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Temporarily Activated Patterns for Multi-trial Functional Connectivity Data

Gaëtan Frusque [1], Julien Jung [2], Pierre Borgnat [3] and Paulo Gonçalves [2]
[1] Univ. Lyon, Inria, CNRS, ENS de Lyon, UCB Lyon 1, LIP UMR 5668, F-69342, Lyon, France
[2] HCL, Neuro. Hosp., Functional Neurology and Epileptology Dept. & Lyon Neurosc. Res. Cent., INSERM, CNRS, Lyon, France
[3] Univ. Lyon, ENS de Lyon, UCB Lyon 1, CNRS, Laboratoire de Physique, F-69342 Lyon, France
E-mail: frusque.gaetan@ens-lyon.fr

Summary: Functional connectivity is a graph-like data structure commonly used by neuroscientists to study the dynamic behaviour of brain activity. We address the problem of decomposing multi-trial functional connectivity data, with potential duration heterogeneity, into a set of common patterns contributing to each trial and their associated trial specific temporal activations. We apply our method on iEEG recording from different epileptic seizures of the same patient.

Keywords: Matrix decomposition, Tensor decomposition, Parafac2, Fused Lasso, iEEG, Functional connectivity.

1. Introduction

Epilepsy is one of the most common neurological disorder in the world population. iEEG electrodes are used to exhibit the stages of a seizure characterized by similar patterns in different areas of the brain. Functional Connectivities (FC) that quantify along time, these similarities are calculated between all pairs of signals, usually through the spectral coherence or the Phase Locking Value [1].

1.1. Problem

The patient stays in the hospital for several days with electrodes implemented in the brain to record multiple epileptic seizures. Since the number of FC to be studied is quadratic with the number of electrodes, the analyses of these FC become complicated and time-consuming. Hence, there is a need in the epileptologic community to use automatic methods to extract the FC dynamic global to all seizures.

Since the stages of seizures distinguish themselves by similar evolution of FC patterns, but with possibly different temporal activation, the joint analysis of these records should ease the identification of dynamical FC patterns common to all seizures but with specific temporal activation for each seizure.

1.2. Notation and Existing Propositions

Let N be the number of recorded seizures and $\boldsymbol{X(n)}$ the FC measures along time for the nth seizure. $\boldsymbol{X(n)}$ is of dimension $I*T(n)$, with I the number of FC and $T(n)$ the number of time samples (which can vary for each seizure n).

In [2], a constrained tensor decomposition method is used to infer FC patterns common to all seizures. However, this method does not exhibit the temporal activations to each seizure. Moreover, seizures time series must have the same number of ($T(n) = T$ for all n), which is sometimes impossible.

The usual tensor decomposition to deal with duration heterogeneity and producing a trial-specific activation matrix is Parafac2 [3], which allows the following approximation:

$$\mathbf{X}(n) \approx \mathbf{F}\mathbf{D}(n)\mathbf{V}(n)^t \quad \forall n \in 1,...,N$$

$\boldsymbol{F}$ is the pattern matrix of dimension $I*K$ and K the number of FC pattern in the seizure. $\boldsymbol{V}$(n) is the time activation matrix is of dimension T*K and $\boldsymbol{D}$(n) is a diagonal matrix characterising the contribution of each pattern in the seizure. The principal default of this decomposition is the difficulty to add structural constraints on matrices $\boldsymbol{F}$ and $\boldsymbol{V}$(n) simultaneously, to get interpretable results.

2. Proposed Decomposition

We propose a modification of the Parafac2 problem. First, a sparse regularization on $\boldsymbol{F}$ is added, this is important in the context of epileptic data where a large number of FC measurements can be passively implied in a neurological process (during the discharge of the seizure, for example). Secondly, a Fused lasso constraint is imposed on the columns of $\boldsymbol{V}$(n), noted $\boldsymbol{v}(n)_{:k}$, to get few consistent and interpretable temporal activation for each pattern in all seizures. $\boldsymbol{F}$ and $\boldsymbol{V}$(n) are also imposed to be non-negative since FC are generally positive measures. Thus, the decomposition consists to find matrices $\boldsymbol{V}$(n) and $\boldsymbol{F}$ minimizing:

$$\underset{\mathbf{F}\geq 0, \mathbf{V(n)}\geq 0}{\operatorname{argmin}} \sum_{n=1}^{N} \| \mathbf{X}(n) - \mathbf{F}\mathbf{V}(n)^t \|_F^2 + a_1 \| \mathbf{F} \|_1$$
$$s.t. \quad b_1 \| \mathbf{v}(n)_{:k} \|_1 + b_2 TV(\mathbf{v}(n)_{:k}) + \| \mathbf{v}(n)_{:k} \|_F^2 \leq 1$$

With a_1, b_1 and b_2 hyperparameters, *TV(.)* is the total variation function. The norms are entrywise and correspond to the Frobenius and the 1-norm respectively.

