Atlas-based Segmentation
Medical Image Registration and Applications

Md. Kamrul Hasan, Basel Alyafi, Fakrul Islam Tushar

January 25, 2019

Contents

1 Introduction

Image segmentation is the process of dividing the image into non-overlapping regions. It is considered as a hard job for specialists who usually spend long times specifying pixels to which region they belong. Automatic segmentation makes that job easier and has a wide range of techniques and a long list of applications. One of the most promising techniques that has been widely used in image segmentation is Atlas-based image segmentation. In this report, atlas is going to be used in the medical domain using brain image of MICCAI challenge to segment the brain into the following non-overlapping regions:

1. Cerebrospinal Fluid (label 1).
2. White matter (label 2).
3. Gray matter (label 3).

2 Atlas Construction

To construct an Atlas, The main steps are as follows:

1. Register the dataset to one representative image (selecting this image is discussed later in 2.1).
2. Apply the transformation got from the previous registration on dataset labels.
3. Average the registered images to get the template image.
4. Extract different regions pixels from registered labels and average them.

To see the bird-eye view, Fig. 1 and Fig. 2 show the complete process of constructing the template image and labels.

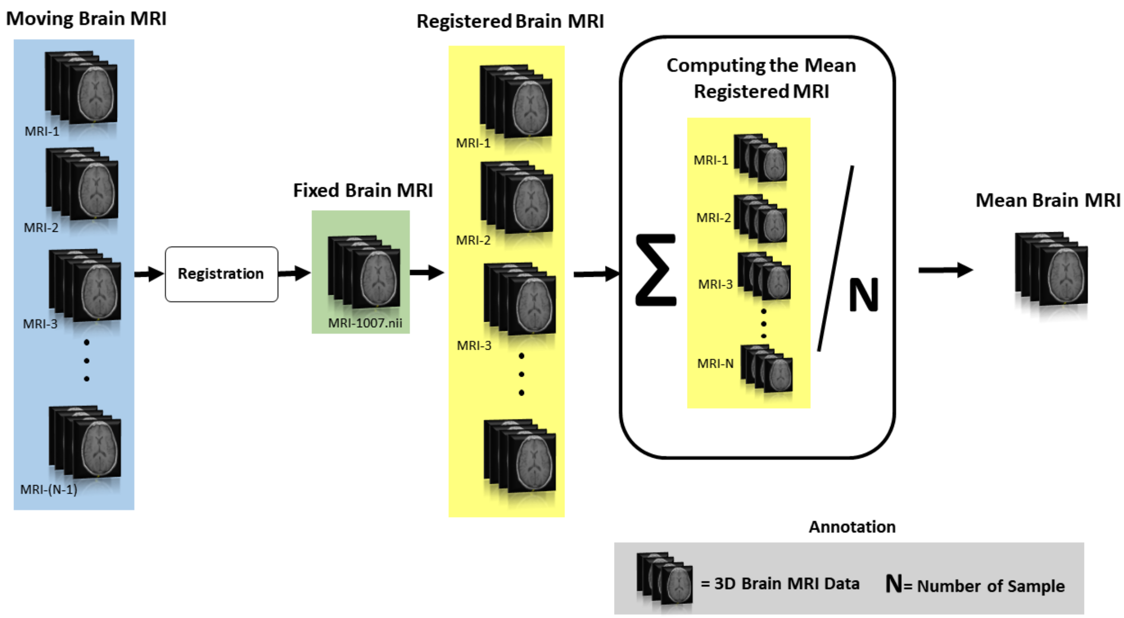

Figure 1: The pipeline of constructing Atlas template image

2.1 Database Registration

To register the database images, a good representative should be selected wisely. The way that was done in this report is as follows:

1. Use one image as fixed and all others as moving
2. Register all moving images (Affine Transform) with the fixed one and measure individual Normalized Cross Correlation.
3. Record metric values
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5. Pick the one with the most-stable, has short legs!, and accepted-median metric values, see Fig. 3

