Spline-Based Probabilistic Model for Anatomical Landmark Detection

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LANDMARKING IMAGES

Anatomical landmarks, i.e. well defined points in the anatomy, provide meaningful information on the local geometry. They are widely used to analyze shapes or as control points for many registration algorithms [1],[2].

However their detection, which remains manual, is a tedious and time-consuming task, even for specialists.

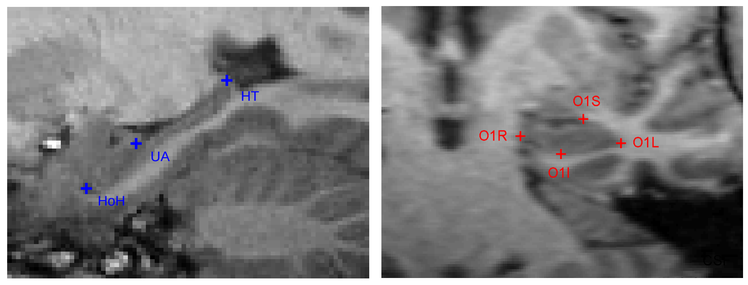


Fig.1 Examples of landmarks.

We propose a **generic** algorithm, for **1 or more** landmarks, based on a **probabilistic model** of the image intensities.

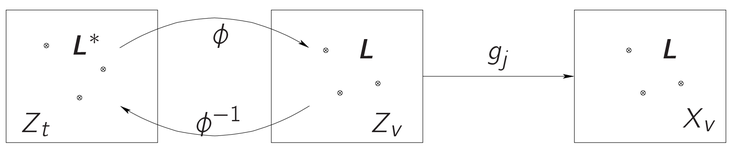
This requires to model the **photometry** and the **geometry**, and to choose a family of **small deformations**.

In this setting, estimating the position of the landmarks in a new image is simply finding, by **likelihood maximization**, the "best" deformation that matches the tissue map onto the image.

PROBABILISTIC MODEL

We use a probabilistic model of the intensities of the image voxels $v \in V$. Let:

- X_v be the image intensity at voxel v, Z_v the unobserved tissue type (CSF, GM, WM) at voxel v,
- $\boldsymbol{L}_i \in V^K$ be the location of the landmarks in the image i, and $\boldsymbol{L}^* = \frac{1}{N}\sum_{i=1}^{N} \boldsymbol{L}_i$ a fixed configuration of K landmarks.



Template $\boldsymbol{T}$ Segmented Image Image

ϕ is a small deformation of $\mathbb{R}^3$ such that $\phi(\boldsymbol{L}^*) = \boldsymbol{L}$.

Assuming conditional independence of the voxels, the conditional distribution of the intensities of an image is:

$$P(\boldsymbol{X}|\phi) = \prod_{v\in V}\sum_{j=1}^{6} \underbrace{P(X_v = x|Z_v = j)}_{\text{Photometry}} \underbrace{P(Z_v = j|\phi^{-1})}_{\text{Geometry}}.$$

Small deformations

We define ϕ a small deformation of $\mathbb{R}^3$ as the spline interpolation of the displacements at the landmarks.

$$\phi : \mathbb{R}^3 \to \mathbb{R}^3$$
$$t \to t + \sum_{k=1}^{K} \frac{\beta_k}{\sqrt{2\pi}^3 \sigma_k^3} \exp\left(-\frac{\|t - L_k^*\|^2}{2\sigma_k^2}\right),$$

where $\sigma_k \in \mathbb{R}$ is a smoothing parameter chosen such that ϕ is invertible and $\beta_k \in \mathbb{R}^3$ is the displacement parameter.

MODEL ESTIMATION

Given N training images and K landmarks, define $\boldsymbol{L}^* = \frac{1}{N}\sum_{i=1}^{N} \boldsymbol{L}_i$.

1) Learn the photometry of each image

Identify the tissues of the brain: CSF, GM, WM, CSF-GM, GM-WM and outliers (skull, blood vessels...). Each intensity x is modeled as a mixture of Gaussian distributions:

$$P(X_v = x) = \sum_{j=1}^{6} \alpha_j g_j(x), \text{ with } \begin{cases} g_j \sim \mathcal{N}(\mu_j, \sigma_j^2) \\ \sum_{j=1}^{6} \alpha_j = 1 \end{cases}$$

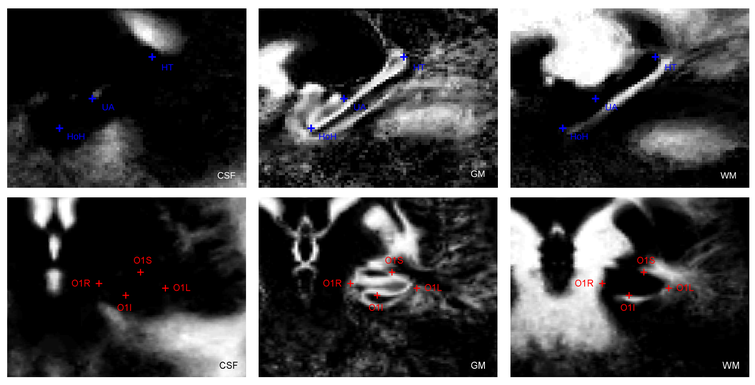
Learn the photometric parameters of each image, (μ_j, σ_j^2), using the EM-algorithm.

