NIREP and LPBA Evaluation of an Open-Source Framework for Cortical Parcellation

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Abstract

Neuroanatomical coordinate systems are essential for the interpretation of structural and functional imaging studies. This work proposes a fully image-based, open-source approach to label-based cortical parcellation that uses existing training data to identify the same structures in new datasets. The driving engine underlying this system is a new N-class EM-MRF algorithm, *Atropos*(distributed with the Advanced Normalization Tools (ANTs) software), that incorporates spatial priors to guide the segmentation. *Atropos*efficiently implements a variety of regularization and statistical models for segmentation and uses an [EM or ICA] energy minimization approach. *Atropos*'s efficient implementation allows one to solve *many class* segmentation problems (here up to 56 classes are used) while using both spatial probability maps and either geodesic or Euclidean distance priors to constrain the segmentation. This work evaluates *Atropos*performance on the parcellation problem given two different training datasets, the LPBA40 dataset from UCLA and the NIREP dataset from University of Iowa. We evaluate three aspects of the problem: (1) the quality of automatic cortical extraction from raw data; (2) the quality of parcellation, given a ground truth cortical extraction; (3) the quality of automated cortical extraction followed by automated cortical parcellation. Component (3) corresponds to the most realistic clinical case, while component (2) eliminates the confound of defining the cortex itself and focuses only on the parcellation problem. We also quantify the effect of using either a parametric or non-parametric appearance model in the segmentation. Finally, we distribute all of the scripts and code from this evaluation.

Key words: segmentation, expectation maximization, spatial prior, brain

1. Introduction

Review segmentation methods , in particular Warfield 2009, FAST and other methods that use spatial priors. Review evaluation of segmentation.

The expectation maximization and markov random field framework (EM-MRF) for segmentation is reliable and efficient for large-scale neuroimage processing in a variety of conditions. However, EM-MRF methods are sensitive to initial conditions which may lead to performance instability across clinical subjects and in longitudinal studies. This paper proposes an open-source N-class extension to the EM-MRF model, *Atropos*, that includes strong use of template-based information in both the initialization and as spatial priors in order to guide the method into a consistent local minimum.

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One advantage of the ANTS-Atropos pipeline is that we parcellate cortex entirely in the image space, thus avoiding the difficulty of transferring labels from the mesh space back to the image space—a problem that is a confound of surface-based methods**?**.

2. Methods

Atropos encodes a family of segmentation techniques that may be instantiated for different applications. We describe the general theory, algorithm and implementation that form *Atropos* and then specify the particular parameters used for the applications of interest to this research.

2.1. Notation

An image, I, maps a domain, Ω into the positive real numbers, such that $I\colon \Omega \to \mathbb{R}^+$. The goal of segmentation, in general, is to define the spatial distribution of a finite set of labels over this domain. We denote the segmentation itself as $\eta\colon \Omega \to L$ where $L = \{L_1 = 1, \cdots, L_N = N\}$, a set of integer indexed segmentation labels. Note that η may be formed as $\eta = \sum_{i=1}^{i=N} L_i \eta_i$ where η_i is the binary segmentation for label L_i. A prior estimate for the label image η_i is here denoted η_i^s with a complete set of priors denoted η^s. The boundary of the binary segmentation – where a $0/1$ transition edge exists – is denoted $\partial\eta_i^s$, for the prior, and $\partial\eta_i$ for the label image.

2.2. Apocrita Theory

A general maximum a posteriori criterion for segmentation seeks,

$$\hat{\eta} = \arg\max_{\eta} \Pr(\eta|I)(\mathbf{x}) = \Pr(I|\eta)(\mathbf{x}) \Pr(\eta)(\mathbf{x}), \tag{1}$$

where I is the input image, η represents the label set configuration taken from the set L, $\Pr$ is the probability, $\mathbf{x}$ is the spatial index and the optimal solution is $\hat{\eta}$. The input image I, here, is an unlabeled T1 MRI indexed by the value $\mathbf{x} \in \Omega$ where Ω is the image's spatial domain. This probability is composed of the likelihood (first term) and the prior (second term). *Atropos* uses a spatially varying likelihood term and a two-component prior term that takes into account both spatial distribution and label smoothness, the latter via a standard MRF prior.

