A Statistical approach to the alignment of fMRI data

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Introduction

Multi-subjects fMRI studies permit to **compare** studies across subjects, to generalize and to validate the results.

The anatomical and functional structure of brains vary across subjects even in response to identical sensory inputs.

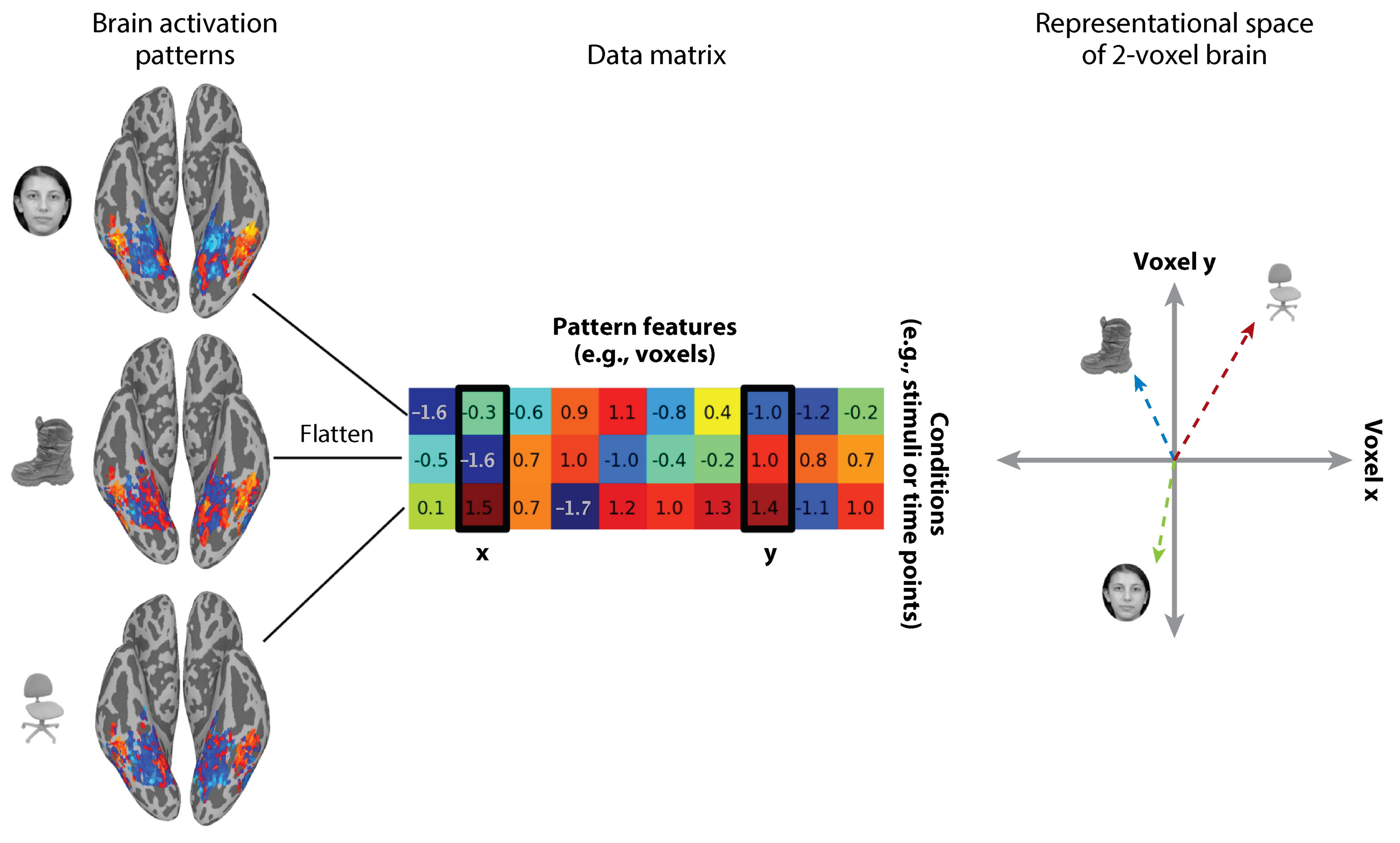
ALIGNMENT STEP

Talairach and Tournoux (1988) proposed **Anatomical Alignment**: the images are aligned to a template by an **affine transformation**.

It doesn't align the functional characteristics

Haxby et al.(2011) proposed **Hyperalignment**: functional alignment using sequential **Procrustes transformations** of the images.