2) Register the images of the training set

Transform each image by ϕ_i^{-1} such that the landmarks lie in the same location, $\phi_i^{-1}(\boldsymbol{L}_i) = \boldsymbol{L}^*$.

3) Learn the tissue probability map

To each voxel t of the Tissue Probability Map, corresponds a vector of observed intensities from the registered training set. Estimate the proportions of each tissue type at each voxel, $P(Z_t = j)$, by a transversal EM-algorithm.



OPTIMIZATION

Given a new image I, the estimated location of the landmarks is given by likelihood maximization over β, the parameters of the transformation ϕ.

1) Learn the image photometry

As in the training step, use the EM algorithm.

2) Maximize the Likelihood

Use a gradient method to maximize the likelihood of I, starting from $\beta = 0$, i.e. $\phi = Id$.

- Project β onto a subspace using the first d ($d \ll 3K$) principal components (PCA).

$$\tilde{\beta} = D\beta, \text{ with } \tilde{\beta} \in \mathbb{R}^d, D \in \mathcal{M}_{d\times 3K}.$$

- The likelihood is approximated by:

$$\ln \mathcal{L}(\beta) \simeq \sum_{t\in T} \ln \sum_{j=1}^{6} g_j(\phi(x)) P(Z_t = j) |J_\phi(t)|$$

with $|J_\phi(t)|$ the absolute value of the deformation's Jacobian. The gradient of $\ln \mathcal{L}(\tilde{\beta})$ with respect to β can be computed explicitly to perform gradient ascent.

3) Locate the predicted landmarks

The predicted position of the landmarks is given by :

$$\hat{\boldsymbol{L}} = \hat{\phi}(\boldsymbol{L}^*)$$

Fig.2 Tissue Probability Map obtained from a training set of 38 images, registered with 15 landmark correspondences. The voxels in white have a high probability to belong to the corresponding tissue type. Top: sagittal view, Bottom: transversal view.

EXPERIMENTS

The algorithm is demonstrated on the simultaneous detection of 15 landmarks, located on the hippocampus (**Fig.1** and **3**) in T1-weighted MRI of resolution $1mm^3$. (38 images in the training set and 9 images in the testing set). The set of landmarks is composed of:

- The apex of the Head of the Hippocampus (HoH), the Tail (HT), the posterior Apex of the hippocampal uncus (UA),
- 3 sets of 4 landmarks located on slices orthogonal to the main axis HoH-HT.

Landmark	mean error (automatic)	mean error (initial)
all	2.75 (0.53)	3.45 (0.55)
HoH	3.32 (1.56)	3.10 (1.75)
HT	2.60 (0.94)	3.55 (1.92)
UA	2.32 (1.03)	2.73 (1.72)
O1*	2.90 (1.34)	3.21 (1.36)
O2*	2.53 (1.21)	3.26 (1.75)
O3*	2.84 (1.78)	4.11 (2.17)

Table 1 Euclidean distance (mm) between estimated and predicted landmarks.

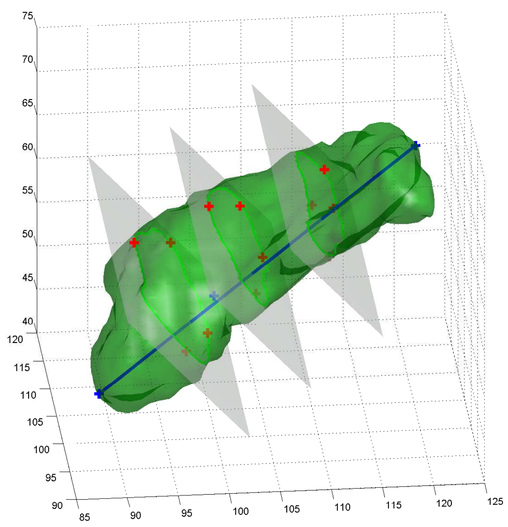


Fig.3 Location of the landmarks on the surface of the hippocampus. The blue crosses designate the three main landmarks while the red crosses correspond to the lateral ones.

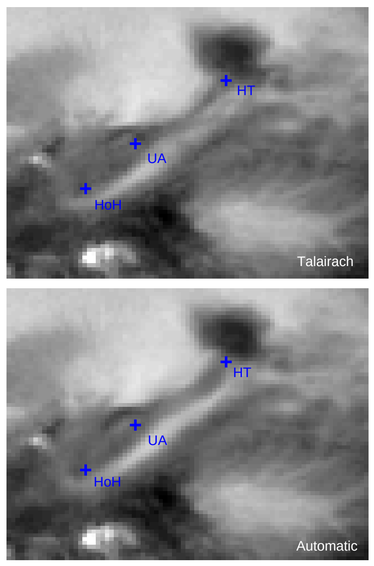


Fig.4 Average image, after registration of the testing set using the Talairach alignment (top left), the automatic landmarks (bottom left) and the manual landmarks (bottom right).

1. Bookstein, F.: Morphometric *Tools for Landmark Data: Geometry and Biology*, Cambridge University Press (1992).
2. Joshi, S., Miller, M.: "Landmark Matching via Large Deformation Diffeomorphisms", in *IEEE Trans. in Image Processing*, 2000, vol. 9,pp 1357-1370.

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