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Reference Target Selection in Registration Based Atlas Construction

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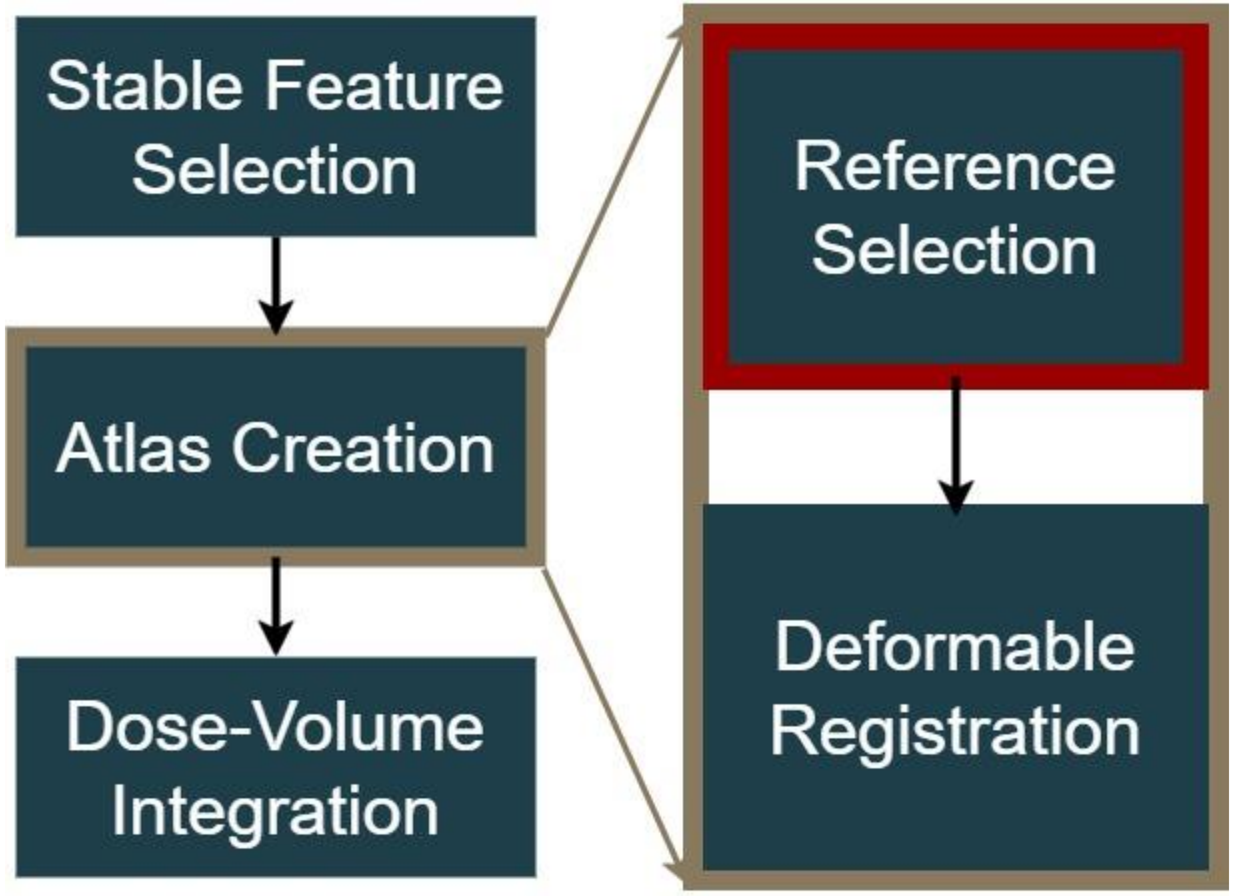
Refresher: Automatic Identification of Critical Areas of the Head and Neck for Dose-Toxicity Analysis

Goals: Develop a system that identifies, and evaluates dose-volume features in inter-organ volumes of the head and neck and allows for the identification of areas that are more or less critical to the patient outcome of radiotherapy.

Method: Create an anatomical atlas via deformable registration of contoured patient anatomy from an extant database to represent the "average" patient, and use it to determine relative location of spatial volumes of interest in particular patient instances.



Roadmap and Relevance

In order to create an atlas from a set of patient images or point clouds (in our case), a “target” image must be chosen, to which all other images are deformably registered.

Problem: The choice of the target image significantly biases the atlas, and effects its validity. We can’t simply choose a patient as the target.

