Exploration of LICA detection in resting state fMRI

Darya Chyzhyk[1], Ann K. Shinn[2], Manuel Graña[1]

1 Computational Intelligence Group
University of Basque Country,
San Sebastián, Spain
www.ehu.es/ccwintco

2 McLean Hospital, Belmont
Massachusetts
Harvard Medical School
Boston, US

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Introduction

- **Lattice Independent Component Analysis** (LICA) approach consists of a detection of lattice independent vectors (endmembers) that are used as a basis for a linear decomposition of the data (unmixing).
- In this paper we explore the network detections obtained with LICA in **resting state fMRI** data from healthy controls and **schizophrenic** patients.
- We **compare** with the findings of a standard Independent Component Analysis (ICA) algorithm.

Introduction

- The main **advantage of ICA** is that it does **not** impose a **priori assumptions** on the selection of observations, thus avoiding double dipping effects biasing the results.
- We have proposed Lattice Independent Component Analysis (LICA). that consists:

  1. Selects Strong Lattice Independent (SLI) vectors from the input dataset using an incremental algorithm, the Incremental Endmember Induction Algorithm (IEIA)

  2. it performs the linear unmixing of the input dataset based on these endmembers.

Introduction

- We **assume** that the data is generated as a convex combination of a set of endmembers which are the vertices of a convex polytope covering some region of the input data.
- This assumption is **similar** to the linear mixture assumed by the **ICA** approach
- Endmembers **correspond** to the **ICA's** temporal independent sources.
- **LICA** is **unsupervised**, as ICA, but it does not impose any a priori assumption on the data.

Resting state fMRI background

- **Resting state fMRI** data has been used to study the connectivity of brain activations.
- **Schizophrenia** is a severe psychiatric disease that is characterized by delusions and hallucinations, loss of emotion and disrupted thinking.
- Functional disconnection between brain regions is suspected to cause these **symptoms**, because of known aberrant effects on **gray and white matter** in brain regions that overlap with the default mode network.
- Resting state fMRI studies have indicated aberrant default mode **functional connectivity in schizophrenic** patients.

The Lattice Independent Component Analysis

The linear mixing model can be expressed as follows:

$$x = \sum_{i=1}^{M} a_i e_i + w = Ea + w$$

where

- ***x*** is the *d*-dimension pattern vector corresponding to the fMRI voxel time series vector,
- ***E*** is a *dxM* matrix whose columns are the *d*-dimensional vectors, when these vectors are the vertices of a convex region covering the data they are called endmembers $\boldsymbol{e}_i$, $i = 1,..,M$.
- ***a*** is the *M*-dimension vector of linear mixing coefficients, which correspond to fractional abundances in the convex case, and
- ***w*** is the *d*-dimension additive observation noise vector.

The Lattice Independent Component Analysis

- The linear mixing model is subjected to two constraints on the abundance coefficients when the data points fall into a simplex whose vertices are the endmembers,
- all abundance coefficients must be non-negative

$$a_i \geq 0, \qquad i = 1, \ldots, M$$

- and normalized to unity summation

$$\sum_{i=1}^{M} a_i = 1$$

The Lattice Independent Component Analysis

- The Lattice Independent Component Analysis (LICA) is defined by the following steps:

  1. Induce from the given data a set of **Strongly Lattice Independent vectors**. In this paper we apply the Incremental Endmember Induction Algorithm. These vectors are taken as a set of affine independent vectors.

