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To cite this version:

HAL Id: hal-01396716
https://hal.archives-ouvertes.fr/hal-01396716
Submitted on 14 Nov 2016

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Towards a unified bayesian geometric framework for template estimation in Computational Anatomy

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Computational Anatomy aims to model and analyze the variability of the human anatomy. Given a set of medical images of the same organ, the first step is the estimation of the mean organ’s shape. This mean anatomical shape is called the template in Computer vision or Medical imaging. The estimation of a template/atlas is central because it represents the starting point for all further processing or analyses. In view of the medical applications, evaluating the quality of this statistical estimate is crucial. How does the estimated template behave for varying amount of data, for small and large level of noise? We present a geometric Bayesian framework which unifies two estimation problems that are usually considered distinct: the template estimation problem and manifold learning problem - here associated to estimating the template’s orbit. We leverage this to evaluate the quality of the template estimator.

Template estimation in Computational Anatomy

Computational Medicine relying on medical images

Computational Anatomy

Non-linear model of Errors-in-Variables

Different estimators of the template’s shape

Maximum-Likelihood (MLE-F)

\( \Theta (1) \), \( \hat{\theta} = \arg \min_{\theta} \sum_{i=1}^{n} d_{\text{Q}}(g_i(\theta), X_i) \)

\( \Theta (2) \) = \arg \min_{\theta} \sum_{i=1}^{n} d_{\text{Q}}(g_i(\theta), g_i(X_i)) \)

Frechet mean in the shape space

Adding priors: \( p(\Theta) = \exp \left( \frac{-d_{\text{Q}}(\Theta, \Theta_0)}{2\eta^2} \right) \) reweights metric in shape space; \( p(g_i) = \exp \left( \frac{-d_{\text{Q}}(g_i, g_i(\theta_0))}{2\eta^2} \right) \) reweights metric in the orbit; \( p(\theta) = \exp \left( \frac{-d_{\text{Q}}(\Theta, \Theta_0)}{2\eta^2} \right) \)

Maximum-A-posteriori (MAP-F)

MLE-S: Consistent but slow
MLE-F: Fast but inconsistent

References:

Acknowledgement: Participation in this conference was supported by the “NSF @ISBA junior travel support”