Standardized Registration Methods for the SATA Challenge Datasets

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Abstract. The 2012 Segmentation: Algorithms, Theory and Applications (SATA) challenge suggests that even subtle variation in registration performance may impact the outcome of multi-atlas segmentation algorithms. The 2013 SATA challenge organizers therefore requested standardized registration that enables entrants to use the same mappings as input to competing algorithms. We therefore collaborated to provide, within a relatively brief window of time, over 22,000 registration results based on Advanced Normalization Tools (ANTs link). The diencephalon component of the challenge presented familiar and easily addressed data requiring only 1,600 mappings between different 3D human T1 neuroimages. The 3D multiple modality MRI "dog leg" dataset (> 7,000 mappings) presented the opportunity to improve performance by using a multivariate similarity metric. The 4D cardiac (or CAP) dataset (> 13,000 mappings) includes highly variable image quality, anatomy and field of view. We detail the ANTs variants that address the most basic brain dataset, where we used a template-based approach, to the more challenging CAP dataset which employed a more customized registration solution based on prior knowledge. The scripts, source code and a small set of example data accompany this paper and are available online. [1]

1 Introduction

Multi-atlas Using a common set of "voters" allows a more direct comparison of the segmentation/fusion methods that are at the heart of this challenge.

"in order to isolate the benefits of specific label fusion algorithms we need to have a standardized registration"

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The Insight ToolKit began a major refactoring effort in 2010. The refactoring aimed to both simplify and extend the techniques available in version 3.x with methods and ideas from a new set of prior work [1,2,3,4,5,6]. To make this technology more accessible, ITK^4 unifies the dense registration framework (displacement field, diffeomorphisms) with the low-dimensional (B-Spline, Affine, rigid) framework by introducing composite transforms, deformation field transforms and specializations that allowed these to be optimized efficiently. A subgoal set for ITK^4 was to simplify parameter setting by adding helper methods that use well-known principles of image registration to automatically scale transform components and set optimization parameters. ITK^4 transforms are also newly applicable to objects such as vectors and tensors and will take into account covariant geometry if necessary. Finally, ITK^4 reconfigures the registration framework to use multi-threading in as many locations as possible. The revised registration framework within ITK is more thoroughly integrated across transform models, is thread-safe and provides broader functionality than in prior releases.

2 Challenge Data

For this year's challenge we are considering 3 datasets: (1) A diencephalon (mid-brain) dataset (2) A canine leg dataset (3) A cardiac atlas dataset

From my perspective, I think that the mid-brain and canine leg datasets would not be terribly difficult to achieve consistent correspondence across the images. However, the cardiac atlas dataset might be significantly more challenging due to the way in which the images are acquired (i.e.,wildly varying orientations and fields-of-view).

3 Methods

3.1 Diencephalon/Brain Data

3.2 Dog Leg Multi-Modality Data

3.3 CAP Cardiac Data

4 Results

4.1 Diencephalon/Brain Data

4.2 Dog Leg Multi-Modality Data

4.3 CAP Cardiac Data

We estimated a failure rate of X% on this data .... look at histogram of correlation

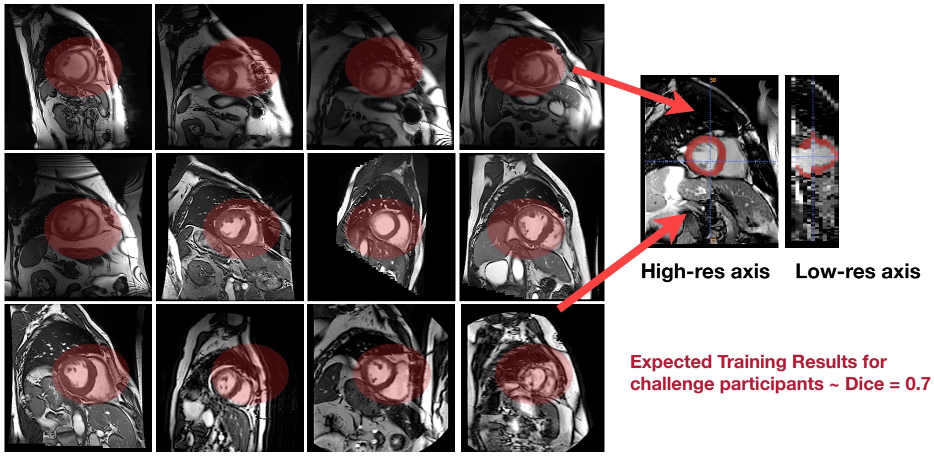

Fig. 1: CAP methods

5 Discussion

The cardiac dataset reveals some of the limitations involved with naive pairwise registration and highlights the benefit of problem-specific strategies and multi-atlas methods.

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