Medical Image Analysis
Report Project 2
Fabian Prada
Team 7. Teammate: Rob Grupp

1 Abstract

In this project we present two different approaches to the problem of finding a bounding box for the left and right thalamus. The first approach (propoused by Fabian) attempts to reduce the 3D registration problem to a 2D registration by identifying the middle Sagital plane and doing 2D registration along the central sagital slice. The second approach (propoused by Rob) solve for the full volumetric registration by taking the gradient of the NCC energy function using a 6D Lie algebra parametrization of the rigid transformations.

2 Background

Registration of 2D and 3D images has been a widely explored research area. The book of Hill[3] provide a review of the most common techniques in the context of medical imaging. To look for state of the art results of brain registration we refer to [1].

Given images I_S (source) and I_T (target) the registration problem can be formulated as the computation of deformation $D : \Omega \to \Omega$ (where Ω is the domain of the signal) that minimize an objective error, $E(I_S \circ D^{-1}, I_T)$, between the target signal and the deformed source.

Form this definition, we can identify 3 characteristics that can assists us in the classification of registration methods: (1) the set of transformations considered, (2) the deformation energy, and (3) the energy optimization approach.

In the context of rigid transfornation, the most principal approach to the registration problem is provided by the the Procruste's method: given landmarks $\{x_i\}_i, \{y_i\}_i$ solve for the optimal rotation and translation minimizing,

$$\min_{R,t} \sum_i ||y_i - (Rx_i + t)||_2^2$$

When landmarks are unknown, the target landmarks are usually defined to be the closest point to the source landmarks. This approach is known as Iterative Closest Point (ICP) registration [2].

Non-rigid deformation methods consider local transformation that are stored in a coarse representation of the signal domain (e.g., a coarse grid or mesh) and can be sampled at any other point of the domain using interpolative kernels like cardinal bsplines or thin splines. Given a (discrete) signal c and a (continuous) reconstruction kernel ϕ the value of the reconstructed signal at any point x, is simply given by,

$$(f * \phi)(x) = \sum_i f[i]\phi(x - i)$$

Some other methods represent the alignment transformation via a deformation field. This is the case of classical Optical Flow methods [4] and Diffeomorphic Demons[5].

When the signals to be registered have similar intensity distribution (e.g., images of an individual captured from the same device) the sum of squares distances (SSD) is an accurate measure of the deformation error. When, the intensity values of the signals does not admit a simple correspondance (e.g., through histogram equalization), a more robust energy is given by the mutual information of the signals:

$$MI(A, B) = H(A) + H(B) - H(A, B) \text{ where } H(A) = -\sum_a p_A(a) \log(p_A(a))$$

Minimization of the energy can be done by differential methods like Gradient Descent and Quasi-Newton, or by methods that does not require derivative computation like adaptive search on a discrete parameter domain.

3 Approach

Given a testing brain J, and a collection of trainning brains $(I_i)_i$ our approach to identifying a bounding box for the right and left thalamus consisted on three major steps:

1. Compute an affine transformations T_i that register brain J to each brain I_i. For such affine transformation, we have:

$$J \circ T_i \approx I_i$$

2. Map the thalamus mask M_i from each of the trainning brains to the testing brain by taking the inverse of the registration transformation:

$$L_i := M_i \circ T_i^{-}1$$

3. Output the bounding box of the testing brain thalamus by consolidating the masks $(L_i)_i$

In this project we considered two different alternatives for computing the affine transformation T. These are discussed in the section below.

3.1 Sagital Plane Dection + 2D Registration

My approach to the problem of doing brain registration looked to simplify the problem from 3D to 2D registration. This was done by identifying the middle sagital plane for each of the brains and applying 2D registration of the middle sagital slice of the testing brain to each of the trainning ones.

3.1.1 Sagital Plane Detection

As we observe in Figure 1, due to the reflective properties of the sagital plane, the axial (right image) and the coronal (left image) slices have almost perfect reflective simmetry along the sagital axis.

The computation of the sagital axis is done in four simple steps:

1. Compute the brain center of mass.
2. Compute the brain principal direction.
3. Sample the slice normal to the principal direction through the center of mass.

