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A Comparison of VBM results by SPM, ICA and LICA

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- Voxel-wise statistical tests
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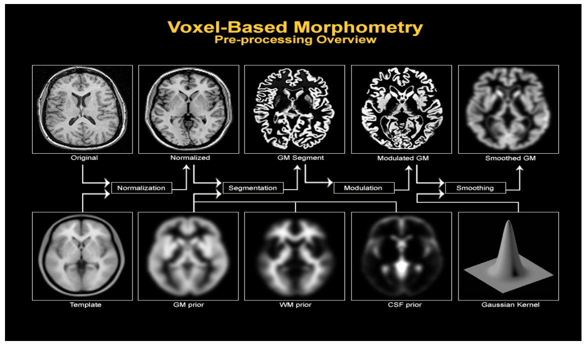
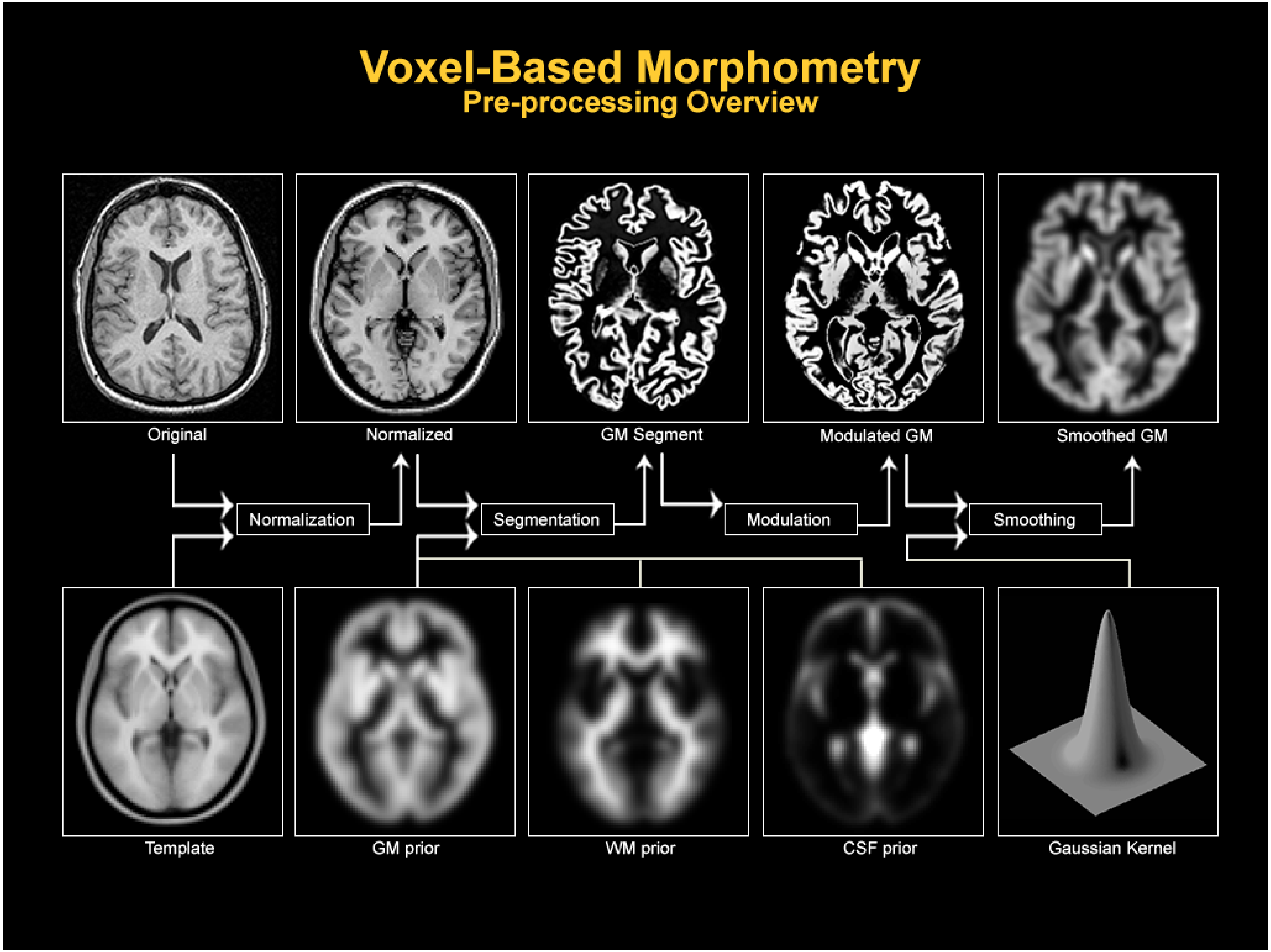
Introduction

