Spatially Adaptive Log-Euclidean Polyaffine Registration based on Sparse Matches

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Take-home messages

- Log-euclidean polyaffine transforms (LEPT) are compact, diffeomorphic and can represent rich deformations.
- It is possible to automatically and robustly register two images, yielding a LEPT.
- Despite their compactness, LEPT can accurately capture inter-subject deformations.

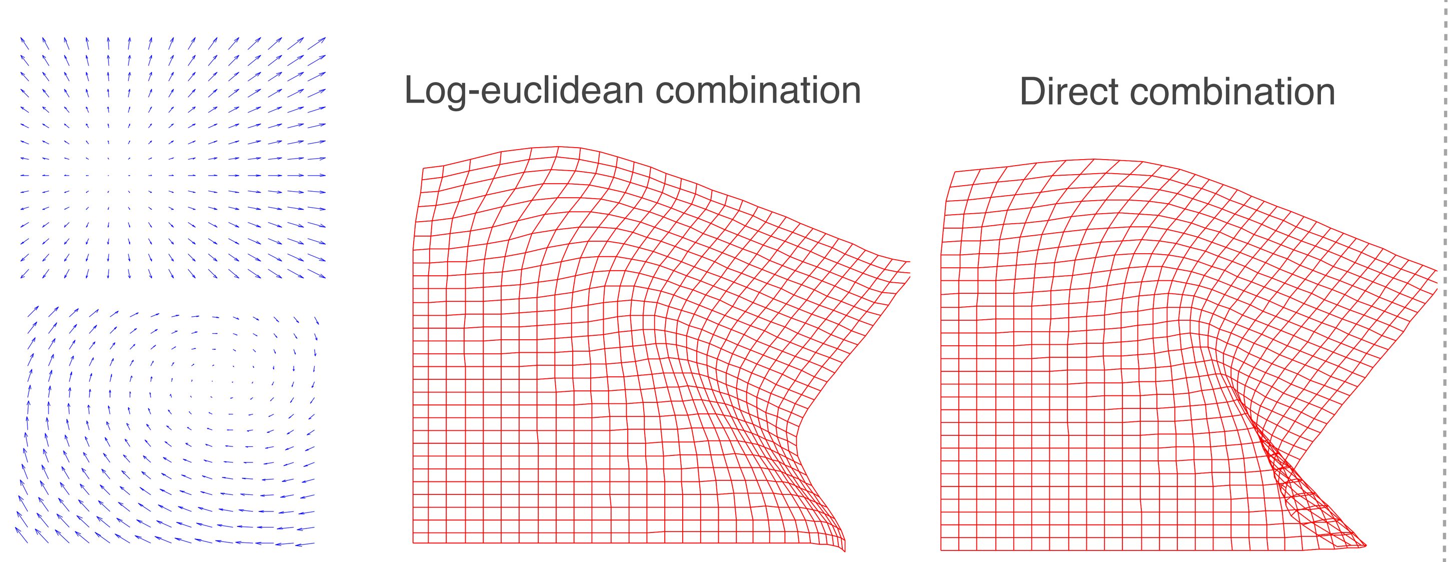
Want more?

Introduction

Log-euclidean polyaffine transforms (LEPT) have proved to be an efficient tool for image registration [1,2].
However, their use required the pre-segmentation of principal tissues and they were limited to few affine components.