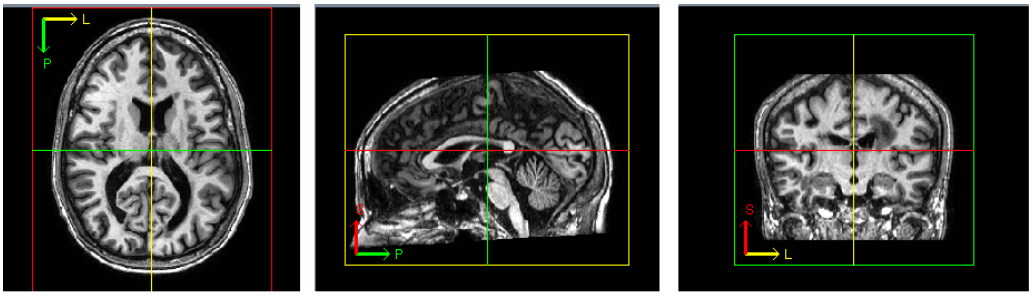

Figure 1: Brain Reflective Symmetry. From left to right: axial, sagital and coronal slices.

4. Align the sampled slice to be left-to-right simmetric.

For the computation of the center of mass, we apply a simple intensity based tresholding to the entire brain (we use $t = 0.05$) to identify the voxels interior to the skull. Taking these voxels coordinates as samples from a distribution, we compute its mean and covariance. The estimated mean of the distribution is the center of mass of the volume, and the largest eigenvector of the covariance is the principal direction. The projection of these entities on a single slice are illustrated in

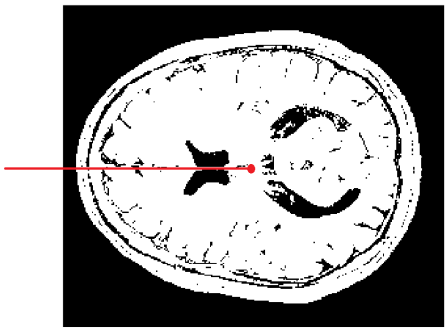

Figure 2: Center of mass and principal direction of the brain.

Due to the elongated shape along the axial plane and the reflective symmetry across it, it is expected the principal direction of the brain to be

contained within the sagital. This was the case for all the trainnng brains.

Once the principal direction is identified, we need a second direction in the sagital plane to completely characterize it. To do this, we sample the slice that is orthogonal to the principal direction of the brain and passes through the center of mass. This slice is presented in the left of Figure Figure 3. Observe that this slice has a one perfect reflective symmtric axis which is highlited in red. This symmetry axis was identified by finding the optimal rotation around the center of mass that minimize the left-to-right symmetric error of the transformed image (depicted in the right image in Figure 3).

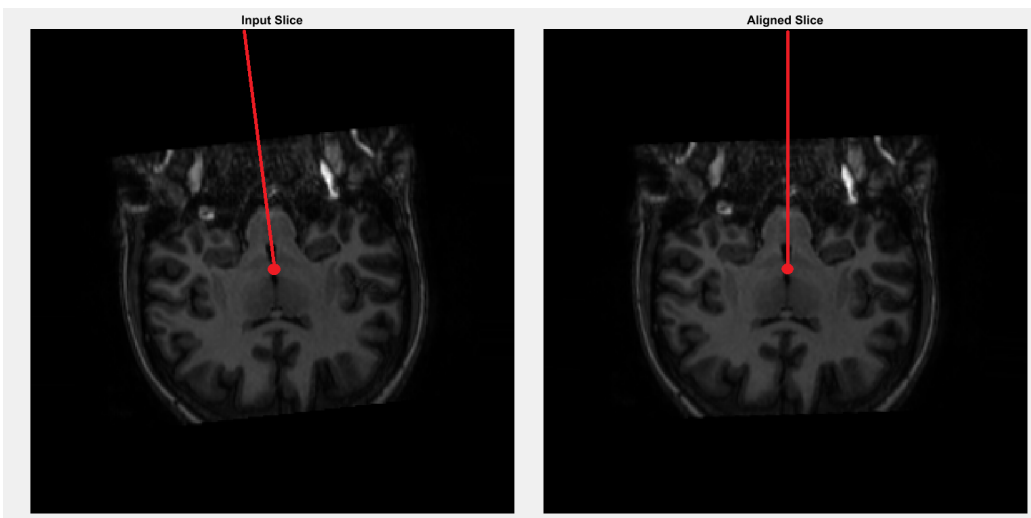

Figure 3: Alignemnet of the normal slice.

