MODELLING MORPHOLOGICAL VARIABILITY OF THE HIPPOCAMPUS USING MANIFOLD LEARNING AND LARGE DEFORMATIONS

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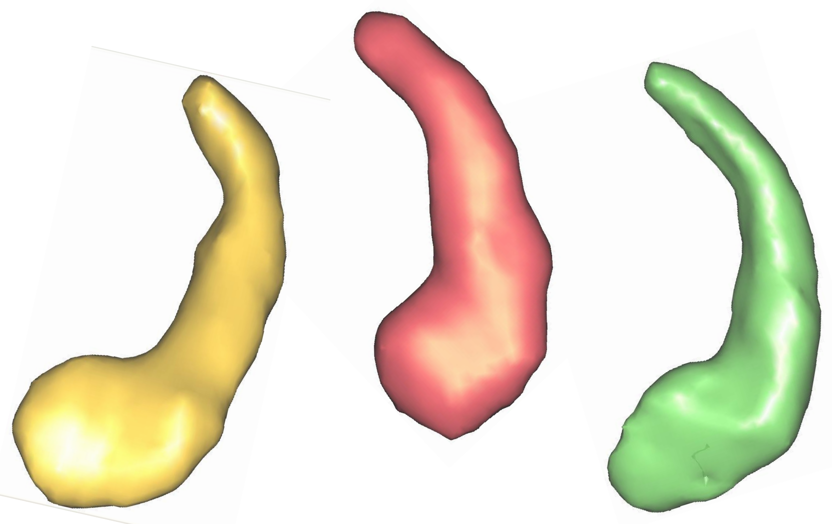
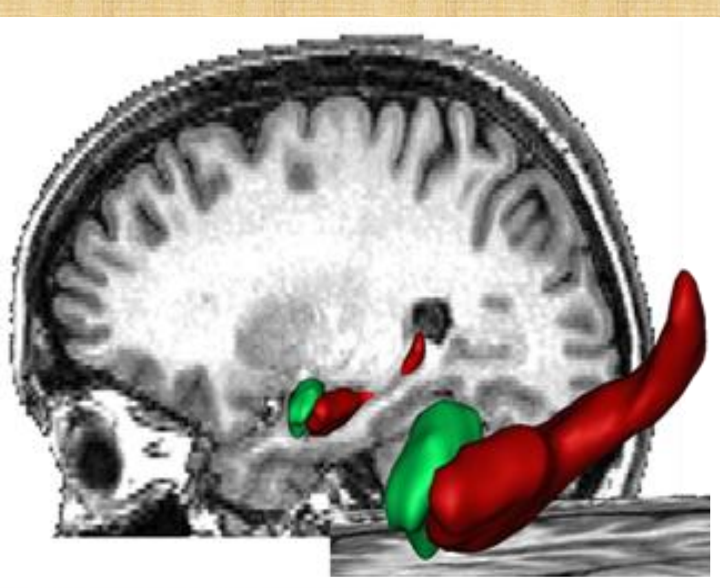
BACKGROUND



Modeling the Anatomical variability of hippocampus is important for many applications: to study its genetic bases, to identify vulnerabilities to pathologies or to study its impact on cognition

Here, we propose an approaches which combines:
- The large deformation diffeomorphic framework to quantify the distance between two hippocampi.
- the Isomap method to reduce the dimension of the space
- template estimation in the framework of currents to represent surfaces



METHODOLOGY

THE DIFFERENCE BETWEEN TWO HIPPOCAMPI IS QUANTIFIED BY THE DIFFEOMORPHIC DEFORMATION DISTANCE OF ONE HIPPOCAMPUS ONTO THE OTHER, USING LDDMM [5].

Large Deformation Diffeomorphic Metric Mapping (LDDMM): composition of an infinite number of infinitely small deformations, which results in very regular diffeomorphic maps.