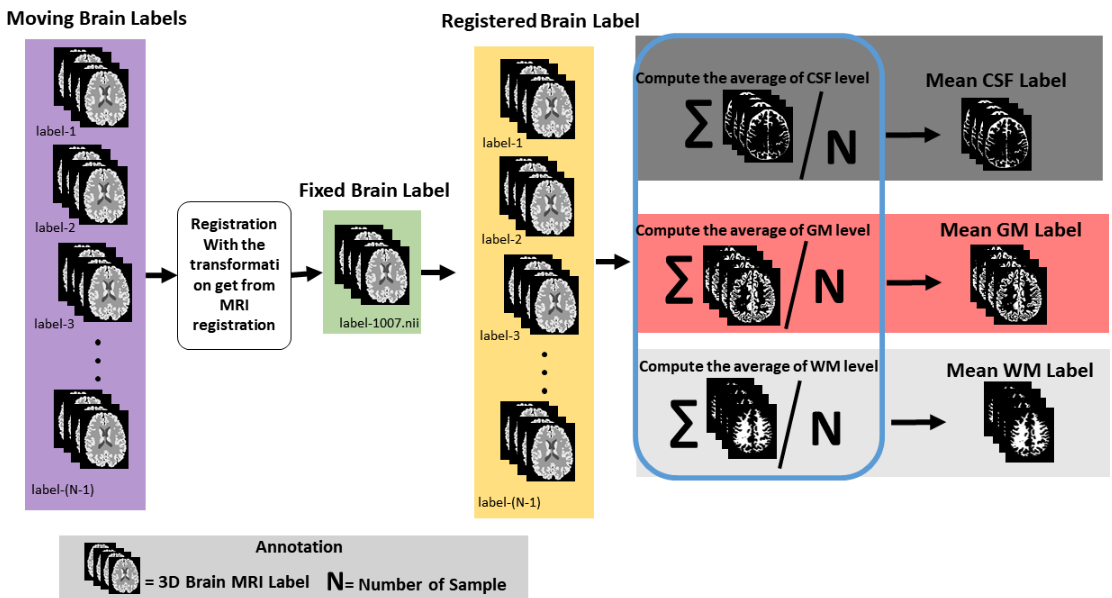

Figure 2: The pipeline of constructing Atlas template labels

After applying the previous algorithm, image 1007 was selected because it showed relatively robust results. Analysis the box-plot we can see NCC is varying a lot for dinned MRI as fixed image. Fig. 3 shown MRI data "1007.nii" and "1008.nii" giving the maximum median for the NCC as fixed image compared to others and there is no outliers in both cases.Now if we compared the outcomes for "1007.nii" and "1008.nii" it can be seen that "1007.nii" has small range for The upper and lower whiskers compared to the "1008.nii" which represents less score outside the middle 50%. considering all this factor "1007.nii" is selected as fixed image for the registration process.