Each of the training brains and the testing brain can be compactly represented by a parameter description of the sagital plane, say $(\rho.\vec{n})$, and its intensity values. For the trainning brains this characterization is precomputed and for the testing brain in is computed at evaluation time.

3.1.2 2D Registration

Once the sagital slices of the trainning and testing brains have been computed we proceed to compute a 2D affine registrations. The error of the registration is measure as the SSD of the target and transformed source image, i.e.,

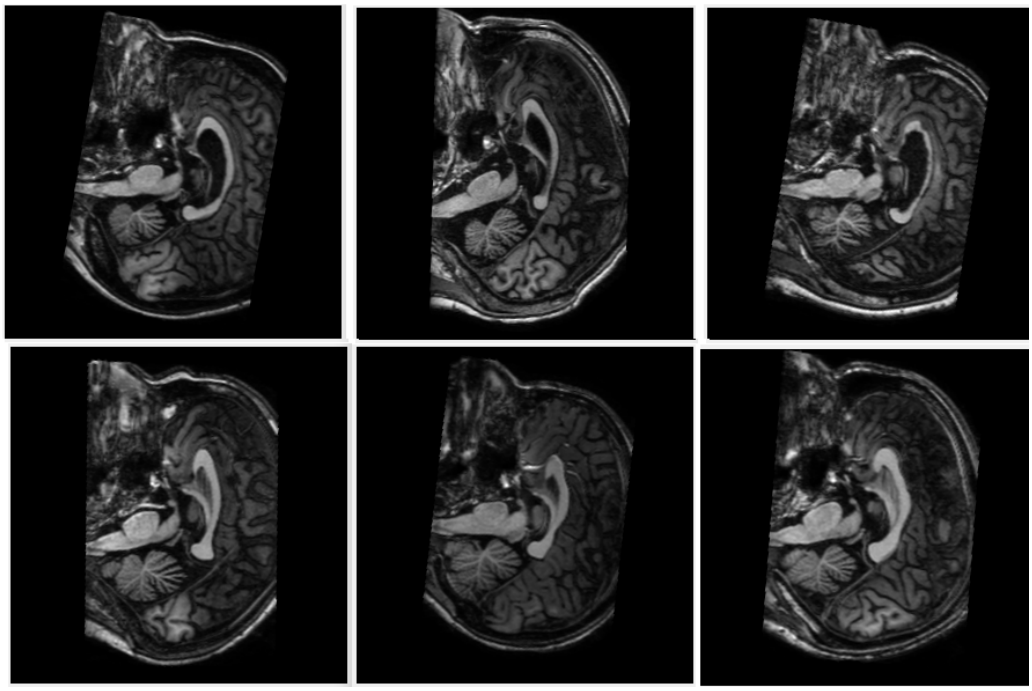

Figure 4: Sagital Slices.

$$SSD(I, J; T) = \sum_{ij} |J(T^{-1}(i, j)) - I(i, j)|^2$$

As shown in class, minimizing the SSD error is equivalent to maximizing correlation,

$$CORR(I, J; T) = \sum_{ij} J(T^{-1}(i, j))I(i, j)$$

In order to make the SSD minimzation more robuts, the histogram of the testing image J was matched to the histogram of each of the trainning images before proceeding to the pairwise registration.

Minimixing this energy using gradient descent tend to produce suboptimal results (i.e., convergence to local minima). Instead I used an Alternating Minimization approach with an adaptive step size. This was still fast and

produced accurate results.

In my current implementation, I only consider stricly rigid transformations (i.e., translations and rotations), but scale and skew transformations should be considered as well. Thus the registering transformation was of the form $T(x) = R_\theta x + t$ where R_θ is a 2D rotation by angle θ. The alternation minimization iterated between two steps: *UpdateRotation* and *UpdateTranslation* (in pratice I used 3 iterations of alternating minimization).

Each method *UpdateTranslation* and *UpdateRotation* performed an adaptive grid search. This is, I explored the error for the transformation with parameters on a uniformly separated grid (20 pixels in x and y directions for translation, 12 degrees for rotation). After I found the minima on this initial grid, I subdivide it around the optimal parameter, and keep improving the accuracy of the optimal parameter by finding minima on refined grids. The result of 2D registration for a pair of images is provided in Figure 5.