We will talk about two different solutions:

1. Create a target image by iteratively performing registration and setting the resulting atlas as the target image.

2. Choose the least biased target image from the data set.

Solution 1: The Iterative Approach

Proposed by Guimond et al in "Average Brain Models: A Convergence Study"[1], the iterative approach consists of:

1. Evaluation of global and intensity (this study used Magnetic Resonance Images). Registration is performed between a chosen target image and each image in the data set. The mean of these registered pairs is calculated to create a target with the average intensity of the data set and the shape of the target image.

2. Registration is performed again between the target image and each image in the data set. The paper assumes that registration results in a vector field R_i representing the corresponding location of each voxel in the target I_R to each voxel in the set image I_i. The vectorwise average $R(x) = \frac{1}{N}\sum_i^N R_i(x)$ is the corresponding residual deformation.

3. The average residual deformation is applied to the average intensity image to create model M. These steps are repeated, replacing the target image I_R with M.

Solution 1: The Iterative Approach, Methodology

The method was tested by computing four models over four iterations of the algorithm with two reference images I_R and I_{R2}, with two sets of five images, S_1 and S_1. Four metrics are used for evaluation:

1. Average Distance from the current reference I_R to all the elements of a set S, where R is the residual deformation.

$$AD(I,S) = \sqrt{\frac{1}{N}\sum_{x}\frac{1}{N}\sum_{i=1}^{N}\|x - R_i(x)\|^2}$$

2. Root Mean Square Norm with deformation field D: $RMSN(D) = \sqrt{\frac{1}{N}\sum_x\|x - D(x)\|^2}$

3. Root Mean Square Norm with residual deformation field R: $RMSN(R) = \sqrt{\frac{1}{N}\sum_x\|x - R(x)\|^2}$

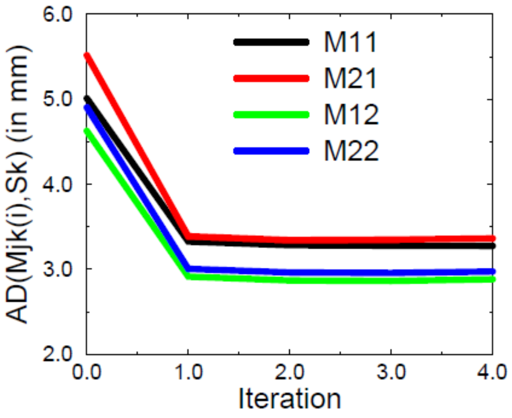
4. Normalized Intensity Difference: $NID\left(I_R^i, I_R^{i+1}\right) = \sqrt{\frac{\sum_x(I_R^i(x) - I_R^{i+1}(x))}{\sum_x(I_R^i)^2}}$

Solution 1: The Iterative Approach, Results

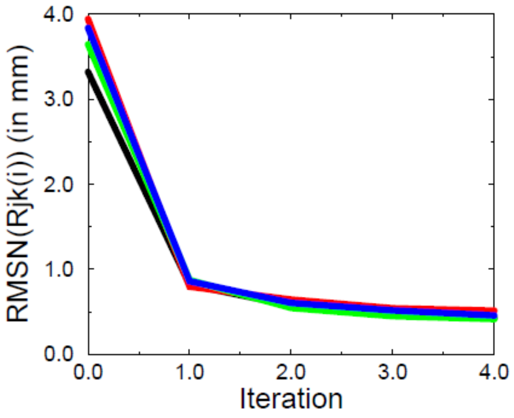
Across all metrics, the improvement in results is minor after the first iteration.

The Average distance drastically decreases, which implies that the target image is closer to the centroid of the image set as iterations progress.

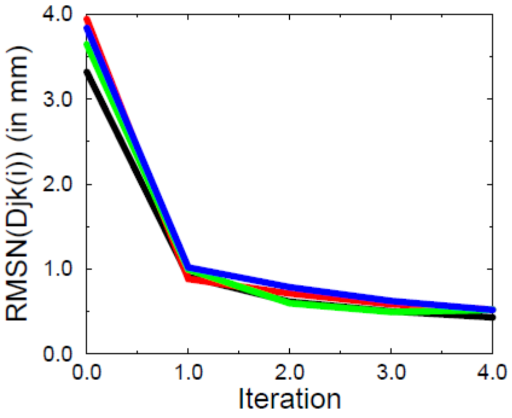
Both root square mean measurements, which supply information regarding the shape variation expressed decrease, as does the NID measurement, which expresses the brightness disparity between each successive model iteration.