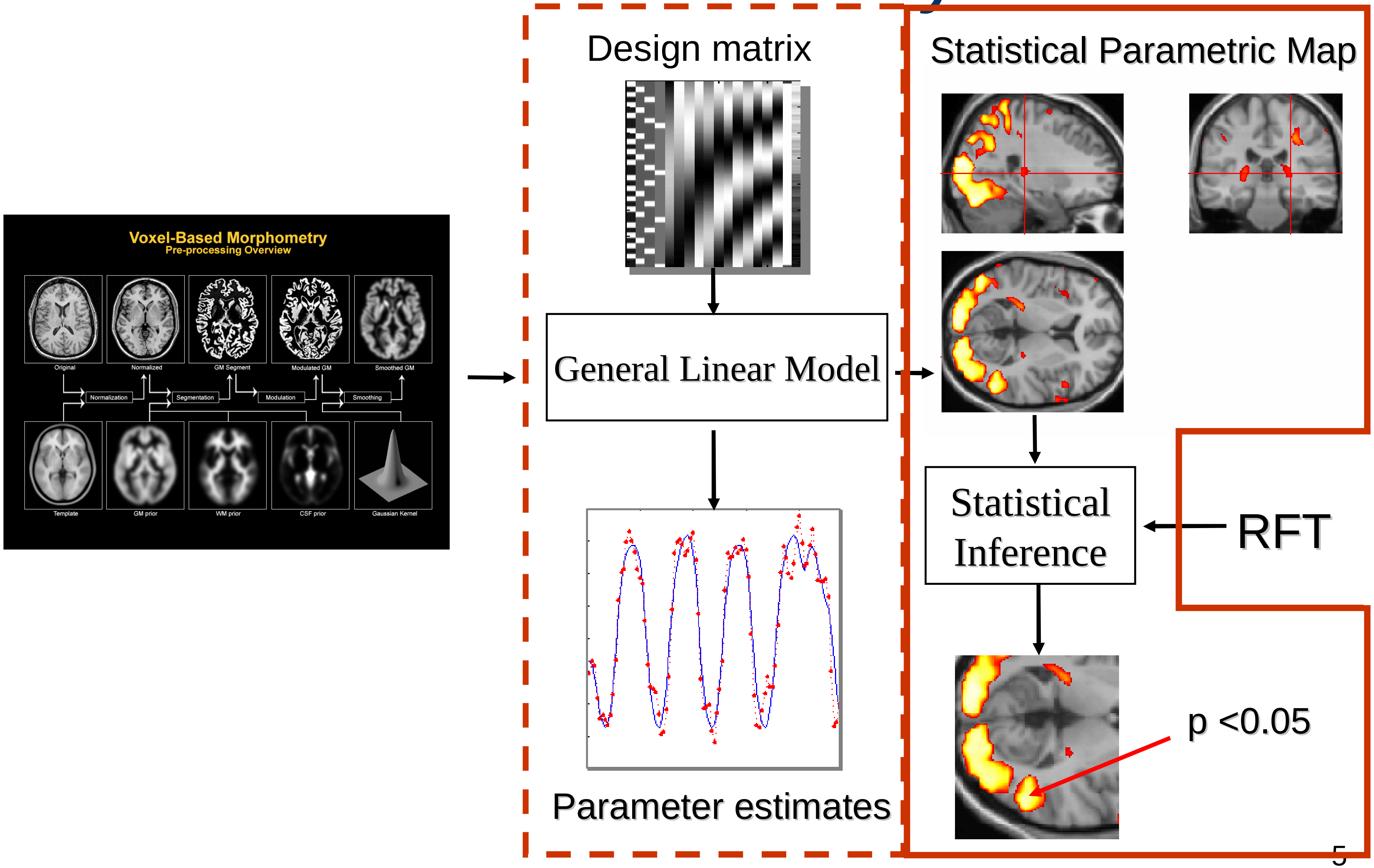
- Voxel-Based Morphometry (VBM)
  - Measures differences in local concentrations of brain tissue through a voxel-wise comparison of multiple brain images.
  - Procedure:
    - Images spatial normalization
    - Segmentation
    - Smoothing
    - Voxel-wise statistical tests