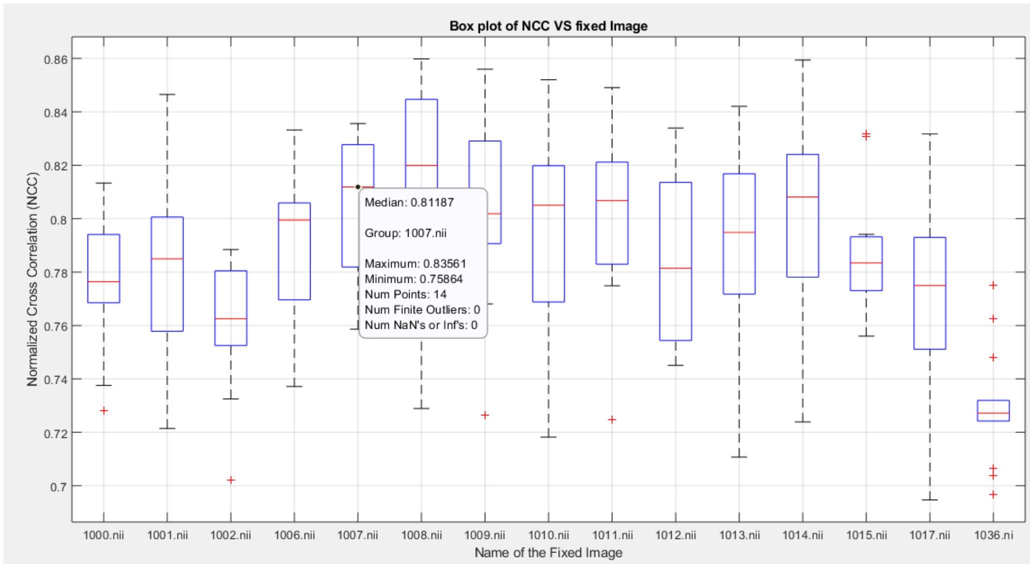

Figure 3: The boxplot showing the statistics for different fixed images and corresponding normalized cross correlation

2.2 Elastix Parametric file Parameters Selection

In this section we will discuss about the registration methods and parameter selection. The desired registration was performed in two steps,first an Affine (rigid registration) registration was applied for initial alignment, afterwards, a non-rigid registration namely B-SPLINE REGISTRATION was applied as a final registration. Below, first, we discuss parameters selection for the initial registration and we elaborate to it to final registration.

2.3 Initial Registration

The main characteristic of this parameter file is the `AffineTransform`. The idea of doing so is to match the large picture (scale, translation, rotation, etc..) without going into details. A picture is worth a thousand words. Fig. 4 shows the 141^{th} axial slice from the following:

- Fixed is 1007 always.
- Moving is 1000.
- Result is the registration result.

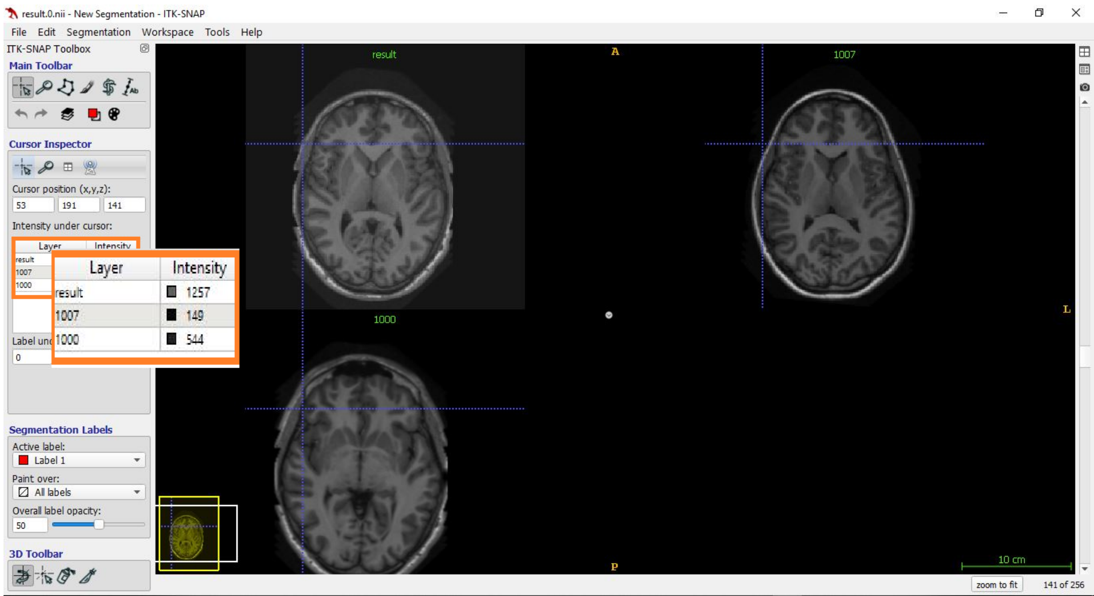

Figure 4: Affine Registration, the 141^{th} axial slice

From the figure, it can be read that, (53, 191) point is on the skull of the registered image while it is background for the fixed image due to unfeasible (using affine transformation) deformations.

