Statistical shape analysis of large datasets using diffeomorphic iterative centroids

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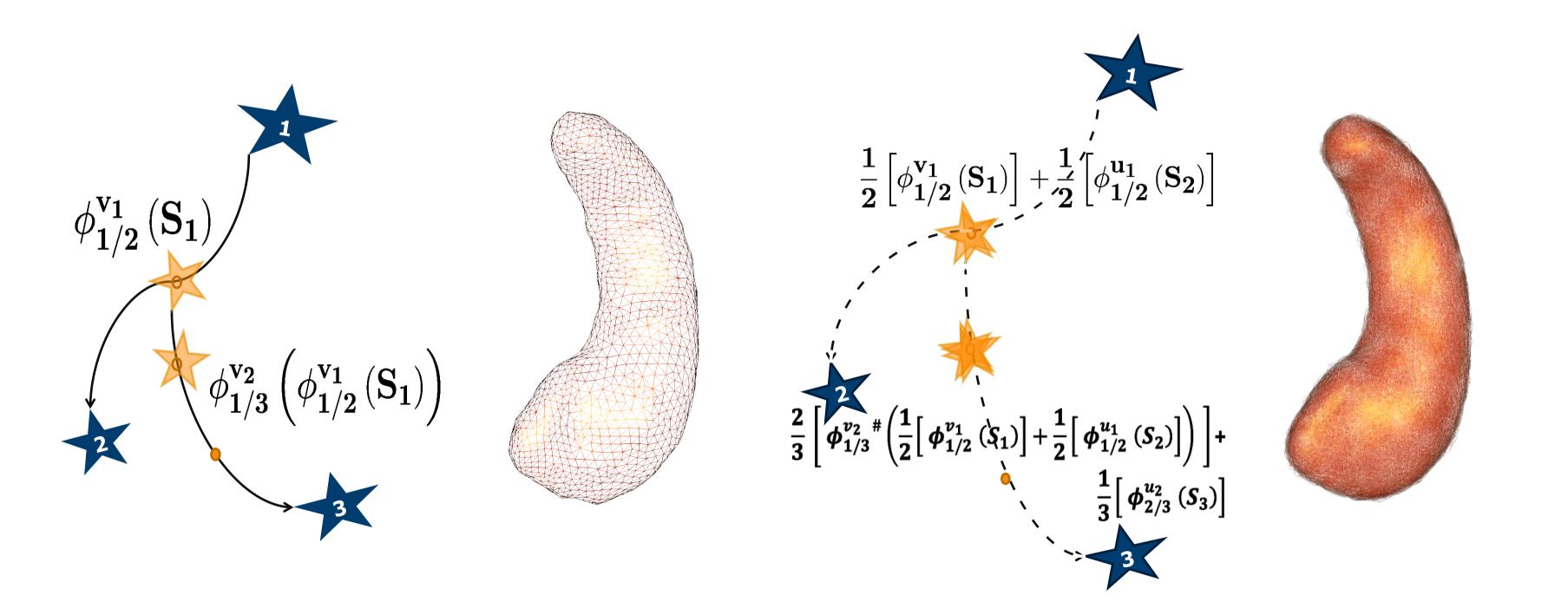
INTRODUCTION	Centroid computation
Statistical shape analysis methods are increasingly used in neuroscience. A challenge: performing statistical analysis on large databases. A	Matching centroid to subjects
common approach: analyzing the deformations that map individuals to a template of the population (Ashburner 1998; Vaillant 2004).	\checkmark

The Large Deformation Diffeomorphic Metric Mapping (LDDMM) framework provides a natural setting for quantifying deformations between anatomical shapes: the diffeomorphic deformations preserve the topology and provides a metric between shapes. We used **the framework of currents** to represent our surfaces, avoiding point to point correspondence issue and providing metric robust to different sampling and taking into account local orientation of the shapes (Vaillant 2005). Various methods have been proposed to estimate a template using the LDDMM framework (Durrleman 2008; Glaunès 2006), they are computationally expensive due to the complexity of the deformation model.

We propose an approach using a **diffeomorphic iterative centroid** using the LDDMM and the current frameworks (Cury 2014) as a template shape for a statistical shape analysis.



PCA on inital momentum vectors



METHODS

→ 3 datasets composed by hippocampal meshes: **SD50** is 50 synthetic meshes build around a hippocampal mesh (the exact centre); **RD50** 50 hippocampal meshes computed from the segmentation of T1 MRI of the IMAGEN database (Schumann 2010); **RD1000** by 1000 hippocampi from IMAGEN.

 \rightarrow **Diffeomorphic Iterative Centroid :** updating the centroid by transporting the actual centroid along the geodesic flow and stopped depending on the iteration number

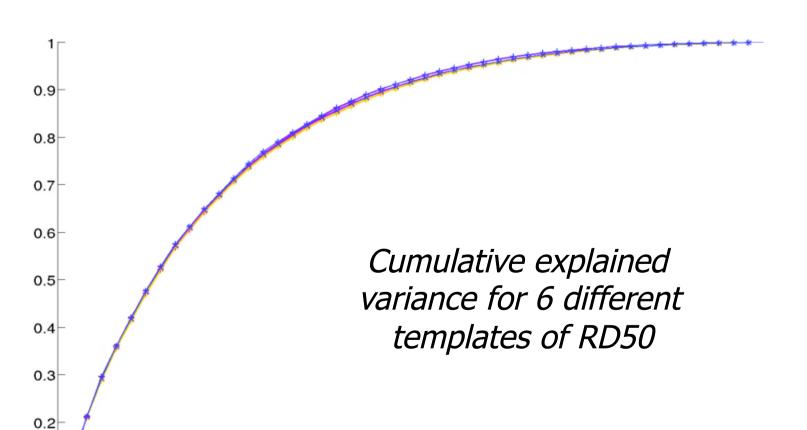
3 different algorithms **IC1**, **IC2 and PW**. We compared this approach to an to an estimated template computed (Glaunès et al. 2006).