Voxel-Based Morphometry
Pre-processing Overview
Original
Normalized
GM Segment
Modulated GM
Smoothed GM
Normalization
Segmentation
Modulation
Smoothing
Template
GM prior
WM prior
CSF prior
Gaussian Kernel

Statistical Analysis



Voxel-wise statistical tests

General Linear Model

$$x = Ea + w$$

SPM FSL ICA, LICA

x	is *d*-dimension pattern vector corresponding to the MRI voxel values across the subjects.
E	is *d*x*M* matrix whose columns are the *d*-dimensional vectors.
a	is *M*-dimension vector of linear mixing coefficients.
w	is d-dimension additive observation noise vector.

Voxel-wise statistical tests

$$x = Ea + w$$

SPM	FSL	ICA, LICA
• Parametric test (t-test, f-test) • Data normally distributed • Random field theory (RFT)	• Nonparametric test (permutation test) • Unknown null distribution • Threshold test	• Unsupervised approach (non parametrical test based on Empirical distribution) • ICA: Source non Gaussian • LICA: No probabilistic assumption • Unknown linear mixing process

Lattice Independent Component Analysis

- Lattice Independent Component Analysis (LICA) Two steps:
  1. Selection of Strong Lattice Independent (SLI) vectors from input dataset using an Endmember Induction Algorithm (EIA).
  2. Perform the linear unmixing of the input dataset based on the endmembers.
     - The endmembers are equivalent to the GLM design matrix columns.
     - Unmixing process is identical to the least square estimator.

Lattice Independent Component Analysis

Linear mixing model:

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

x is *d*-dimension pattern vector corresponding to the MRI voxel time series vector.

E is *d*x*M* matrix whose columns are the *d*-dimensional vectors.

a is *M*-dimension vector of linear mixing coefficients.

w s d-dimension additive observation noise vector.

Theoretical constraints

- non-negative $a_i \geq 0, i = 1,\dots,M$
- and normalized to unity summation $\sum_{i=1}^{M} a_i = 1$

Lattice Independent Component Analysis

- It is expected that:
  - Vectors in E are affinely independent
  - Convex region defined by E includes all the data points.
- Unmixing
  - Least Squared Error (LSE) Estimation.

$$\tilde{a} = (E^T E)^{-1} E^T x$$

  - Even when vectors in E are affinely independent, obtained coefficients do not necessarily fulfill both restriction.

Lattice Independent Component Analysis

- Induce from the given data a set of Strongly Lattice Independent vectors, taken as a set of affine independent vectors.
- Apply the unrestricted LSE to obtain the mixing matrix.

Lattice Independent Component Analysis

- Advantages:
  - No imposition of statistical assumptions.
  - One pass algorithm and very fast.
  - Unsupervised and incremental.
  - Natural detection of endmembers numbers.

A VBM case study

- Experimental data:

Ninety eight right-handed women (aged 65-96 yr) were selected from the Open Access Series of Imaging Studies (OASIS) database (http://www.oasis-brains.org).

	Very mild to mild AD	Normal
No. of subjects	49	49
Age	78.08 (66-96)	77.77 (65-94)
Education	2.63 (1-5)	2.87 (1-5)
Socioeconomic Status	2.94 (1-5)	2.88 (1-5)
CDR (0.5 / 1 / 2)	31 / 17 / 1	0
MMSE	24 (15-30)	28.96 (26-30)

Image parameters: TR= 9.7 msec., TE= 4.0 msec., Flip angle= 10, TI= 20 msec., TD= 200 msec., 128 sagittal 1.25 mm slices without gaps and pixels resolution of 256 × 256 (1 × 1mm)

A VBM case study

- Algorithms applied:
  - SPM and FSL approach (Figure 1).
  - Preprocesed volumes are used as inputs for ICA and LICA algorithms.
    - Significative voxel detection given by threshold on mixing/abundance coeff = 95% of the histogram.
    - Figure 2 shows the activation results corresponding to the 3d endmember detected by LICA.