Deformation maps $\phi : \mathbb{R}^d \to \mathbb{R}^d$ are defined as flows of velocity fields v(t) parametrized by a finite number of momentum vectors $\alpha_i(t)$ located at control points

Velocity vector field

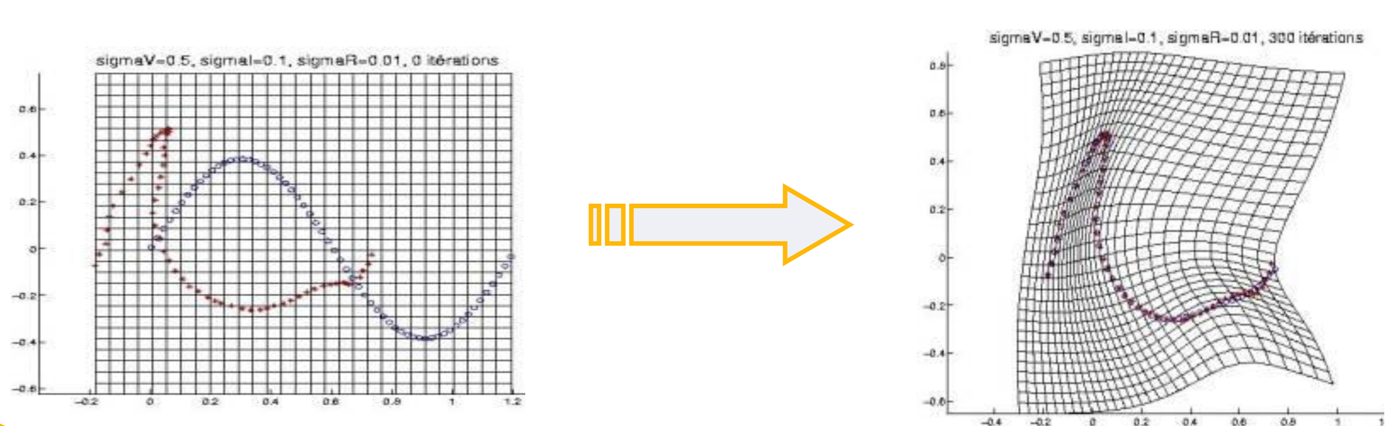
$$\frac{d\phi(t,x)}{dt} = v(t,\phi(t,x)), t \in [0,1] \quad \text{where} \quad v(t,x) = \sum K_V(x_i(t),x)\alpha_i(t)$$

Momentum vectors

DIFFEOMORPHIC DEFORMATION DISTANCE

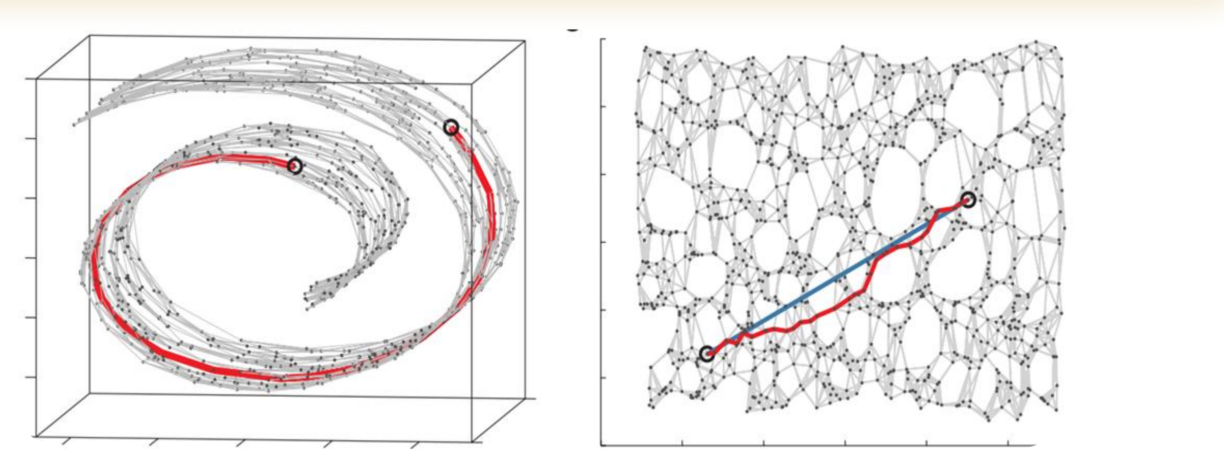
$v(t,.) \in V$ Hilbert space of regular vectors fields, and must be a RKHS with kernel K_V. The energy of deformation is defined by