Data



Procrustes problem in fMRI data

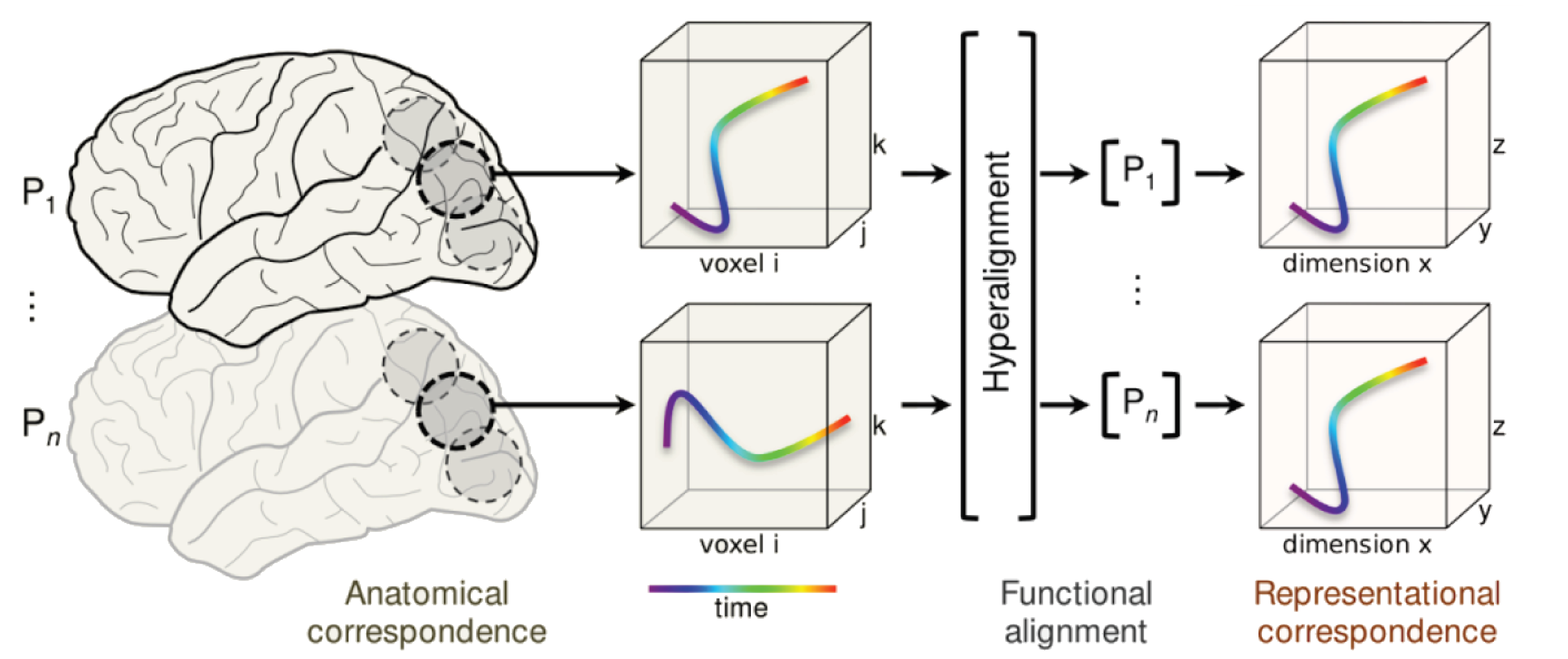
Let $X_i \in \mathbb{R}^{n \times v}$, where $i = 1, \dots, N$ represents the subject:

- the n **rows** represent the **response stimuli activation** of v voxels → the stimuli are time synchronized;
- the **columns** represent the **time series of activation** for each v voxel → not assumed to be in correspondence across subjects.

The **Orthogonal Procrustes problem** is expressed as:

$$\min_R ||X_i - X_j R||_F^2 \quad \text{subject to} \quad R^T R = I_v$$

Hyperalignment



Statistical model

Hyperalignment is a sequential approach of the Procrustes solution → No statistical approach and optimization criteria.

The main idea is to rephrase the Procrustes problem in terms of a **statistical model**:

$$X_i = M R_i^\top + \varepsilon \quad \text{subject to} \quad R_i R_i^\top = R_i^\top R_i = I_v.$$

- ε is the **error term** having a **Multivariate Normal Matrix** distribution $n \times v$, each row having $\sim N(0, \Sigma)$.
- M is the **mean** matrix with dimension $n \times v$.

The maximum likelihood estimate for R_i equals to the Procrustes solution founded by Schonemann (1966)→ let the Singular Value Decomposition (SVD) of $X_i^\top M = UDV^\top$, $\hat{R}_i = UV^\top$.

Prior distribution

Analyze the most plausible rotation → **Prior information** into R_i.

IDEA: closer voxels have similar rotation loadings

The Matrix Fisher-Von Mises distribution was introduced by Down(1972):

$$f(R_i) \sim C \exp(k_0 \, tr(Q^\top R_i))$$

where C normalizing constant, k_0 **concentration** parameter and Q matrix **location** parameter $v \times v$.

The matrix Q can be expressed as a **similarity matrix** considering the euclidean distance of the 3d **coordinates** of the voxels.

We modify the Procrustes solution in the **SVD** step → we decompose $X_i^\top M + k \cdot Q$ instead of $X_i^\top M$.

Experiments

We align the images of the Ventral Temporal Cortex of 10 subjects watching static, gray-scale images of faces and objects. The **Linear Support Vector Machine** is used as classifier.

	Anatomical	GPA with prior
Accuracy	0.31	0.67

Error of classification reduction: **10%** respect to the Hyperalignment method; **17%** respect to the classical GP solution.

Conclusions

- It doesn't depend on the **order of the subjects** as Hyperalignment;
- It returns a **unique solution** of the rotation matrix having **anatomical information** → rotation matrices are more understandable;
- It reaches the **global minimum** imposed by GP;
- It improves the **between-subjects classification** (fine-grained patterns).

References

[1] Down, T. D. *et al.* (1972)Orientation statistics. Biometrika, 59(3): 665-676;

[2] Haxby, V. J. *et al.* (2011) A common model of representational spaces in human cortex. Neuron, 72(2): 404-416;

[3] Schonemann, P. H. (1966). A generalized solution of the orthogonal Procrustes problem. Psychometrika, 31(1):1-10.