Flexible Double Coupled Factorization for EEG and fMRI Fusion

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***Abstract*— Data fusion refers to the joint analysis of multiple datasets providing complementary views of the same process. In this paper, the problem of jointly analyzing electroencephalography (EEG) and functional Magnetic Resonance Imaging (fMRI) data is considered. A double coupling model is proposed which allows for subject variation in the Hemodynamic Response Function (HRF) and misspecifications in the coupling of the two modalities, by using a prior on the neural-hemodynamic coupling *and* soft coupling constraints of spatial modes of fMRI among the different subjects.**

I. INTRODUCTION

In an attempt to better understand a system as complex as the human brain, multimodal measurements can be beneficial since they are able to provide complementary information. In the field of neuroimaging and brain mapping, the complementary nature of the (spatiotemporal) resolutions of electroencephalography (EEG) and functional Magnetic Resonance Imaging (fMRI) motivates their fusion for a better localization of the brain activity, both in time and space [1].

A wide variety of fusion models have been proposed, including "late" (using features of both modalities) and "early" (using the raw data). Similarly to [2], our aim is to fuse simultaneously recorded EEG and fMRI in a data-driven fashion in the form of an early flexible temporal coupling between the two modalities, with a-priori unknown HRF. To accommodate for subject-specific HRF variation in the multi-subject setting, we represent the EEG (resp. fMRI) data of every subject by a separate tensor (resp. matrix), to allow multiple "time modes." Instead of using a concatenated matrix or a 3rd-order tensor for the fMRI of each subject [3], multiple soft coupled matrices (one for each subject) are considered (Fig. 1). Each matrix is coupled with the respective EEG tensor via a subject-specific HRF (in contrast to the more restricted, less flexible existing approaches).

To incorporate prior physiological knowledge, we constrain the HRF to a class of "plausible" waveforms, which are estimated from the data itself [2]. Different models can be used, such as the canonical HRF. In this paper, we opt for a new model, that can be described by only three parameters, based on the Lennard-Jones potential [4] $h(t,z) = \Gamma^{-3}(z_{(1)}t) - z_{(2)}\Gamma^{-6}(z_{(3)}t)$. When all subjects engage in the same cognitive task, neural activity in the same functional brain regions is elicited. Hence, the spatial mode of fMRI can be (approximately/softly) coupled over subjects.

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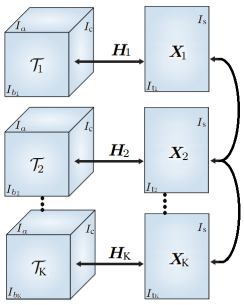

Fig. 1. DCMTF for K subjects

Method	Low overlap	High overlap
Parallel ICA	0.95	0.70
Uncoupled	0.85	0.80
Coupled Tensors	0.95	0.92
Double Coupled MTF	0.92	0.91

TABLE I

SAME SPATIAL MAPS PER SUBJECT

Method	Low overlap	High overlap
Parallel ICA	0.94	0.70
Uncoupled	0.85	0.80
Coupled Tensors	0.75	0.65
Double Coupled MTF	0.90	0.90

TABLE II

DIFFERENT SPATIAL MAPS PER SUBJECT

We formulate this problem as a Double (in time among EEG and fMRI and in space among subjects in fMRI) Coupled Matrix Tensor Factorization (DCMTF). The 3rd-order EEG tensors, $\boldsymbol{\mathcal{T}}_k$, describe the variation over the temporal ($\boldsymbol{a}_{k_r}$), the spatial ($\boldsymbol{b}_{k_r}$) and the spectral ($\boldsymbol{c}_{k_r}$) modes, for K different subjects. The fMRI matrices, $\boldsymbol{X}_k$, contain the variation over the temporal and spatial ($\boldsymbol{e}_{k_r}$) modes, with the matrix $\boldsymbol{E}_k = \left[\boldsymbol{e}_{k_1}, \boldsymbol{e}_{k_2}, \ldots, \boldsymbol{e}_{k_R}\right]$ comprising the weights of the R spatial components of the kth subject and $\boldsymbol{E}$ being a spatial map to which all the subject spatial maps are similar (imposed as regularization term). The parameter sets $\{z_k\}$ describe the subject-specific HRF matrix, $\boldsymbol{H}_k$. The proposed cost function to minimize is given by:

$$\sum_{k=1}^{K}(\|\boldsymbol{\mathcal{T}}_k - \sum_{r=1}^{R}\boldsymbol{a}_{k_r}\circ\boldsymbol{b}_{k_r}\circ\boldsymbol{c}_{k_r}\|_F^2 + \|\boldsymbol{X}_k - \sum_{r=1}^{R}(\boldsymbol{H}_k(t,\{z_k\})\boldsymbol{a}_{k_r})\circ\boldsymbol{e}_{k_r}\|_F^2 + \lambda\|\boldsymbol{E}_k - \boldsymbol{E}\|_F^2) \quad (1)$$

II. RESULTS

A simulation setup similar to [3] was considered for our analysis. $R = 6$ different sources were assumed, both with low and high temporal and spatial overlap. In a second simulation study, subject variability was introduced in the spatial domain of two of the sources; rotation (in increments of 4 degrees per subject) of one of the sources and voxel shifts at increments of 2 voxels with respect to the 1st subject in the other source. DCMTF in (1) was performed via Tensorlab [5]. The mean Pearson correlation of the obtained sources with the ground truth is given in Tables I and II for the two scenarios. The DCMTF model allows to successfully estimate the underlying sources, even under spatial mismatch among subjects. More experiments with different HRF models will be conducted, also for real data.

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