A VBM case study

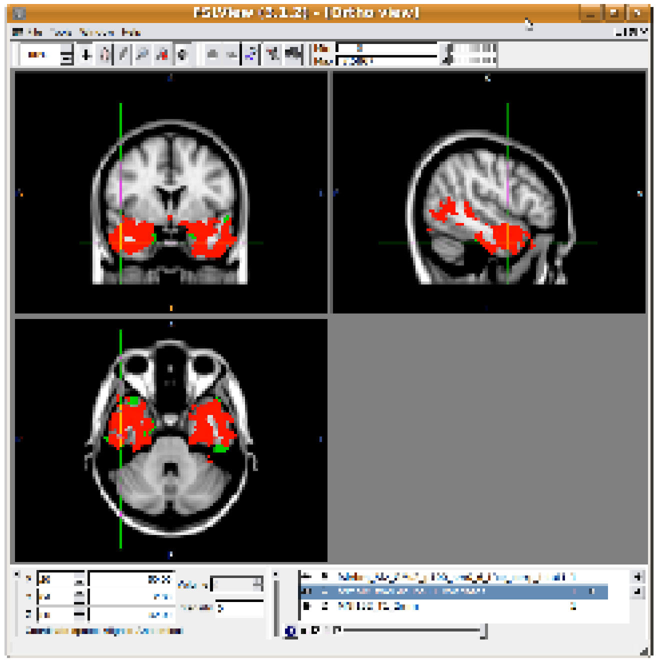


Figure 1. FSL significative voxel detection

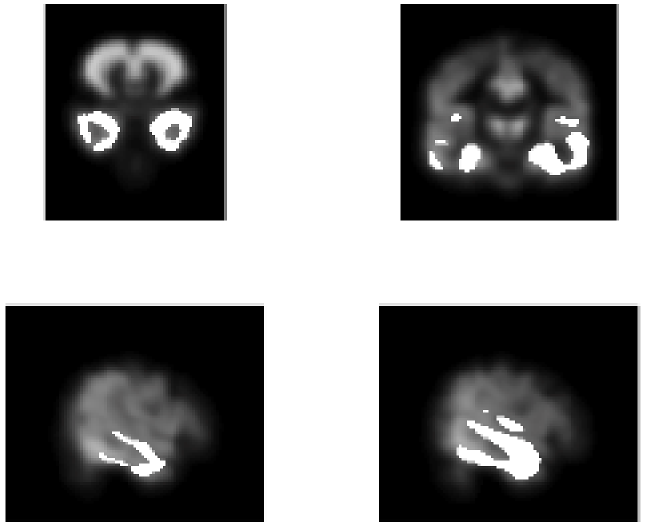


Figure 2. LICA activation results for endmember #3

A VBM case study

Table1. Correlation among ICA and LICA mixing coefficients, before (left) and after (right) thresholding for activation detection.

	ICA ML					ICA ML			
LICA	#1	#2	#3	#4	LICA	#1	#2	#3	#4
#1	0.05	0.24	0.44	-0.01	#1	0.003	0.09	0.34	0.03
#2	0.19	[illegible]	-0.28	-0.60	#2	0.15	[illegible]	-0.02	-0.02
#3	[illegible]	0.67	0.30	0.24	#3	0.01	0.66	0.007	0.08
#4	0.69	0.04	0.26	-0.18	#4	0.26	-0.01	0.13	-0.00

Best relation is between the third LICA endmember and the second ICA source, because their correlation does not drop after thresholding, contrary to LICA#4 with ICA#1 whose correlation drops dramatically after thresholding for significance detection.

A VBM case study

Table2. Agreement between SPM, FSL, ICA and LICA.

	#1	#2	#3	#4
ICA vs SPM	-0.11	**0.32**	-0.02	0.02
LICA vs SPM	-0.03	-0.03	**0.23**	-0.06
ICA vs FSL	0.08	**0.56**	0.03	0.07
LICA vs FSL	0.07	0.02	**0.58**	0.20

The agreement between the third endmember of LICA and the second source of ICA ML obtains a further support, because both are the ones that show maximal agreement with SPM and FSL, and in both ICA and LICA the agreement with FSL is greater than with SPM results.

Summary and Conclusions

- We have proposed and applied LICA to the model-free (unsupervised) VBM analysis.
- LICA is based on the EIA algorithm for the endmembers selection and the linear unmixing of the data based on these endmembers.
- We find:
    - Strong agreement between LICA and ICA results.
    - Results compared with SPM and FSL algorithms and also with ICA unsupervised approach, and we identify endmembers and sources that correspond closely to the significative detection of results in SPM and FSL, providing a validation of the approach.

Thank You for Your Attention!