The likelihood term for a single label value $L_i \in L$ is,

$$\Pr(I|\eta_i)(\mathbf{x}) = \frac{1}{Z_i} \exp(-\|I(\mathbf{x}) - \mu_i(\mathbf{x})\|^2/\sigma_i^2), \tag{2}$$

where Z_i is a normalizing constant, $\mu(\mathbf{x})$ is a spatially varying estimate of the tissue mean and σ is a standard deviation. The prior term is given by,

$$\begin{aligned} \Pr(\eta_i)(\mathbf{x}) &= \frac{1}{Z_i'} \exp(-f(\mathbf{x} - \mathbf{y}_{\partial\eta_i^s})/\sigma_{\eta_i^s}^2) p(\eta_i|\eta_i^{\aleph}), \\ f(\mathbf{x} - \mathbf{y}_{\partial\eta_i^s}) &= (1 - \eta_i^s(\mathbf{x}))\|\mathbf{x} - \mathbf{y}_{\partial\eta_i^s}\|, \end{aligned} \tag{3}$$

where $p(\eta_i|\eta_i^N)$ is the MRF smoothness probability based on the local neighborhood $\aleph$, the Z is a normalizing constant and $\mathbf{y}_{\partial\eta_i^s}$ is the nearest point to $\mathbf{x}$ on the boundary of this labeling. *Atropos* requires a user or template-defined η_i^s and the standard deviation $\sigma_{\eta_i^s}$ if a non-unity spatial prior component is desired for that label. The free parameters, that must be estimated iteratively, are therefore μ_i, σ_i and the label

Figure 1: The spatial prior.

set itself $\hat{\eta}$, which defines the (locally) optimal spatial distribution of L through Ω. Figure 1 shows the distribution of the spatial prior as a function of the distance from prior-defined object boundary. Note that f may easily be varied for other applications or that fixed probability images may also be substituted here. This choice of f is motivated by the fact that it allows compressed storage of the priors in a single image, η^s, while also maintaining the ability to manipulate – for each η_i^s – the spatial influence of the prior via $\sigma_{\eta_i^s}$. Practically, this is especially valuable when, N, the number of labels, is large.

2.3. Apocrita EM Algorithm

The EM approach.

2.4. Apocrita Implementation

The command line and practical example, ITK, etc. Template-based initialization.

2.5. The LPBA40 Dataset

The LPBA40 dataset **?** was collected at the North Shore Long Island Jewish Health System imaging center and is maintained at UCLA. LPBA40 contains 40 images (20 male + 20 female) from normal, healthy ethnically diverse volunteers with average age of 29.2 $\pm$ 6.3 years. Each subject underwent 3D SPGR MRI on a 1.5T GE system resulting in $0.86 \times 0.86 \times 1.5mm^3$ images. Each MRI in the LPBA40 dataset was manually labeled with 56 independent structures at the UCLA Laboratory of Neuro Imaging (LONI). The test-retest reliability of the labeling, across raters, was reported as a minimum Jaccard ratio of 0.697 in the supramarginal gyrus to a maximum of 0.966 in the gyrus rectus. A single labeling of each image is made available to the public and used, here, as silver-standard data for both training and testing in our cross-validation scheme.

2.6. The NIREP Dataset

The non-rigid image registration evaluation project (NIREP http://www.nirep.org/) is a resource of 16 high quality labeled brain images at $1mm^3$. Each brain was labeled with 32 cortical regions (16 on each hemisphere) and an additional class of other gray matter tissue. Regions vary in size from large (inferior temporal region) to small (temporal pole, insula gyrus, frontal pole). The main drawback is a lack of inter-rater reliability numbers – in particular because visual inspection and comparison of labelings reveals a degree of inconsistency in labeling of particular regions across subjects. Nevertheless, the NIREP dataset is perhaps the highest quality evaluation dataset currently available for the cortex.

3. Results

4. Discussion

5. Conclusion

To our knowledge, this is the first demonstration of a consistent and

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