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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

Intra-subject

Inter-subjects

Computational Anatomy

Computational Physiology

Electromechanical model of the heart

Aging model of the brain

Brain manifold learning

Image from: Durrleman and Trouve 2015

Images from: Data and study conclusions on template and shape estimation are from M. Trouve 2013

Template estimation as a non-linear model of Errors-in-Variables

Generative model of organs' shapes

Goal: Estimate the template $T$

Non-linear model of Errors-in-Variables

Regression curve parameterized by $T$

Goal: Estimate the curve parameterized by $T$

Different estimators of the template's shape

Functional model: $g_i$'s are parameters

Maximum-Likelihood (MLE-F)

Adding priors: $p(T) = \text{cte. exp} \left( -\frac{g(T, g) - g_0}{2\sigma^2} \right)$ reweights metric in shape space; $p(\eta_i) = \text{cte. exp} \left( -\frac{(\eta_i - \eta_0)^2}{2\sigma^2} \right)$ reweights metric in the orbit

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

Maximum-a-Posteriori (MAP-F)

Maximum-Likelihood: Expectation-Maximization algorithm (MLE-S)

No closed form solution


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