  The **advantages** of this approach are

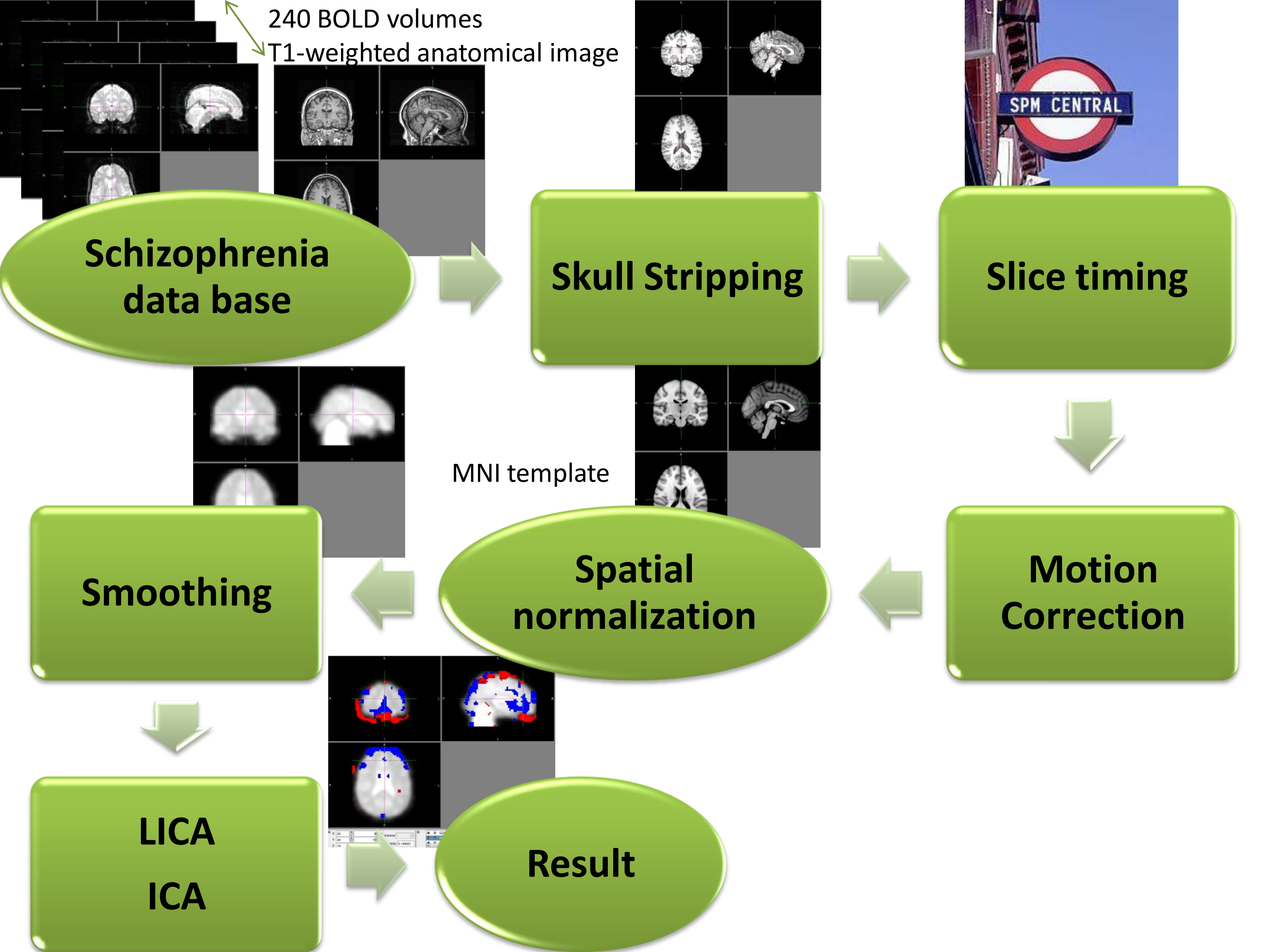
  (1) we are not imposing statistical assumptions,

  (2) the algorithm is one-pass and very fast ,

  (3) it is unsupervised and incremental

  (4) it detects naturally the number of endmembers.

  2. Apply the unconstrained least squares estimation to **obtain the mixing matrix**. The approach is a combination of **linear** and **lattice** computing: a linear component analysis where the components have been discovered by non-linear, lattice theory based, algorithms.



240 BOLD volumes
T1-weighted anatomical image
SPM CENTRAL
Schizophrenia data base
Skull Stripping
Slice timing
MNI template
Motion Correction
Spatial normalization
Smoothing
LICA
ICA
Result

A resting state fMRI case study

- The application of LICA with nominal parameters give **8 endmembers**
- For each endmember, we set the **95% percentile** of its abundance distribution as the threshold for the detection of the corresponding endmember in the abundance volume
- We do the **same** with the **ICA** mixture distributions.
- To explore the agreement between ICA and LICA detections, we have computed the **Pearson's correlation** between the abundance/mixing volumes of each source/endmember,
  - table 1 - the **schizophrenia** patient
  - table 2 - the **control** subject.

