Two Greedy SyN Variants for Pulmonary Image Registration

Nick Tustison[1], Gang Song[2], Jim Gee[2], and Brian Avants[2]

[1] University of Virginia, Charlottesville VA 22903, USA
[2] University of Pennsylvania, Philadelphia PA 18104,USA

Abstract. We briefly describe two greedy SyN variants for CT lung image registration as applied to the EMPIRE10 data set which complements our previous submission "Lung CT Image Registration Using Diffeomorphic Transformation Models." Whereas the previous submission explored diffeomorphic lung registration using the `ANTS` program off the Advanced Normalization Tools software package, we look at registration performance of the well-performing greedy SyN using the newly developed tool `antsRegistration`. In addition to the original SyN implementation which uses Gaussian regularization of the vector fields, we also assess performance of a new variant which uses B-splines for regularization.

Keywords: ANTs, antsRegistration, B-splines, DMFFD, Regularization

1 Introduction

SyN, or Symmetric Normalization, was introduced in [1] (including a "greedy" version for tractable solutions to common image normalization problems). Follow-up work included a large-scale evaluation on brain T1-weighted MRI conducted in [2] and our original EMPIRE10 submission [3] which demonstrated good performance on lung CT. Both these evaluations utilized the `ANTS` program which comprises a core component of our open source Advanced Normalization Tools (ANTs).

As part of the recent ITK[3] development efforts, the image registration framework was extended and enhanced which included the development of several diffeomorphic transforms. To take advantage of this work, we introduced a new registration program called `antsRegistration` which is also offered with the ANTs package. `antsRegistration` offers a generic architecture for user-specific image registration solutions permitting matching of various similarity metrics with a wide range of transform including the original greedy SyN transform. As a variant of the original SyN offering, we developed the so-called "B-spline SyN" transform which, differing from its Gaussian SyN analog, uses the B-spline basis functions for explicit regularization of the vector fields. Theoretical discussion

[3] http://www.itk.org

and a large-scale comparative evaluation with the original SyN transform in the context of brain normalization are given in [4].

In order to continue to make improvements, we applied `antsRegistration` to the EMPIRE10 data using both SyN variants. Additionally, to promote reproducibility, we detail specific command line calls so that the interested user can reproduce the results submitted for evaluation.

2 Methods

Preprocessing of both the moving and fixed images included the following steps:

- mask out the lungs using the provided lung masks,
- rescale image intensities within the lung masks to be between 0 and 1,
- invert image intensities within the lung masks, and
- pad images by 100 voxels at each dimension (50 at each face).

Following preprocessing, each image pair is registered as illustrated in Listing 1.

```
# Register the $fixed and $moving images with initial alignment of the
# centers of intensity followed by the following three stages:
#   rigid -> affine -> SyN (Original or B-spline)
#
# To make an original syn call, replace the option
#
#    --transform BSplineSyN[0.1,40,0,3]
#
# with the option
#
#    --transform SyN[0.1,3,0]
#
# Output consists of the warped image (${prefix}Warped.nii.gz), linear
# (${prefix}0GenericAffine.mat) and SyN (${prefix}1Warp.nii.gz)
# components of the final transform.
#

antsRegistration --dimensionality 3 \
                 --output ${prefix} \
                 --use-histogram-matching 1 \
                 --initial-moving-transform [${fixed},${moving},1] \
                 --transform Rigid[0.1] \
                 --metric MI[${fixed},${moving},1,32,Regular,0.25] \
                 --convergence 1000x500x250x100 \
                 --smoothing-sigmas 3x2x1x0 \
                 --shrink-factors 8x4x2x1 \
                 --transform Affine[0.1] \
                 --metric MI[${fixed},${moving},1,32,Regular,0.25] \
                 --convergence 1000x500x250x100 \
                 --smoothing-sigmas 3x2x1x0 \
                 --shrink-factors 8x4x2x1 \
                 --transform BSplineSyN[0.1,40,0,3] \
                 --metric CC[${fixed},${moving},1,4] \
                 --convergence 100x70x50x20 \
                 --smoothing-sigmas 3x2x1x0 \
                 --shrink-factors 6x4x2x1
```

Listing 1.1. Representative `antsRegistration` call used for the EMPIRE10 evaluation

These parameters are identical to the parameters used in the evaluation reported in [4] except for the B-spline knot distance which, instead of 40 mm, was 26 mm for that study. The brain study required less regularization due to the large deformation nature of the problem. To make it easier for other to reproduce our results in the work, we wrote a well-documented shell script, `antsRegistrationSyN.sh`,[4] employing these parameters which has demonstrated robust accuracy in a number of brain data sets. Due to its availability and previous vetting, we applied the same script to the EMPIRE10 data set with the only change being the B-spline SyN distance used.

`antsRegistration` uses the concept of "registration stages" to string together transforms for normalization. Each stage is characterized by the following:

- fixed and moving images,
- transform,
- shrink factors (i.e. by what factor are the fixed and moving images down-sampled at each resolution level),
- smoothing factors (i.e. how much Gaussian smoothing is applied to each image at each resolution level),
- similarity metric, and
- convergence criteria (e.g. number of iterations per number of levels).

Note that different fixed and moving images can be specified for each stage and multiple metrics/image pairs can be specified for a single stage.

With respect to the Listing 1—initially, the fixed and moving images are used to find the translation transform which aligns center of intensity masses between the fixed and moving preprocessed images. A rigid transform is then optimized (via gradient descent) using the mutual information metric with four resolution levels followed by an affine transform with similar parameter choices. The final stage consists of the SyN or B-spline SyN transform optimization using a local cross correlation metric with a radius of 4 pixels. For comparison, in [3] we used the same CC metric in the diffeomorphic registration with a radius of 2 and 5 multi-resolution levels.[5]

All processing (preprocessing and image registration) was performed on the linux cluster at the University of Virginia.[6] Each processing job was assigned one node with single-threading. Given the relatively large image sizes (original size plus 100 voxels padding in each dimension), the maximum memory requested for each job was 40 gb with a maximal alloted time of 100 hours. Note that times varied between approximately 20 and 90 hours which was largely dependent on

[4] https://github.com/stnava/ANTs/blob/master/Scripts/antsRegistrationSyN.sh

[5] We should remind the reader that our related submission used the `ANTS` program which does not have the developed notion of stages that `antsRegistration` has. In fact, the implementation can be quite different between the two programs which can be expected given the experience gained between the development of the former to the latter.

[6] http://www.uvacse.virginia.edu

image size and algorithm. For the image data sets reported in [4], B-spline SyN took anywhere between 15 to 40 % longer than Gaussian-based SyN.

References

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