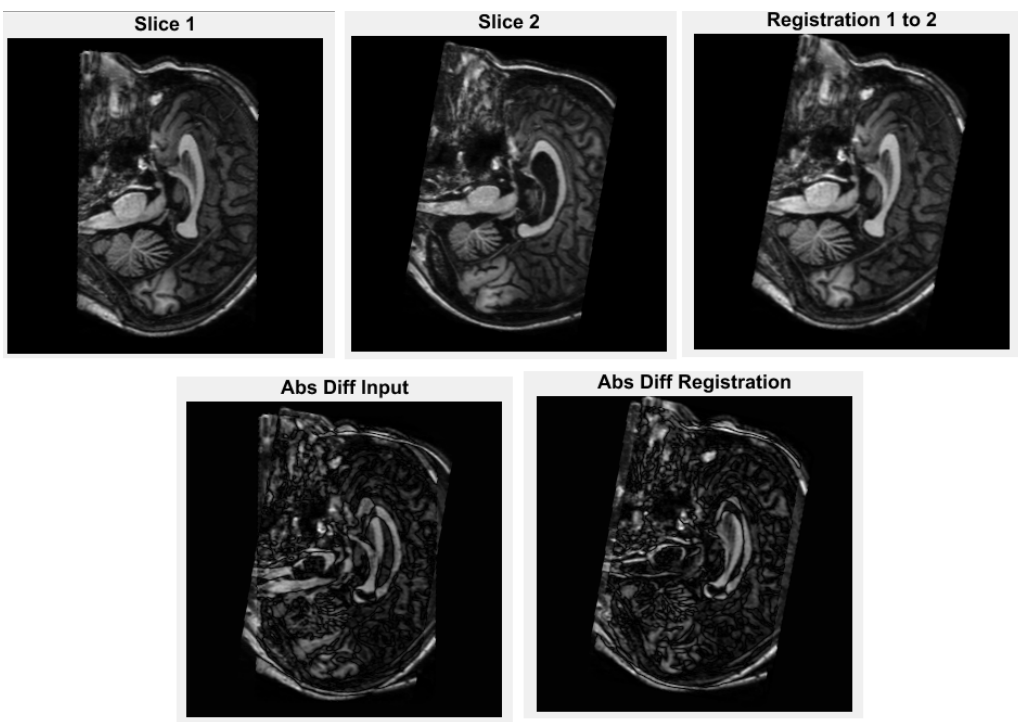

Figure 5: 2D Registration.

3.2 Full 3D Registration

This approach was developed by teammate and was the one we presented in the contest.

In this approach, the energy to be minimized is the normalized cross correlation of the signals,

$$NCC(I, J; T_\theta) = \sum \frac{(I(x) - \bar{I})(J(T^{-1}(x)) - \bar{J})}{\sigma_I \sigma_J}$$

whose parameter gradient is given by,

$$\frac{\partial}{\partial \theta} NCC(I, J; T_\theta) = \frac{1}{\sigma_I \sigma_J} \sum (I(x) - \bar{I}) \nabla (J(T_\theta^{-1}(x)) \frac{\partial}{\partial \theta} T_\theta^{-1}(x)$$

The way this energy is minimized is done is also by alternating between different groups of transformations. More specifically our method iterate between solving for the best translation, rotation , scale, general linear, and general affine transformation.

Computation of the best translation, rotation and scale is done using a Quasi-Newton BFGS minimization. The Quasi-Newton method requires the estimation of the gradient of the correlation energy respect to these parameters. This was done using the MATLAB's symbolic toolbox.

For rigid transformation we choose a 6D Lie Algebra parametrization. This parametrization allows a smooth transitions on the manifold of rigid transformation compared to other parametrizations (e.g., euler angles).

For general linear and general affine transformation we did not Quasi-Newton optimization but Neldar-Mead method.

In Figure 6 we observe the accuracy of our method when solving for the optimal rigid alignment.

In order to satisfy the imposed time constraints the intial volume was subsampled by a factor of 4 and 6.