2.3.1 Multi-resolution Framework

Our experience from the previous lab works proved that multi-resolution framework increases the chance of successful registration. So, here we have used multi-resolution frame. We used Gaussian pyramid for our registration. In Elastix parametric file its defines as,

```
(FixedImagePyramid "FixedRecursiveImagePyramid")
(MovingImagePyramid "MovingRecursiveImagePyramid")
```

In Elastix, Gaussian pyramid applies smoothing and down-sampling. Next, we defined the number of resolution or level of pyramid we want to use. In general 3 resolution is good starting point but as recommended in [1] for 3D data is better to use up-to 5. we use 5 resolution. The default scheduler was used smoothing and down-sampling which smooth the fixed image by a factor of 2 in each dimension.

2.3.2 Image Sampler

In general, during registration looping over all the voxels of the of the fixed image is not necessary a subset is enough for the registration. In Elastix Image Sampler defines this sampling strategies with different options as random, on a grid, etc. We used A random coordinate sampler as it states in [1] to be performed well in conjunction with the AdaptiveStochasticGradientDescent optimizers which is been used a optimizer for the registration.

```
(ImageSampler "RandomCoordinate")
```

Then we defined the amount of samples, randomly selected in every iteration and enforce the selection of new samples in every iteration by the 2 lines below respectively.

```
(NewSamplesEveryIteration "true")
```

2.3.3 Interpolation

During Optimization for evaluating the non-voxels position the interpolation is used. Elastix provides a range of interpolation option such as Nearest neighbor, Linear and n-th order B-spline. In our registration Linear interpolation is used as it fast and a good trade-off between quality and speed.

```
(Interpolator "LinearInterpolator")
```

For generating the final result is Elastix we need to define ResampleInterpolator. Which is shown below,

```
(ResampleInterpolator "FinalBSplineInterpolator")
(Resampler "DefaultResampler")
```

2.3.4 Transformation

We have performed a rigid registration using affine transformation. Affine transformation allows the translation, rotation,scaling and sharing. The parameter vector for the affine transformation is a vector of 12 parameters for 3D volume.Elastix using following line in parameter file we defined affine transformation,

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(Transform "AffineTransform")
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Affine transform require a centre of rotation, by default the geometric centre of the fixed image is taken, which is recommended [1]. In affine a important parameter is scale that we need to set. It is recommended in [1] to let the elastix compute it automatically. the line below was used to perform this.

```
(AutomaticScalesEstimation "true")
```

2.3.5 Metric

To optimize the error and perform better registration elastix provides numbers of similarity measures such as, Mean Square Differences (MSD), Normalized Correlation Coefficient (NCC), Mutual Information (MI) etc. In our registration we used NCC as metric which is defined by this equation.

$$NCC = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2(y_i - \overline{y})^2}} \tag{1}$$

where x_i=fixed image, $\overline{x} = mean\ of\ fixed\ image$, y_i=Moving Image, $\overline{y}$ =mean of moving image.

In Elastix it's defined as below,

```
(Metric "AdvancedNormalizedCorrelation")
```

NCC assumes a linear relation between the intensity values of the fixed and moving image [1].

2.3.6 Optimizer

In our registration as a optimizer we have used AdaptiveStochasticGradientDescent which is advanced version of StandardGradientDescent but avoids the gain factor initialization problem of StandardGradientDescent. AdaptiveStochasticGradientDescent it estimate proper initial value automatically. It is defined in the Elastix parameter file as below,

```
(Optimizer "AdaptiveStochasticGradientDescent")
```

Reasonable values for the parameters was estimated using displacement distribution using following line.

```
(ASGDParameterEstimationMethod "DisplacementDistribution")
```

2.4 Final Registration (B-spline)

For the final registration we applied Bspline non-rigid registration. For the final registration all the parameters discussed in the initial parameter Section 2.3 except for final registration the Transformation used it's `BSplineTransform`

In this case, the major difference is that the transformation here is `BSplineTransformation`. Fig. 5 shows a comparison with Fig.4.