A resting state fMRI case study

The best correlation is ICA #8 versus LICA #5 for the schizophrenia patient.

	ICA							
LICA	#1	#2	#3	#4	#5	#6	#7	#8
#1	0.02	0	-0.04	-0.02	0.02	0.03	0.01	0.01
#2	0.03	0.08	-0.1	-0.04	0	0.01	-0.33	0
#3	-0.01	**0.36**	0.01	-0.07	-0.01	-0.02	0.13	-0.01
#4	0.03	0	-0.03	-0.11	0	-0.01	0	-0.01
#5	-0.03	-0.02	**0.16**	-0.01	-0.01	-0.11	-0.02	**0.46**
#6	0.38	-0.03	0.01	-0.13	**0.17**	0	-0.01	0.01
#7	0	-0.02	0.06	-0.02	-0.01	-0.02	-0.02	-0.01
#8	0.25	0.01	-0.22	0.04	-0.52	0.05	0.02	-0.05

Pearson's Correlation coefficients between ICA and LICA endmember detections for the **schizophrenia patient.**

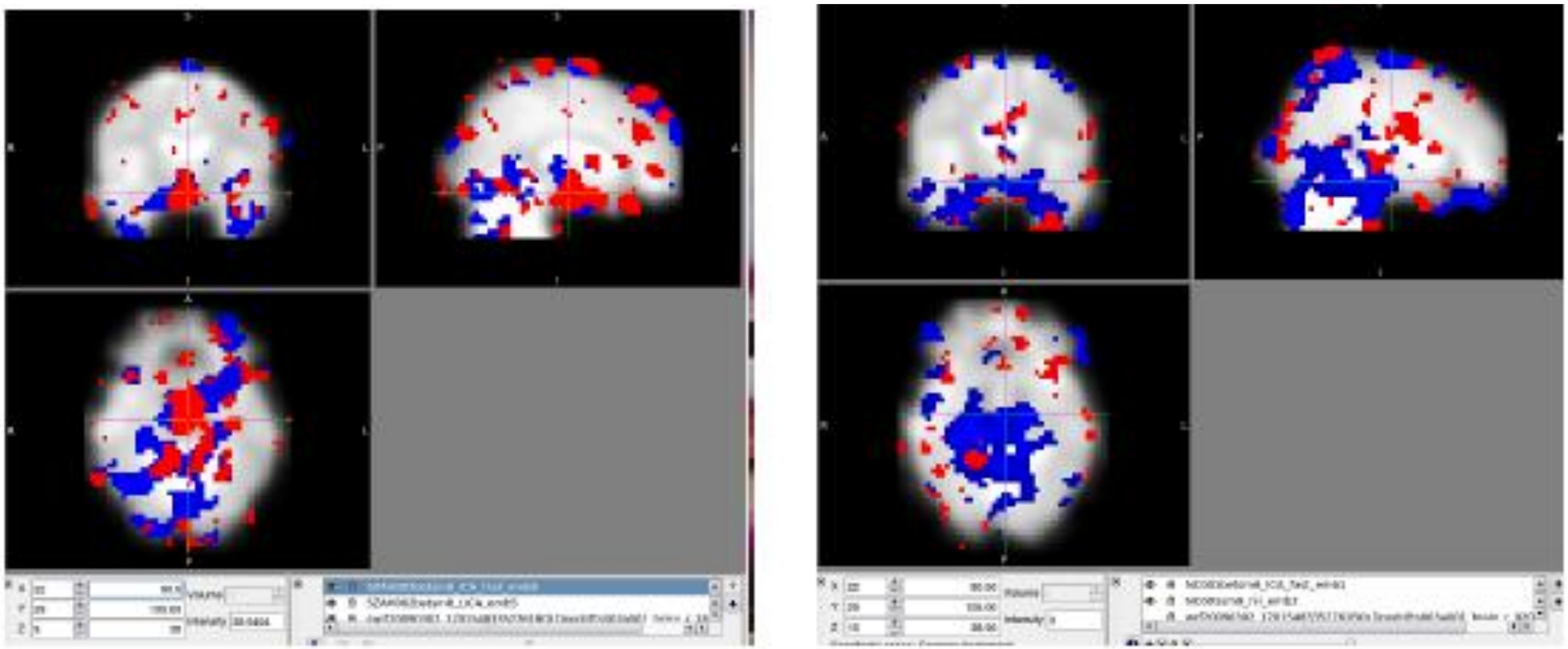
A resting state fMRI case study

In both cases, agreement between detections of LICA and ICA is low.