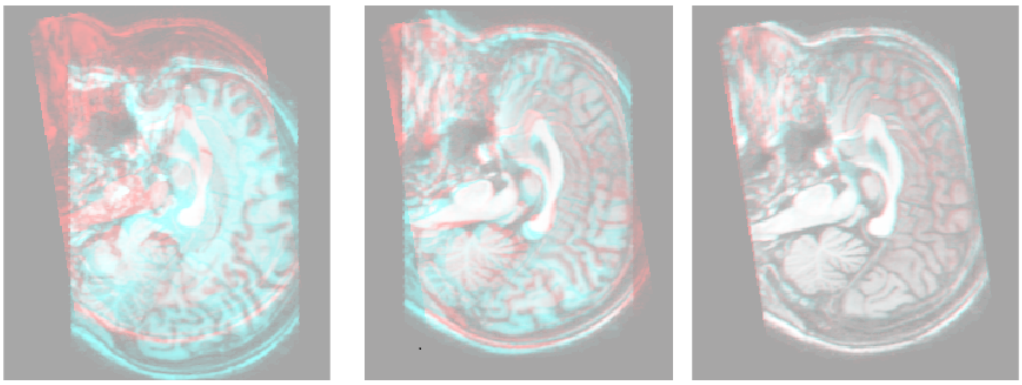

Figure 6: 3D Registration. From left to right: missalingned sagital views, results after translation correction,result after rigid correction.

4 Results

In the following table we report the results of the Sagital Detection + 2D Registration on the provided trainning data. An average score of 0.72 was obtained for pairwise registration, and an average score of 0.78 when using one-to-all registration with median box consolidation.

Cross Registration Score						
Brain ID	2000501	2000301	2000101	1003101	1001701	1000901
2000501		0.438	0.820	0.683	0.750	0.506
2000301	0.506		0.382	0.714	0.660	0.726
2000101	0.853	0.349		0.698	0.739	0.732
1003101	0.749	0.717	0.773		0.806	0.658
1001701	0.851	0.657	0.795	0.844		0.847
1000901	0.549	0.670	0.781	0.655	0.793	

Bounding Box Selection Score			
Brain ID	Lowest SSD Box	Cummulative Box	Median Box
2000501	0.506	0.459	0.733
2000301	0.726	0.607	0.655
2000101	0.732	0.463	0.794
1003101	0.658	0.727	0.805
1001701	0.847	0.734	0.908
1000901	0.549	0.577	0.777

For the Full3D registration we got an average score of 0.8163 for the one-to-all registration using a majority vote consolidation. For Full3D registration the average Dice Coefficient was 0.8391 the average distance 5.8676.

5 Team Evaluation

We compared the performance of Sagital Detection + 2D Rotation and Full3D, and observed superior performance on the latter. Thus, this was the approach we submitt for the course contest. The Full3D method was entirely developed by Rob so we must deserve a contribution score of 3. We interchanged ideas about both registration methods and about how was the best way to consolidate a bounding box (or a thalamus mask) after computing the alignment transformations. Since I also implemented a registration method for the task, that despite its simplicity provides an acceptable performance I would give a score of 2 to my contribution. Our submitted method (Full3D) got a slightly lower performance than the expected in the contest. According to the contest results our method performed well on the imges prefixed by 100 but did not do as well for those prefixed by 200.

6 Conclusions

Full3D registration provided a superior performance compared to my symmetry based approach. This is sound given that Full3D registration coupled with a Quasi-Newton solver allow a wider parameter space search. My method is also prone to a poor initialization : if the central sagital plane is not properly identified at the beginning this wont be corrected at further steps of the algorithm. Also the use of a NCC energy was more robust than

the more simple SSD. Our best method (Full3D) performed satisfactory both in trainning data and int the contest.

References

[1] Brian B. Avants, Charles L. Epstein, Murray Grossman, and James C. Gee. Symmetric diffeomorphic image registration with cross-correlation: Evaluating automated labeling of elderly and neurodegenerative brain. *Medical Image Analysis*, 12(1):26–41, 2008.

[2] Paul J. Besl and Neil D. McKay. A method for registration of 3-d shapes. *IEEE Trans. Pattern Anal. Mach. Intell.*, 14(2):239–256, February 1992.

[3] Derek LG Hill, Philipp G Batchelor, Mark Holden, and David J Hawkes. Medical image registration. *Physics in medicine and biology*, 46(3):R1, 2001.

[4] Berthold K.P. Horn and Brian G. Schunck. Determining optical flow. Technical report, Cambridge, MA, USA, 1980.

[5] Tom Vercauteren, Xavier Pennec, Aymeric Perchant, and Nicholas Ayache. Diffeomorphic demons: Efficient non-parametric image registration. *NeuroImage*, 45(1, Supplement 1):S61 – S72, 2009. Mathematics in Brain Imaging.