RESULTS

\rightarrow Computation times (min)

		Centroid	T(centroid)	Total
RD50 SD50	IC1/PW	31	81	112
	IC2	85	87	172
	IC1/PW	75	188	263
	IC2	174	252	426

For RD1000: 832 min for IC1



\rightarrow Centering of the templates: Ratio R

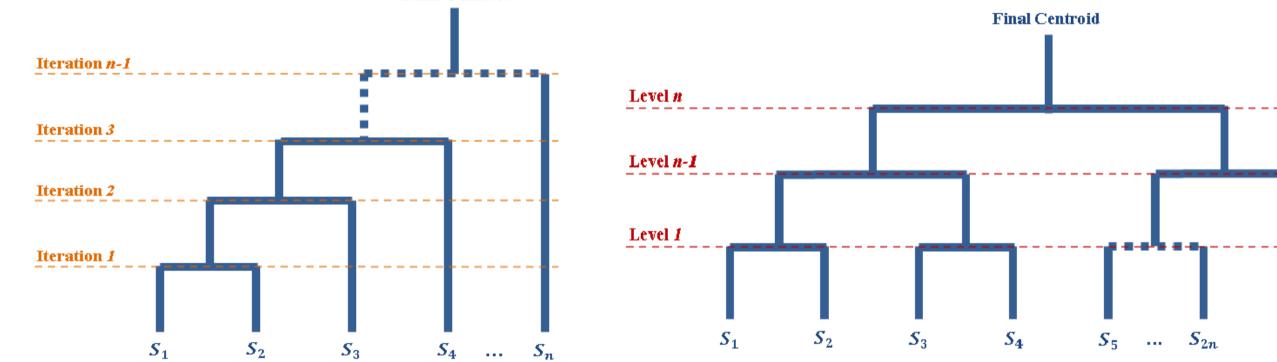
 $R = \frac{\|\frac{1}{N} \sum_{i=1}^{N} v^{i}(\cdot, 0)\|_{V}}{\frac{1}{N} \sum_{i=1}^{N} \|v^{i}(\cdot, 0)\|_{V}}$

			Centroid	T(centroid)
	RD50 SD50	IC1/PW	0.05	0.04
		IC2	0.03	0.04
		IC1/PW	0.30	0.21
RD	IC2	0.33	0.31	

For RD1000: R = 0.10

\rightarrow Results of the PCA

For SD dataset, PCA results from the different templates are very similar to the analysis make from the exact center. As for RD50 (see figure on left).



CONCLUSIONS

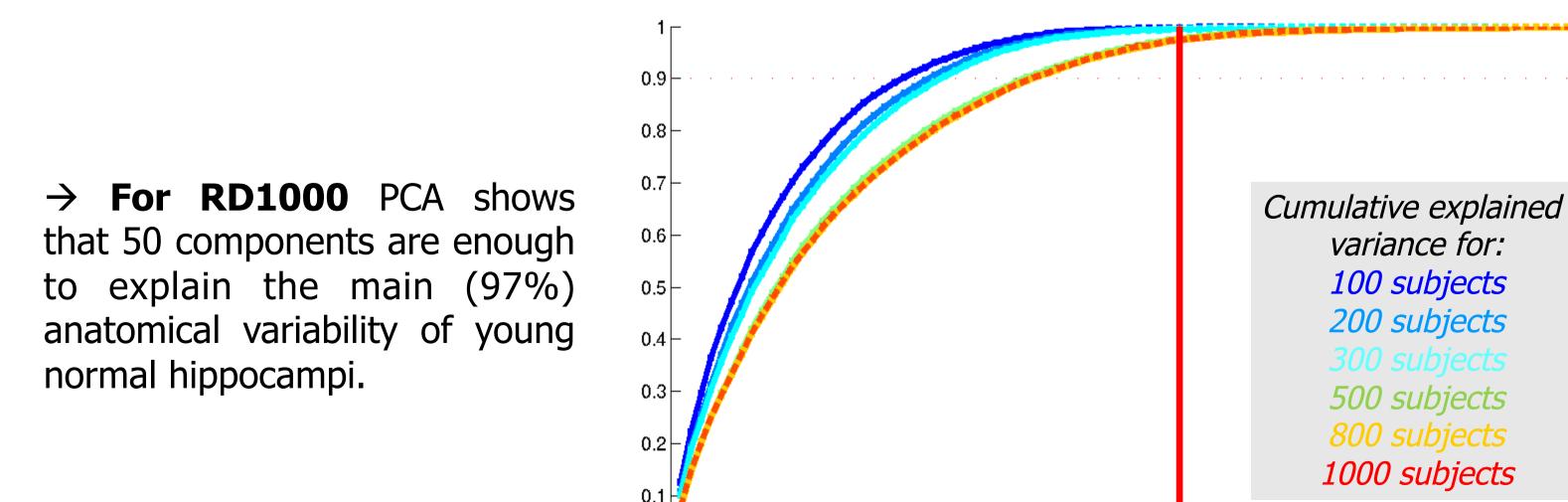
We proposed a fast approach for template-based shape analysis of large datasets. When applied to hippocampal shapes of young healthy subjects, the approach adequately captured the variability of the population with a reasonable number of dimensions.

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