	ICA							
LICA	#1	#2	#3	#4	#5	#6	#7	#8
#1	0.04	-0.02	-0.04	0.05	-0.06	-0.07	0.03	0.01
#2	-0.02	0.02	0	-0.08	-0.03	-0.03	**0.15**	-0.01
#3	**0.22**	-0.05	**0.13**	0.06	0.01	0.08	-0.03	0.07
#4	0.05	-0.22	0.06	-0.09	0.06	0.08	0.08	-0.03
#5	0.03	0.07	-0.07	**0.12**	**0.14**	-0.13	0.04	-0.01
#6	0.04	0	0.05	-0.06	-0.1	0.02	-0.05	-0.03
#7	0.08	**0.1**	0	0.03	-0.03	-0.02	0.09	0.03
#8	-0.02	-0.04	0.02	0.04	-0.05	-0.07	0.07	0.03

Pearson's Correlation coefficients between ICA and LICA endmember detections for the **healthy control**.

A resting state fMRI case study



(a) (b)

Figure 1: Simultaneous visualization of the best correlated detection results.

Red corresponds to **ICA** detection, **Blue** to **LICA** detection. (a) Patient, (b) Control.

LICA detections appear as more compact clusters.

Some spurious detections are shown in the surroundings of the brain due to the difusion produced by the smoothing filter.

A resting state fMRI case study

- We have computed the **correlations** intra-algorithm of the **patient vs. control** data, meaning that we compute the correlations of the abundance/mixing volumes obtained by the LICA/ICA on the patient and the control data.
- If we find **negative correlations** of high magnitude then we can say that the corresponding approach has a great potential to generate features that **discriminate patients from controls.**

A resting state fMRI case study

We are interested in finding the most negatively correlated.

	patient							
control	#1	#2	#3	#4	#5	#6	#7	#8
#1	-0.17	-0.04	-0.03	0.24	0.08	0.08	0.09	0.01
#2	0.02	**-0.21**	0.04	0.1	0.15	0.09	0.02	-0.09
#3	**-0.32**	0.05	-0.05	0.14	0.24	0.13	0.13	0.15
#4	0.01	0.15	0.08	0.05	-0.03	0.02	0.05	0.17
#5	-0.14	-0.13	**-0.18**	0.13	0.14	0.11	0.12	-0.04
#6	0.01	-0.06	0.11	0.02	0.02	0.02	-0.02	-0.02
#7	0.06	-0.11	-0.05	-0.15	-0.05	-0.05	-0.12	0.03
#8	**-0.32**	-0.19	-0.02	0.23	0.22	0.2	0.05	0.02