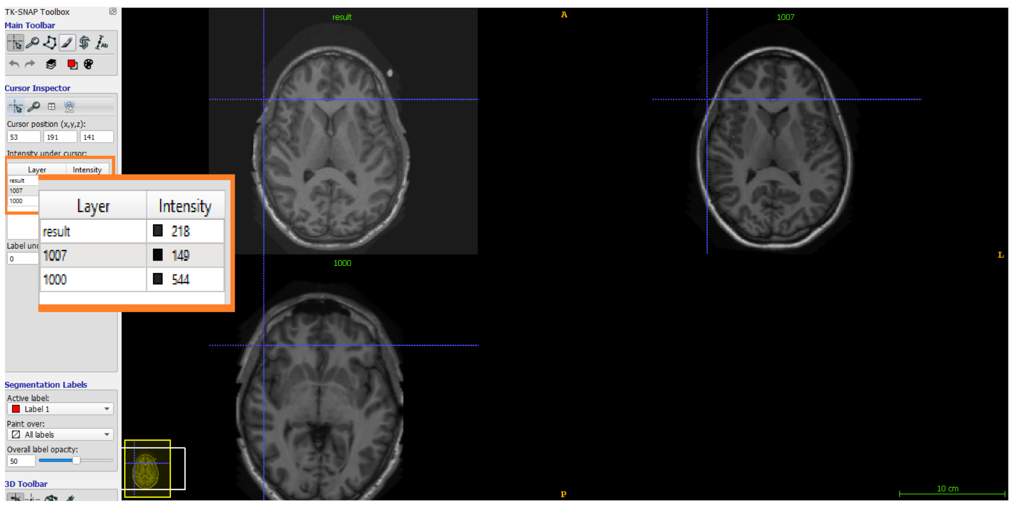


Figure 5: Using BSpline Transformation, the axial slice 141 becomes more similar to the fixed one

From Fig.5, it is obvious that point (53,191) in both the registered and fixed image is on the skull with closer intensities that using the affine transformation.

2.4.1 Transformation:BSplineTransform

The B-spline nonrigid transformation is defined by a uniform grid of control points. This grid is defined by the spacing between the grid nodes[1].Following line dine the transformation

```
(ResampleInterpolator "FinalBSplineInterpolator")
```

according to [1] most of the literature used cubic B-spline which ic is the 3rd order B-spline. following line was used to define the 3d order B-spline.

(FinalBSplineInterpolationOrder 3)

Initial and Final registration elastix's parameter files were shown below.

Elastix Parameter File

Initial Registration (Affine)
`(Registration "MultiResolutionRegistration")`
`(Metric "AdvancedNormalizedCorrelation")`
`(ImageSampler "RandomCoordinate")`
`(Interpolator "LinearInterpolator")`
`(ResampleInterpolator "FinalBSplineInterpolator")`
`(Resampler "DefaultResampler")`
`(Transform "AffineTransform")`
`(Optimizer "AdaptiveStochasticGradientDescent")`
`(FixedImagePyramid "FixedSmoothingImagePyramid")`
`(MovingImagePyramid "MovingSmoothingImagePyramid")`
`(NewSamplesEveryIteration "true")`
`(NumberOfResolutions 5)`
`(FinalBSplineInterpolationOrder 3)`
`(AutomaticScalesEstimation "true")`
`(ASGDParameterEstimationMethod "DisplacementDistribution")`
`(FixedInternalImagePixelType "float")`
`(MovingInternalImagePixelType "float")`
`(HowToCombineTransforms "Compose")`
`(ResultImageFormat "nii")`

2.5 Atlas Template and Labels

After applying the algorithm described in the previous two sections, the representative template and transformed (three) labels are available to play with. Fig. 7, Fig. 8, and Fig. 9 show a few slices of the template image. Figures 10, 11, 12, 13, 14, 15, 16 show different slices from average labels.