$$d(id,\phi)^2 = \inf_{v,\phi_1^v=\phi} \int_0^1 |v_t|_V^2 \, dt$$



HYPOTHESIS: THE HIPPOCAMPI SHAPES LIVE ON A NON-FLAT MANIFOLD:
➔ DATA REPRESENTATION IN A EUCLIDEAN SPACE
➔ MANIFOLD LEARNING METHODS

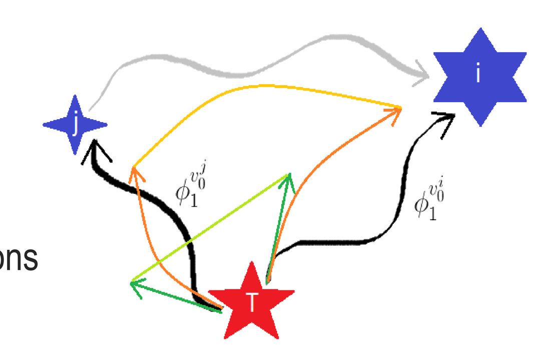
ISOMAP [4]



Problem: computational complexity
Need to compute distances between all pairs of shapes ➔ computationally expensive (needs **O(N^2)** registrations where N is the number of shapes)

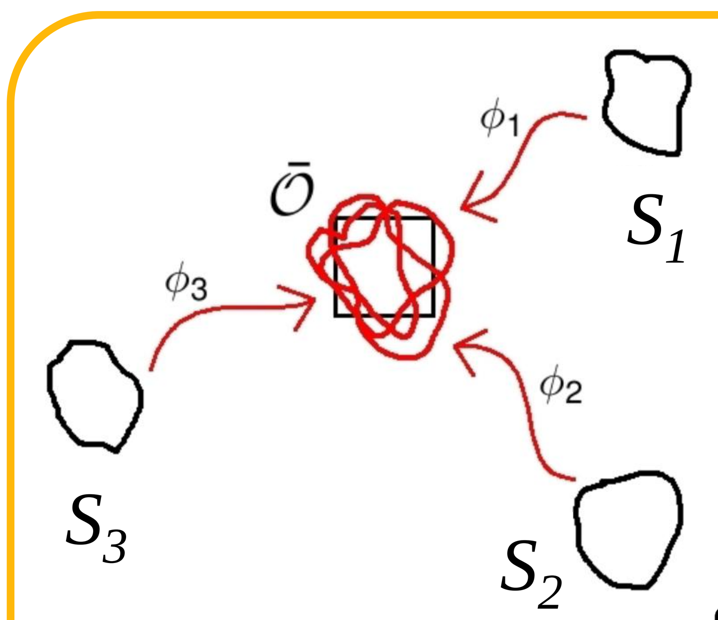
Solutions
1) Distance approximation (Yang and al. [7]) to the first order.
The distance approximation requires to compute a template and registrations of it to every shape, which requires only O(N) registrations

2) Use GPU implementation



Registrations of hippocampi	CPU computation	GPU computation
1 registration	4200 seconds	45 seconds
50 registrations (N = 10)	3500 minutes (58h20)	37 minutes 30s
5000 registrations (N = 100)	5833.3 hours (8 months)	62.5 hours

TEMPLATE ESTIMATION FROM UNLABELED DATA [2], WITH CURRENTS [6]

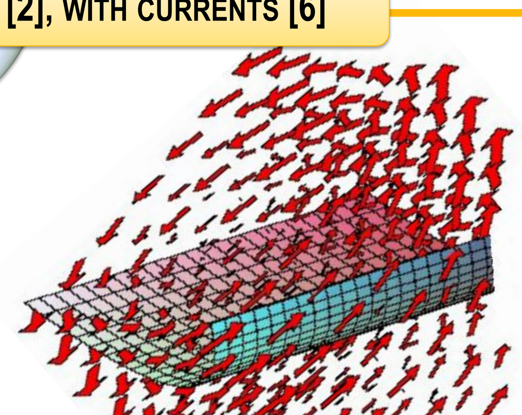


- What is the common shape of a population?
- How to estimate it?