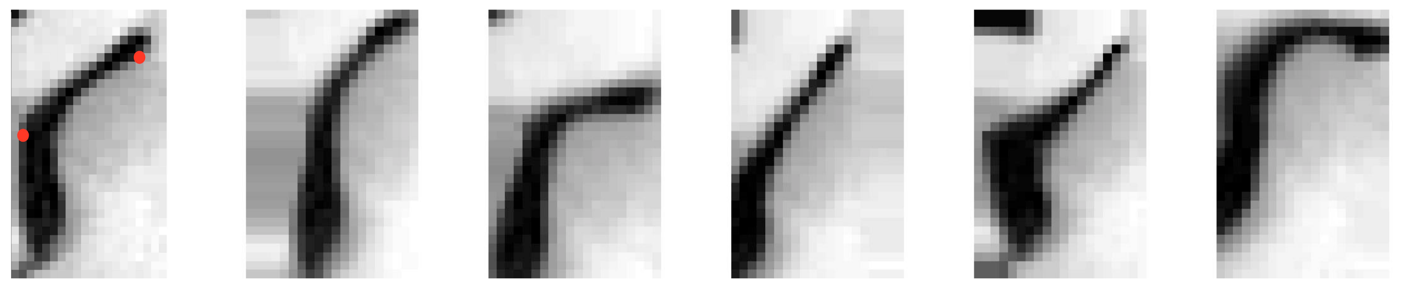
Methods

Log-Euclidean Polyaffine Transforms (LEPT)



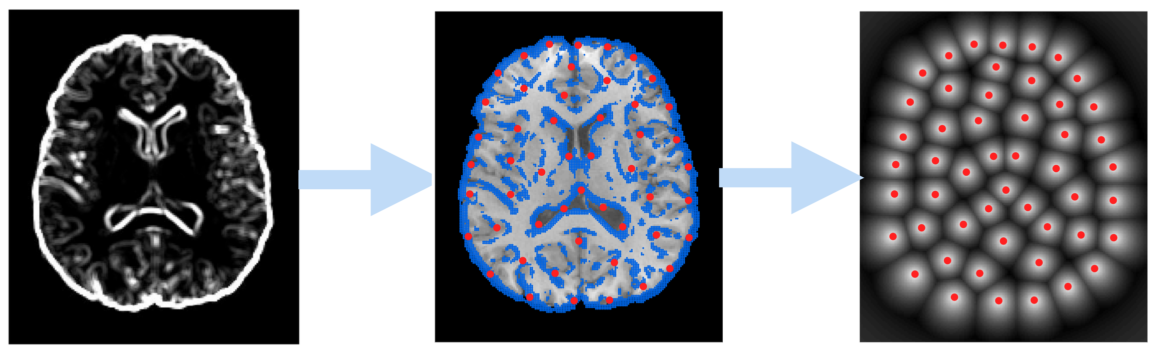
$$T(x) = \exp\left(\sum_{k=1}^{K} w_k(x) L_k \tilde{x}\right)$$

LEPT consists in a linear combination of K affine transforms applied in the log-domain at each location x with weights that depend on the distance between the location and the anchor of the affine component.



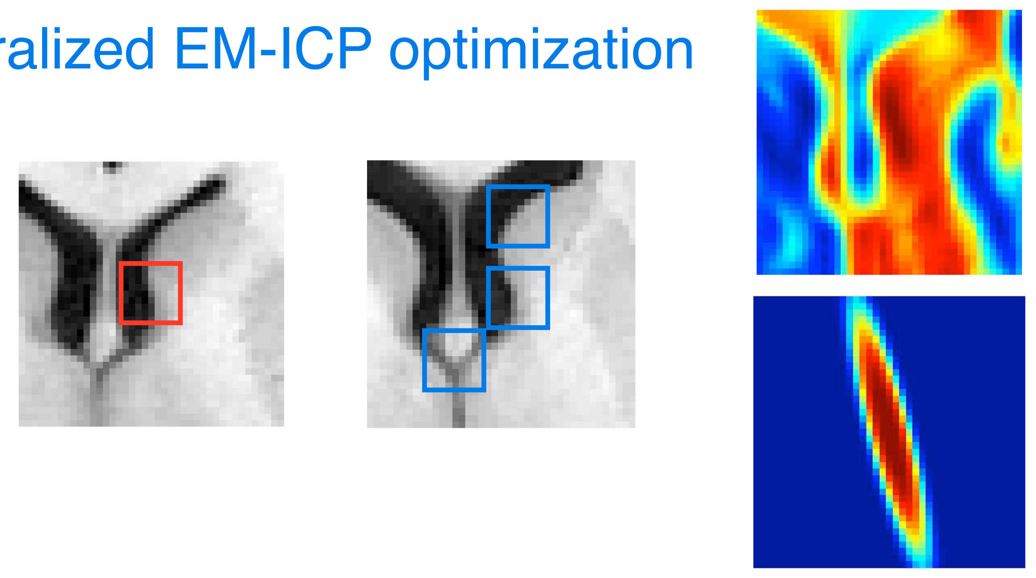
With a few parameters, LEPT can capture rich deformations. All these images were produced by transforming the image on the left by a LEPT with two components centered at the anchors depicted by red dots.

