An Inspiring Title for the MELBA Journal Sample Article

Adrian V. Dalca adalca@mit.edu
EECS, Massachusetts Institute of Technology, Cambridge, MA, USA

Mert R. Sabuncu msabuncu@cornell.edu
School of Electrical and Computer Engineering, Cornell University, Ithaca, NY, USA

Abstract

We develop a learning framework for building deformable templates, which play a fundamental role in many image analysis and computational anatomy tasks. Conventional methods for template creation and image alignment to the template have undergone decades of rich technical development. In these frameworks, templates are constructed using an iterative process of template estimation and alignment, which is often computationally very expensive. Due in part to this shortcoming, most methods compute a single template for the entire population of images, or a few templates for specific sub-groups of the data. In this work, we present a probabilistic model and efficient learning strategy that yields either universal or *conditional* templates, jointly with a neural network that provides efficient alignment of the images to these templates. We demonstrate the usefulness of this method on a variety of domains, with a special focus on neuroimaging. This is particularly useful for clinical applications where a pre-existing template does not exist, or creating a new one with traditional methods can be prohibitively expensive. Our code is available at `http://yoururl.com`.

Keywords: Machine Learning, Image Registration

1. Introduction

A deformable template is an image that can be geometrically deformed to match images in a dataset, providing a common reference frame. Templates are a powerful tool that enables the analysis of geometric variability. They have been used in computer vision, medical image analysis, graphics, and time series signals.

2. Related Works

Spatial alignment, or registration, between two images is a building block for estimation of deformable templates. Alignment usually involves two steps: a global affine transformation, and a deformable transformation (as in many optical flow applications).

Use `\cite{}` for reference that is part of the sentence, and `\citep{}` for references in parenthesis. For example, Viola and Wells III (1997) is awesome. Also, this is a citation (Viola and Wells III, 1997).

3. Methods

3.1 Equations

We estimate the deformable template parameters θ_t and the deformation fields for every data point using maximum likelihood. Letting $\mathcal{V} = \{\boldsymbol{v}_i\}$ and $\mathcal{A} = \{a_i\}$,

$$\begin{aligned} \hat{\theta}_t, \hat{\mathcal{V}} &= \arg\max_{\theta_t, \mathcal{V}} \log p_{\theta_t}(\mathcal{V}|\mathcal{X}, \mathcal{A}) \\ &= \arg\max_{\theta_t, \mathcal{V}} \log p_{\theta_t}(\mathcal{X}|\mathcal{V}; \mathcal{A}) + \log p(\mathcal{V}), \end{aligned} \tag{1}$$

where the first term captures the likelihood of the data and deformations, and the second term controls a prior over the deformation fields.

Proof Awesome proof. ∎

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Ethical Standards

The work follows appropriate ethical standards in conducting research and writing the manuscript, following all applicable laws and regulations regarding treatment of animals or human subjects.

Conflicts of Interest

The conflicts of interest have not been entered yet.

References

Paul Viola and William M Wells III. Alignment by maximization of mutual information. *International journal of computer vision*, 24(2):137–154, 1997.

Appendix A.

In this appendix we prove the central theorem and present additional experimental results. *Remainder omitted in this sample.*