• Build an « average » template of the curves or surfaces of the population by registering the shapes all together
• Find the N deformations that minimize the following functional :

$$\{\hat{\phi}_i\} = \underset{\phi_i}{argmin} \sum_{i=1}^{N} \left\{ \left\| \left(\frac{1}{N} \sum_{j=1}^{N} \phi_j[S_j] \right) - \phi_i[S_i] \right\|_{W^*}^2 + \gamma d^2(Id,\phi_i) \right\}$$

With W* the space of currents (Glaunès, 2005 [6]).



S. Durrleman, Phd thesis, 2010

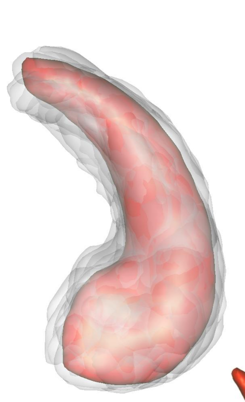
An oriented surface S can be characterized by the collection of flux integrals of all possible vector fields ω over it.

$$[S](\omega) = \int_S \omega(x)^t n(x) d\lambda(x)$$

$[S](\omega)$ is a current associated to S. It is a linear functional. When the space of vector fields W is a Reproducing Kernel Hilbert Space (the set of convolutions between any square integrable vector fields and a smoothing kernel), the corresponding space of currents is its dual space W*.

RESULTS & DISCUSSION

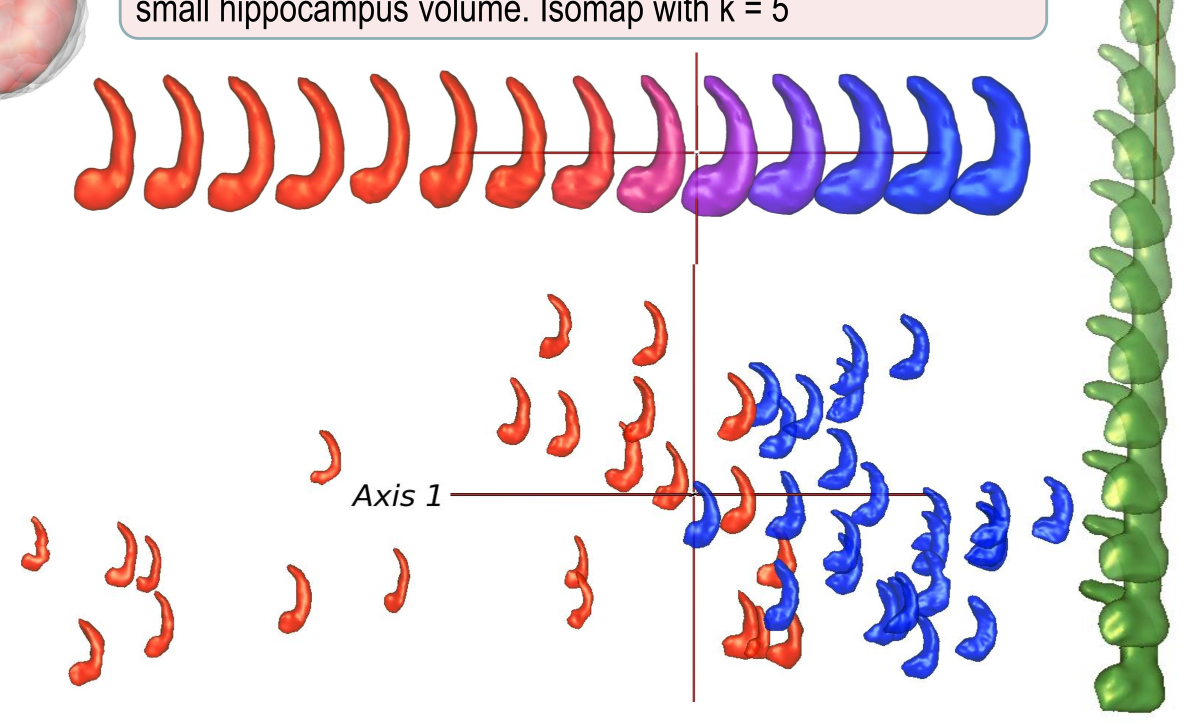
Pre-processing: Segmentation of hippocampi with the SACHA software (M. Chupin, Cogimage [1]). Then computing the mesh with the BrainVISA software.