Here the diagonal matrices $\boldsymbol{D}$(n) are imposed to be identity, which constitutes the principal difference with the Parafac2 model. In addition to simplify the implementation, identity matrices $\boldsymbol{D}$(n) prompts to reveal only FC patterns contributing in each seizure.

The algorithm of our proposed decomposition consists to alternate two steps, first we fix and concatenate matrices $\boldsymbol{V}$(n), and a lasso regression is done to estimate $\boldsymbol{F}$. Then knowing $\boldsymbol{F}$, a constrained regression for each seizure estimates the matrices $\boldsymbol{V}$(n). We can show that this procedure ensures convergence of the loss function.

3. Application on iEEG Data

3.1. Data

We use the same dataset as in [2]: it consists of four FC measures $\boldsymbol{X}$(n) (N = 4), computed employing Phase Locking value from iEEG recording of different seizures of the same patient (read [2] for more details). Here, *T(n)* = *T* for all *n* because the temporal activations of each FC pattern are similar through all seizures, which is an essential condition to use the methodology from [2]. We expect the proposed decomposition to produce similar FC patterns as in [2], and in addition specific and coherent temporal activation for each seizures.

3.2. Results

From matrices $\boldsymbol{X}$(n), we compute the FC patterns $\boldsymbol{F}$ and their temporal activations $\boldsymbol{V}$(n) using the proposed decomposition. We empirically fix K = 5 patterns, and $a_1 = 2$, $b_1 = 1$ and $b_2 = 1$. Fig. 1 shows the temporal activation profile of each FC patterns for all seizures. For each seizure, patterns activate in the same order, showing a succession of temporally coherent states.

Fig. 2 shows the position of the 33 electrodes projected on the transverse plane (according to the Tailarach coordinate). For each pattern, the FC *i* such that $\boldsymbol{F}_{ik} > 0$ is displayed by a link between involved pairs of electrodes. We recover FC patterns very similar to the four patterns found in [2], we also find another pattern (k = 2), which gives supplementary information on the seizure dynamic.

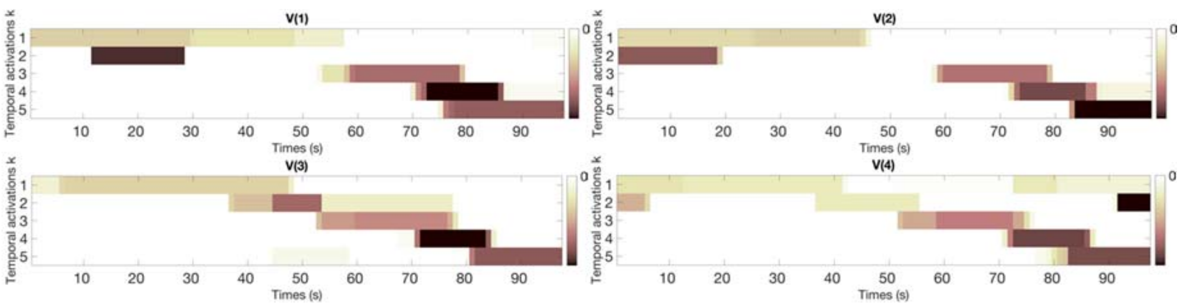

Fig. 1. Temporal activation matrices $\boldsymbol{V}$(n) for the four studied seizures.

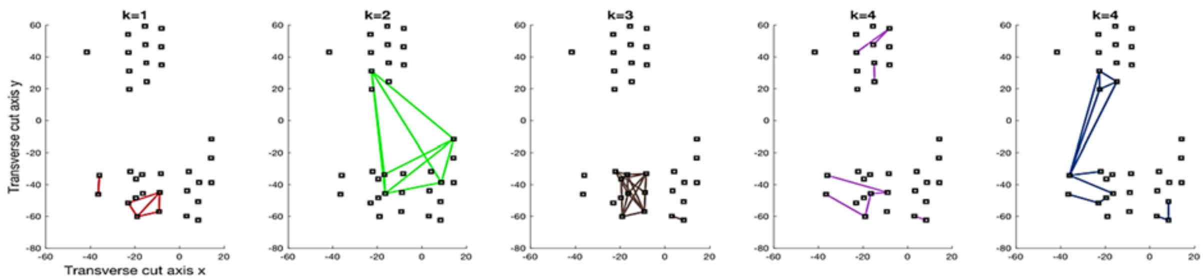

Fig. 2. Five common patterns $\boldsymbol{F}_{:k}$, FC *i* is displayed as a link when $\boldsymbol{F}_{ik}$.>0.

4. Conclusions

In this work, we propose a method decomposing a multi-trial dynamic graph of functional connectivity, with potential duration heterogeneity. The application of our method on iEEG recording reveals the patterns common to all seizures, and identifies their specific temporal activation relevant to each seizure.

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