Decompositions," *Computer*, vol. 41, pp. 34–42, Oct. 2008.

[5] E. Acar and B. Yener, "Unsupervised Multiway Data Analysis :," *IEEE transactions on knowledge and data engineering*, vol. 21, no. 1, pp. 6–20, 2009.

[6] H. Lee and S. Choi, "Group nonnegative matrix factorization for EEG classification," *Proceedings of the International Conference on Artificial Intelligence and Statistics*, vol. 5, pp. 320–327, 2009.

[7] F. Miwakeichi, E. Martínez-Montes, P. Valdés-Sosa, N. Nishiyama, H. Mizuhara, and Y. Yamaguchi, "Decomposing EEG data into space-time-frequency components using Parallel Factor Analysis.," *NeuroImage*, vol. 22, pp. 1035–45, July 2004.

[8] F. Estienne, N. Matthijs, D. Massart, P. Ricoux, and D. Leibovici, "Multi-way modelling of high-dimensionality electroencephalographic data," *Chemometrics and Intelligent Laboratory Systems*, vol. 58, pp. 59–72, Sept. 2001.

[9] E. Acar, C. Aykut-bingol, H. Bingol, R. Bro, and B. Yener, "Multiway Analysis of Epilepsy Tensors," *Bioinformatics*, vol. 23, no. 13, pp. 10–18, 2007.

[10] F. Mormann, T. Kreuz, C. Rieke, R. G. Andrzejak, A. Kraskov, P. David, C. E. Elger, and K. Lehnertz, "On the predictability of epileptic seizures.," *Clinical Neurophysiology*, vol. 116, pp. 569–87, Mar. 2005.

[11] M. Mørup, L. Hansen, J. Parnas, and S. M. Arnfred, "Decomposing the time-frequency representation of EEG using nonnegative matrix and multi-way factorization," 2006.

[12] M. Ihle, H. Feldwitch-Drentrup, C. A. Teixeira, A. Witon, B. Schelter, J. Timmer, and A. Schulze-Bonhage, "EPILEPSIAE - A common database for research on seizure prediction," *Computer Methods and Programs in Biomedicine*, 2010.

[13] C. Teixeira, B. Direito, H. Feldwisch-Drentrup, M. Valderrama, R. Costa, C. Alvarado-Rojas, S. Nikolopoulos, M. Le Van Quyen, J. Timmer, B. Schelter, and A. Dourado, "EPILAB: A software package for studies on the prediction of epileptic seizures," *Journal of Neuroscience Methods*, vol. 200, pp. 257–271, July 2011.

[14] C. Andersson, "The N-way Toolbox for MATLAB," *Chemometrics and Intelligent Laboratory Systems*, vol. 52, pp. 1–4, Aug. 2000.

[15] H. Lee, Y.-D. Kim, A. Cichocki, and S. Choi, "Nonnegative tensor factorization for continuous EEG classification.," *International Journal of Neural Systems*, vol. 17, no. 4, pp. 305–317, 2007.