Anchors and weights



1) A measure of the local contrast is computed.
2) All points with local contrast over a local threshold are recorded (.)
3) The anchors are computed as the k-means centroids (.).
4) Weights are computed by the Kriging estimator (linear system)

Generalized EM-ICP optimization



$p(\square \text{ matches } \square)$
Similarity between block contents
Normalized correlation coefficient

$\square|\square, T \sim \mathcal{N}(T(\square), \mathcal{S})$
Similarity between block locations
Multivariate gaussian parameterized by the structure tensor ($\mathcal{S}$)
Accounts for matching ambiguities along edges and surfaces.

Sparse Block Matching: the best N corresponding pairs of blocks are selected.

Parameters of the affine transforms jointly optimized in an EM-ICP fashion

- **E-step**: maximize for the correspondences (C) with fixed transform (T)

$$C_{\square,\square} \sim p(\square \text{ matches } \square)\, p(\square|\square, T)$$

- **M-step**: maximize for the transform (T) with fixed correspondences (C)

$$T^* = \arg\max_T \underbrace{E\{\log P(C|T)\}}_{\text{Correspondences}} + \underbrace{E\{\log P(T)\}}_{\text{Prior}}$$

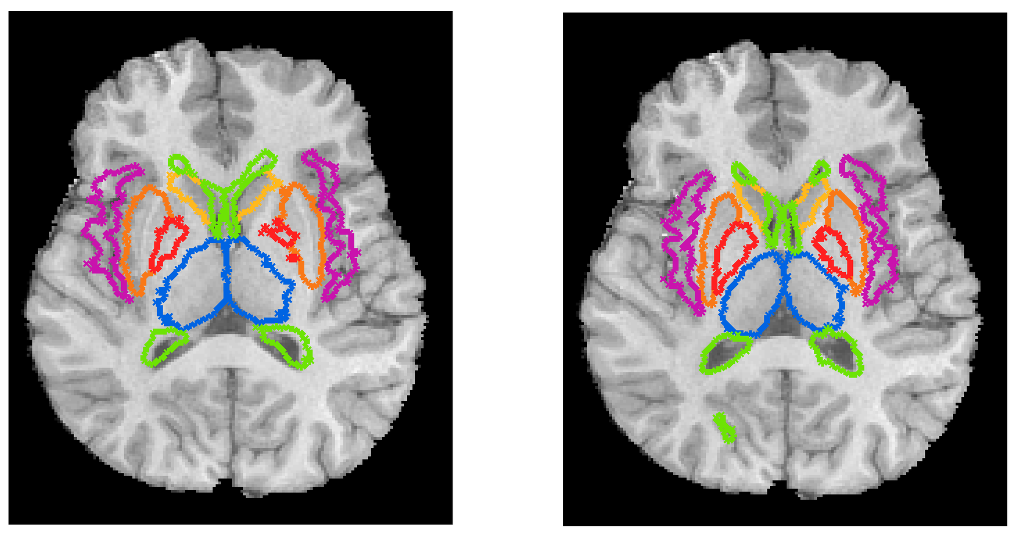
➡ After first order approximation, sum up to solving a linear system