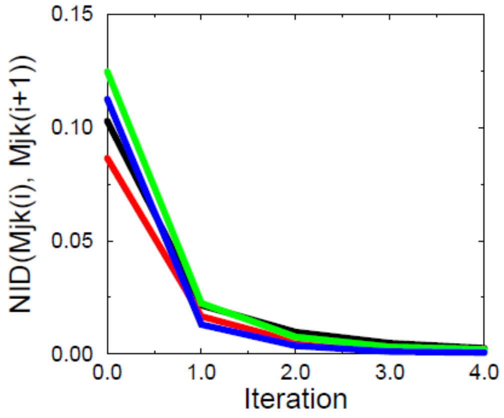
(a) Average distance to the reference of the current iteration.



(b) Shape variation of the reference for the current iteration.



(c) Shape difference between models computed at successive iterations.



(d) Brightness disparity between models computed at successive iterations.

Solution 1: The Iterative Approach, Assessment

Pros:

- Guimond et al show that the iterative approach approaches the centroid of the data set reliably. The tests sets started with root mean square ranges of 4.62 to 5.51 mm and stabilized in a range of 2.88 to 3.36 mm.
- Regardless of the choice of starting reference image, the algorithm approaches the centroid, removing bias.
- Because our data does not include intensity, we do not need to normalize intensity in our algorithm

Cons:

- With our database of over 900 patients, and our currently chosen registration algorithm, multiple iterations could prove to be prohibitively time-consuming
- The ability to quickly update an atlas would be difficult to implement.
- Although Guimond et al show that the first iteration provides the majority of the model improvement, such a test on a set of only five images is not necessarily generalizable to a large patient database.

Solution 2: Least Biased Target Choice

Proposed by Park et al in “Least Biased Target Selection in Probabilistic Atlas Construction”[2], the idea is to choose a target image or data that is closest to the geometric mean of a data set, as defined by bending energies.

Background:

- Pairwise registration was performed using Mutual Information as the similarity measure and thin-plate spline as the geometric interpolant.
- The distance between two images (the bending energy) is defined as the sum of squared second partial derivatives of the geometric transform. Note the following definition is for 2D.

$$d^2 = \iint \left(\frac{\partial^2 f_x}{\partial x^2}\right)^2 + 2\left(\frac{\partial^2 f_x}{\partial x \partial y}\right)^2 + \left(\frac{\partial^2 f_x}{\partial y^2}\right)^2 + \left(\frac{\partial^2 f_y}{\partial x^2}\right)^2 + 2\left(\frac{\partial^2 f_y}{\partial x \partial y}\right)^2 + \left(\frac{\partial^2 f_y}{\partial y^2}\right)^2 dxdy$$

f_x; displacement in x $\quad f_y$; displacement in y.

Solution 2: Least Biased Target Choice, The Method

The method can be summarized as follows:

1. Perform N(N-1)/2 pair-wise registrations, where N is the number of images.
2. Calculate the bending energies from the registrations.
3. Form the Distance Matrix D
4. Apply multidimensional scaling and find the relative locations of images.
5. Calculate the mean location of the images.
6. Choose target image that is closest to the mean.

The Distance Matrix D is defined as element d_{ij} as being the bending energy between images i and j.

Multidimensional scaling (MDS) is a technique that produces positional coordinates from a collection of distances via an eigenvalue decomposition of a distance matrix. It allows the approximate geometric plotting of data sets on a coordinate system. It is also known as Principle Coordinates Analysis.

The mean location of the images can simply be computed by taking a average of the coordinates assigned by MDS

