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 multimodal 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. In this section 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. `antsJointFusion.cxx` is the interface for the underlying ITK-style class:

- `itkWeightedVotingFusionImageFilter.h`
- `itkWeightedVotingFusionImageFilter.hxx`

```
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.

`antsJointFusion` has a number of available parameters (see Listing 1) permitting operation on 2-, 3- or 4-dimensional data. The default input parameters and corresponding definitions are given below:

Target image set. This input (or set of inputs) comprises the image set to be matched by the input atlases. If more than one target image is specified, it is assumed that all modalities are spatially normalized. If JIF is to be performed then all target modalities are inferred with only the first image being used for atlas weighting. For example, suppose the set of input atlases consists of N modality images per atlas. Only the first image needs to be specified for the set of target input images although all N target modalities will be estimated using JIF.

Atlas images. Each atlas set specified by the `-g` option consists of one or more modality. It is assumed that these atlases have already been normalized to the target image. The ordering of the modalities for each atlas is assumed to match the ordering specified for the target image and the other atlases.

Atlas labels. When performing JLF, a set of atlas labels is provided with each atlas set. Pairing of each atlas label, `-l` option, with each atlas, `-g` is assumed from the order of appearance on the command line. Note that specification of the atlas labels is optional for performing JIF.

Alpha. The damping parameter `Alpha` is the constant value added to the diagonal elements of the weight(???) matrix (see Equation ()) to prevent the possible inversion of a singular matrix. The larger the value, the greater the stability for matrix inversion but the further away from the true solution. The default value is 0.1.

Beta.

Constrain non-negative. As described previously, least squares estimation is required for solving the atlas weights at each voxel. The default method for matrix decomposition is Cholesky given its speed.[1] However, such a choice could potentially produce negative weights which is unintuitive. This led us to include a non-negative least squares solution option [14] to ensure non-negative weights.

Patch metric. To determine the weights at a current voxel in the target image, a neighborhood patch centered at the current voxel is compared with neighboring patches in each atlas. The similarity between the target and atlas neighborhood patches can be calculated using a variety of intensity similarity metrics. Contributions from additional modality images are simply concatenated into the similarity metric calculation. The original JLF work employed Pearson's correlation [1, 2] which works very well. Future work includes the possible inclusion of other patch-based metrics (e.g., mean squares [15]).

[1]Although other techniques, such as QR and singular value decomposition, are more stable, a sufficiently large `Alpha` value ensures non-singularity. However, if the condition number is too small, SVD is used.

Results

Discussion

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