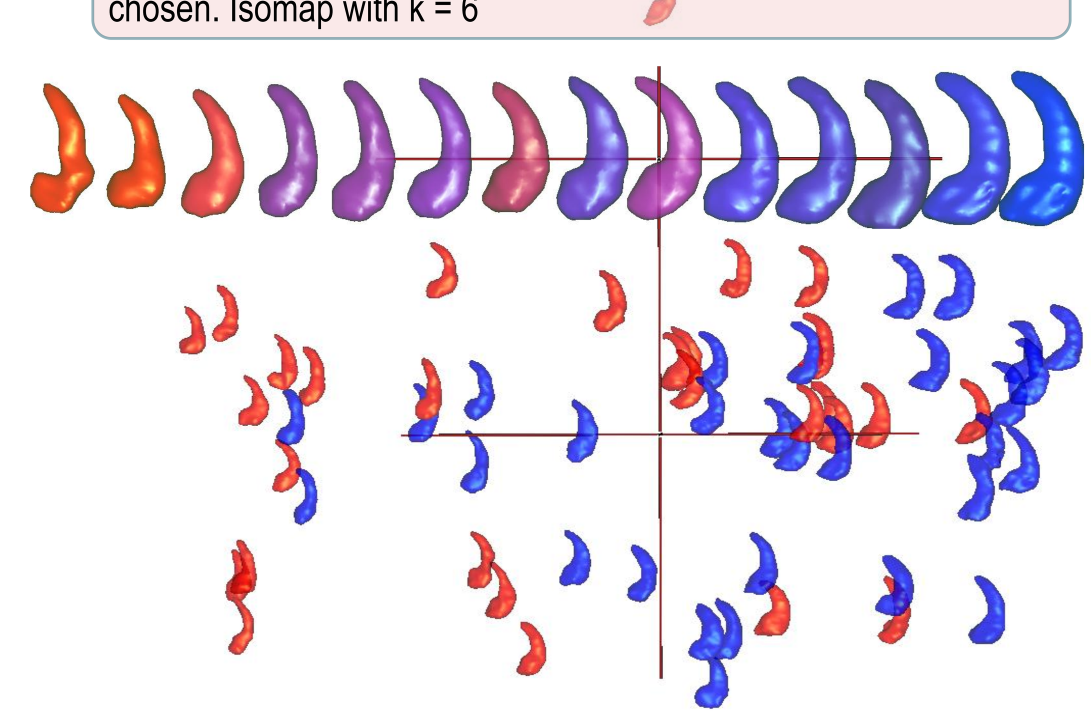
Computation of the hippocampus template of the population, after a first affine registration (cancels out volume differences)

WE TEST THE METHODOLOGY WITH DATA FROM THE ALZHEIMER'S DISEASE NEUROIMAGING INITIATIVE (ADNI) DATABASE (adni.loni.ucla.edu).

Experiment 1: 25 control subjects and 25 AD subjects with small hippocampus volume. Isomap with k = 5



Experiment 2: 30 control subjects and 30 AD subjects randomly chosen. Isomap with k = 6



Discussion:

Variance captured by Isomap axis :	Exp. 1	Exp. 2
The first 2 axes	75,5%	64,2%
The first 3 axes	80,4%	70,8%
The first 10 axes	91,2%	85,4%

The coordinates along the first axis are significantly different between AD patients and controls (Student's t-test, p<0.001)

The method is able to capture morphological differences between AD patients and controls, that are independent of hippocampal volume (which has been corrected for by the affine registration step).

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