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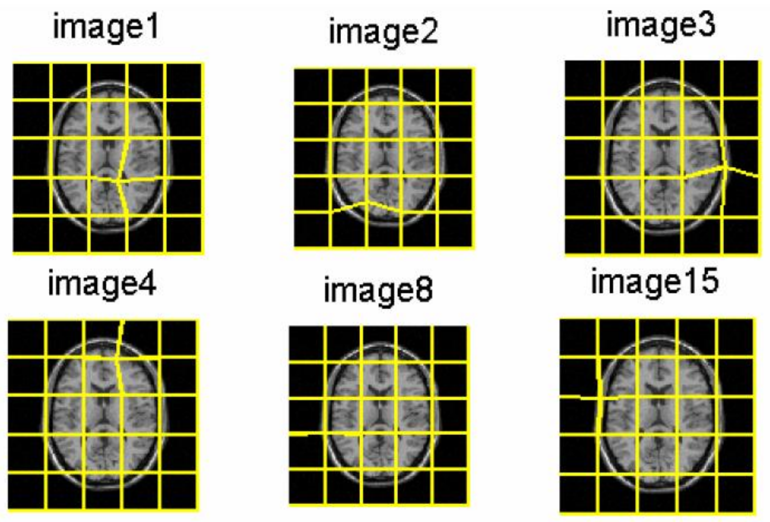
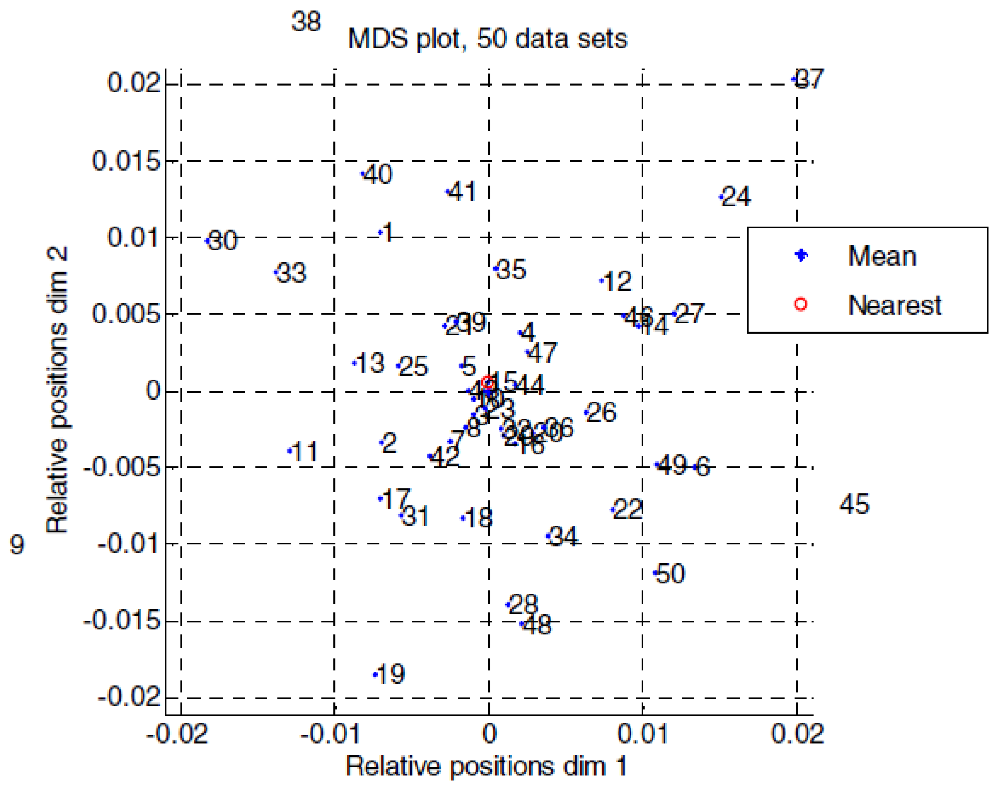
Solution 2: Least Biased Target Choice, Validation and Results

- Synthetic experiments were carried out using MRI slices deformed in a known way in 2D.
- 50 images were prepared using a knot based deformation.
- 1225 pairwise registrations were done to fill up a 50x50 distance matrix.
- The resulting choice was found to be within 0.106 distance (bending energy) of the ground truth average image, and the coordinates match the order of the ground truth geometrical relationship of the test images.





Above: An MDS plot of 50 images from the data set used for validation.
Left: Examples of the deformed images used.

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Solution 2: Least Biased Target Choice, Assessment

Pros:

- Registration across the database only needs to be computed once for a given set of chosen contours from the database.

- Although potentially more time consuming, iterations are not necessary upon each update of the atlas, as would be required with the first solution.

Cons:

- The calculation of the mean image requires a significant number of pairwise registrations.

- The paper provided no metric regarding the efficacy of choosing the least biased target vs. either an iterative method, or simply choosing a random patient. There is not an easy way to compare the two proposed solutions directly.

References

Any Questions?

1. Guimond, A., Meunier, J., & Thirion, J. (2000). Average Brain Models: A Convergence Study. *Computer Vision and Image Understanding, 77*(2), 192-210. doi:10.1006/cviu.1999.0815

2. Park, H., Bland, P. H., Hero, A. O., & Meyer, C. R. (2005). Least Biased Target Selection in Probabilistic Atlas Construction. *Lecture Notes in Computer Science Medical Image Computing and Computer-Assisted Intervention – MICCAI 2005,* 419-426. doi:10.1007/11566489_52