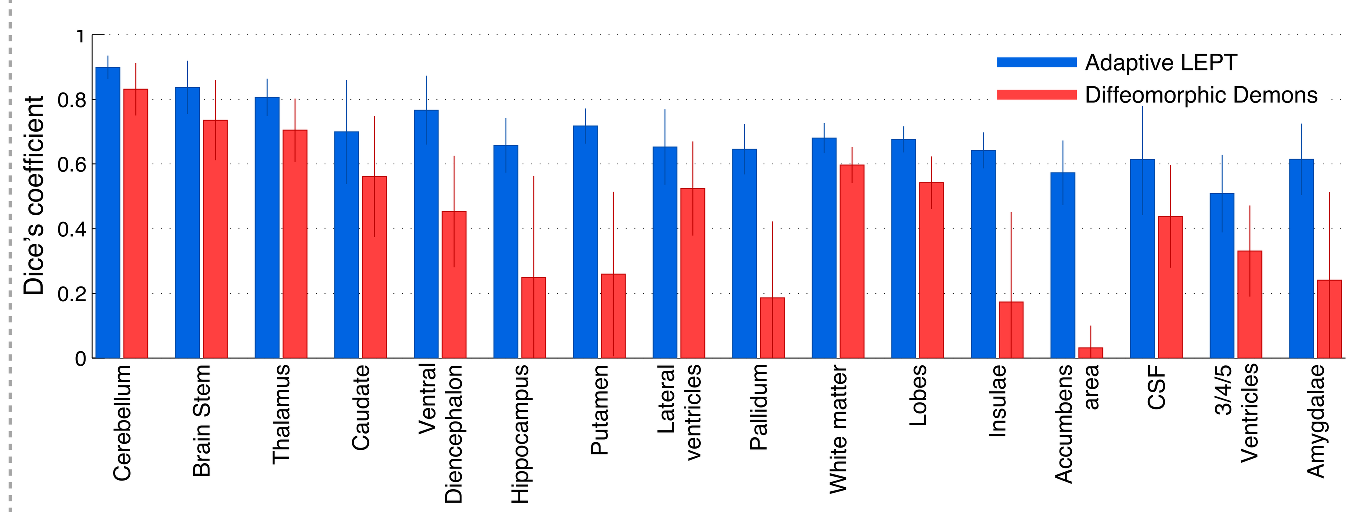
Experiments

Set-up

- 11 T1-weighted brain MRI
- 10 multiple-sclerosis patients
- 1 healthy control
- 256x256x176 voxels
- 500 affine components
- Inter-subject registration of the patients on the control.

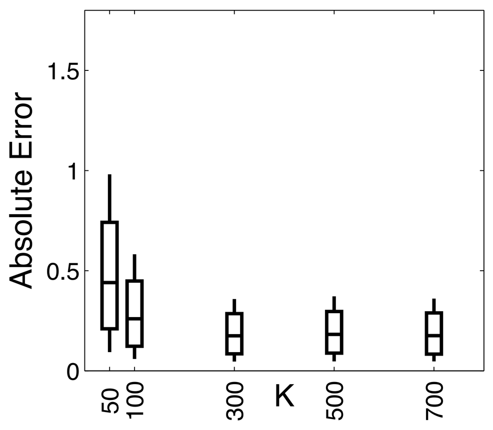
Results



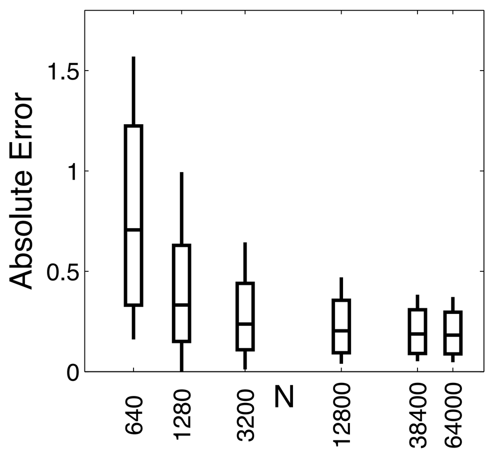


The method accurately align the tissues.
The accuracy is independent of the tissue contrast.

Influence of the parameters



The accuracy decreases with the number of affine components due to the lack of flexibility incurred.



The accuracy decreases with the number of sparse matches due to the lack of robustness of the transform estimate.

References
(1) Arsigny et al., A Fast and Log-Euclidean Polyaffine Framework for Locally Linear Registration. JMIV, 2009
(2) Commowick et al., An Efficient Locally Affine Framework for the Smooth Registration of Anatomical Structures. MedIA, 2008

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