Joint Intensity Fusion

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Abstract

Consensus techniques have demonstrated remarkable utility in various medical imaging segmentation tasks. Joint label fusion (JLF) employs spatially normalized atlas sets—gray-scale intensity images with corresponding segmentation labels—to segment unlabeled images using various weighting schemes. The technique of [1, 2] avoids informational redundancy in the atlas voting scheme by considering the atlas set as a whole (versus individually) in determining the optimal weights. In this work we extend this methodology to the estimation of intensity information in multi-modal image data sets, which we denote as *joint intensity fusion (JIF)*. JIF has several potential applications including removal of imaging artifacts (e.g., motion), removal of pathologies (e.g., tumour, lesions), imputation of missing modality data, and template enhancement. Evaluation is performed on a variety of data ...need more here. We provide an open-source implementation in the the well-known Advanced Normalization Tools (ANTs) software package, based on the Insight Toolkit coding standards, which subsumes the functionality reported in [2] in addition to offering further enhancements such as multi-threading and a non-negative least-squares calculation of the atlas weights.

Keywords: ANTs, atlases, denoising, motion correction, non-negative least squares.

Introduction

Coupled with advanced image registration algorithms, techniques such as single atlas label assignment [3] and majority voting [4] of atlases provided early, well-performing prior knowledge segmentation alternatives to related segmentation techniques which employ intensity-based partitioning of the gray-scale histogram constrained by local image neighborhood-based spatial priors (e.g., Markov Random Field) [5–7]. As pointed out in a recent comprehensive survey of the field [8], the popularization of multi-atlas segmentation techniques extend more than a decade ago with early pioneering efforts (e.g., [9–11]).

These multi-atlas techniques, which is an instantiation of "wisdom-of-crowds" [12] solution strategies, have proven remarkably successful. Recent international competitions such as the brain labeling challenge of the *MICCAI 2012 Workshop on Multi-Atlas Labeling* and the *2013 MICCAI Challenge Workshop on Segmentation: Algorithms, Theory and Applications* have demonstrated the superiority of these consensus-based approaches when paired with high-performing image spatial normalization algorithms (e.g., [13]).

Methods

A brief review of joint label fusion

Joint intensity fusion

ITK implementation

Similar to the other ANTs programs, the software encapsulating the methods discussed in this work are built upon the Insight Toolkit (ITK) and conform to ITK coding standards. Here we describe the implementation and usage interface. The program `antsJointFusion.cxx` uses an intuitive command line interface developed specifically for the ANTs toolkit. See Listing 1 for the short help menu available at the command line. A more comprehensive long help menu can be produced (not shown). The latter provides references and documentation concerning parameter options.

```
COMMAND:
     antsJointFusion

OPTIONS:
     -d, --image-dimensionality 2/3/4
     -t, --target-image targetImage
                        [targetImageModality0,...,targetImageModalityN]
     -g, --atlas-image atlasImage
                       [atlasImageModality0,...,atlasImageModalityN]
     -l, --atlas-segmentation atlasSegmentation
     -a, --alpha 0.1
     -b, --beta 2.0
     -c, --constrain-nonnegative (0)/1
     -p, --patch-radius 2
                        2x2x2
     -m, --patch-metric (PC)/MSQ
     -s, --search-radius 3
                         3x3x3
                         searchRadiusMap.nii.gz
     -e, --exclusion-image label[exclusionImage]
     -x, --mask-image maskImageFilename
     -o, --output labelFusionImage
                  intensityFusionImageFileNameFormat
                  [labelFusionImage,intensityFusionImageFileNameFormat,
                              <labelPosteriorProbabilityImageFileNameFormat>,
                              <atlasVotingWeightImageFileNameFormat>]
     --version
     -v, --verbose (0)/1
     -h
     --help
```

Listing 1: The antsJointFusion short command line menu which is invoked using the '-h' option. The expanded menu, which provides details regarding the possible parameters and usage options, is elicited using the '–help' option.

Results

Discussion

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