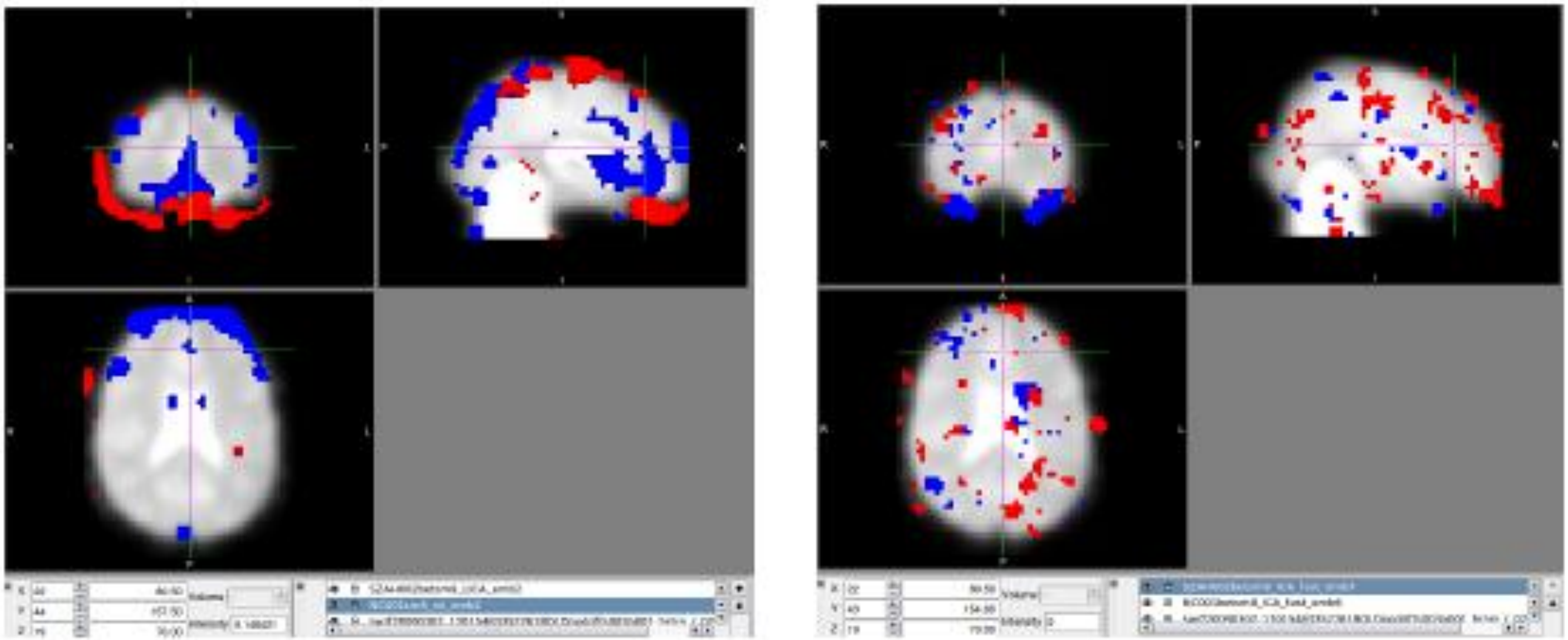
Table : Correlation between patient and control detections obtained by **LICA**

A resting state fMRI case study

	patient							
control	#1	#2	#3	#4	#5	#6	#7	#8
#1	0.41	0.01	-0.15	0.01	**-0.18**	0.02	0.02	-0.04
#2	-0.12	0.02	0.06	-0.04	0.08	-0.01	0.01	0.05
#3	0.02	-0.02	**-0.24**	-0.02	0.01	0.01	0	0.03
#4	0.03	0	0	0	0.02	0.02	0.02	0
#5	0.04	-0.01	0.06	-0.03	-0.05	-0.01	0.01	0.36
#6	0.04	0.07	-0.05	0.01	0	0	**-0.25**	0
#7	0.03	0	-0.02	0	-0.01	0.06	0	-0.03
#8	0.02	0.03	-0.01	0	-0.02	0	0.01	0

Table : Correlation between patient and control detections obtained by **ICA**

A resting state fMRI case study



(a) (b)

Figure 2: Greatest negative correlated detections (a) by LICA, (b) by ICA.

Red corresponds to the **patient** volume detection, **blue** - to the **control**.

LICA detections produce **more compact clusters**.

The **greatest** discrimination is obtained by **LICA**.

Summary and Conclusions

- We are exploring the application for **Lattice Independent Component Analysis** to resting state fMRI.
- We present results on selected subjects from a **schizophrenic data** base from the McLean Hospital.
- We **compare LICA and ICA** findings in the form of detections based on the thresholding of the abundance images and mixing matrices.
- **LICA** detections are **less sparse** than those of ICA and show greater negative correlation than the results of ICA.
- There is **little agreement between LICA and ICA** on this data.
- We interpret this result as pointing to a greater **capability** to produce features for **discrimination between control and patients** based on resting state fMRI data.

Thank you for your attention!

Darya Chyzhyk, Manuel Graña

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