Final Registration (B-spline)
`(Registration "MultiResolutionRegistration")`
`(Metric "AdvancedNormalizedCorrelation")`
`(ImageSampler "RandomCoordinate")`
`(Interpolator "LinearInterpolator")`
`(ResampleInterpolator "FinalBSplineInterpolator")`
`(Resampler "DefaultResampler")`
`(Transform "BSplineTransform")`
`(Optimizer "AdaptiveStochasticGradientDescent")`
`(FixedImagePyramid "FixedSmoothingImagePyramid")`
`(MovingImagePyramid "MovingSmoothingImagePyramid")`
`(NewSamplesEveryIteration "true")`
`(NumberOfResolutions 5)`
`(FinalBSplineInterpolationOrder 3)`
`(AutomaticScalesEstimation "true")`
`(ASGDParameterEstimationMethod "DisplacementDistribution")`
`(FixedInternalImagePixelType "float")`
`(MovingInternalImagePixelType "float")`
`(HowToCombineTransforms "Compose")`
`(ResultImageFormat "nii")`

3 Results and Discussion

To evaluate the results, two ways were used: quantitative (Normalized Cross Correlation) and qualitative (by looking at results on ITK-snap). First, let's look at the NCC values for registering the dataset to image 1007, in other words, 1007 is fixed image and all others are moving. Table 1 shows the values with the average and standard deviation at the end. Those results were taken from `elastix` log files for the final registration (`BSplaineTransformation`) and last iteration and resolution. By comparing values for the boxplot shown in Fig.3 for 1007 as fixed and the median shown in Table 1, the benefit of using `BSplineTransformation` becomes clear.

3.1 Registered Tissue Models

To have a look at the distributions of pixels after registration, alg. 1 was followed.

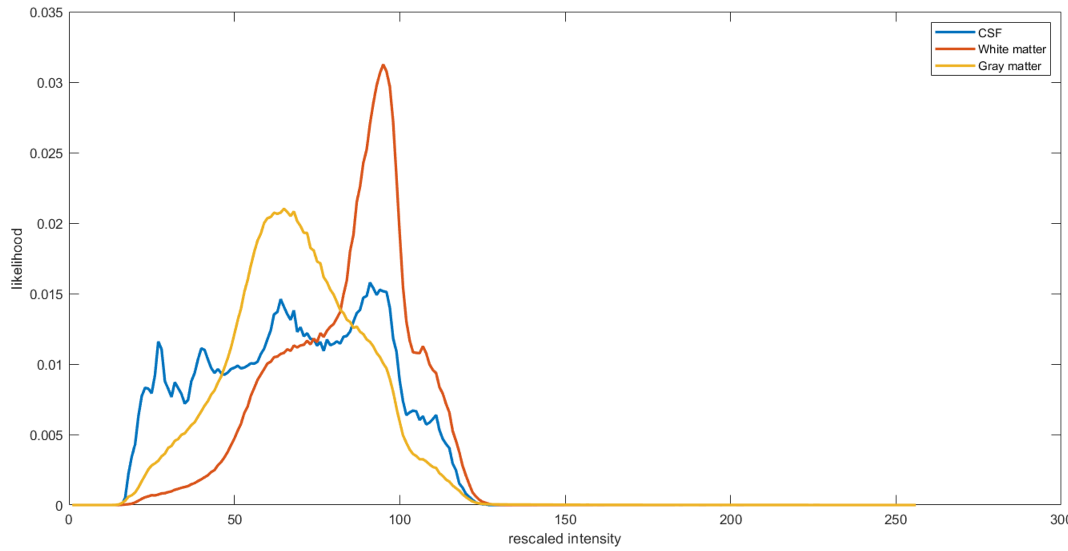
Algorithm 1 Tissue model calculation

1: rescale the image to have a predefined range [0,N]
2: extract regions pixels $(R_{CSF}, R_{WM}, R_{GM})$
3: $H_1 = Normalized\_Histogram(R_{CSF}, N+1)$; //N+1 bins
4: $H_2 = Normalized\_Histogram(R_{WM}, N+1)$
5: $H_3 = Normalized\_Histogram(R_{GM}, N+1)$
6: $H_j(i) = H_j(i)/\sum_{j=1}^{3} H_j(i);\ i = 0, 1, 2, \ldots, N$

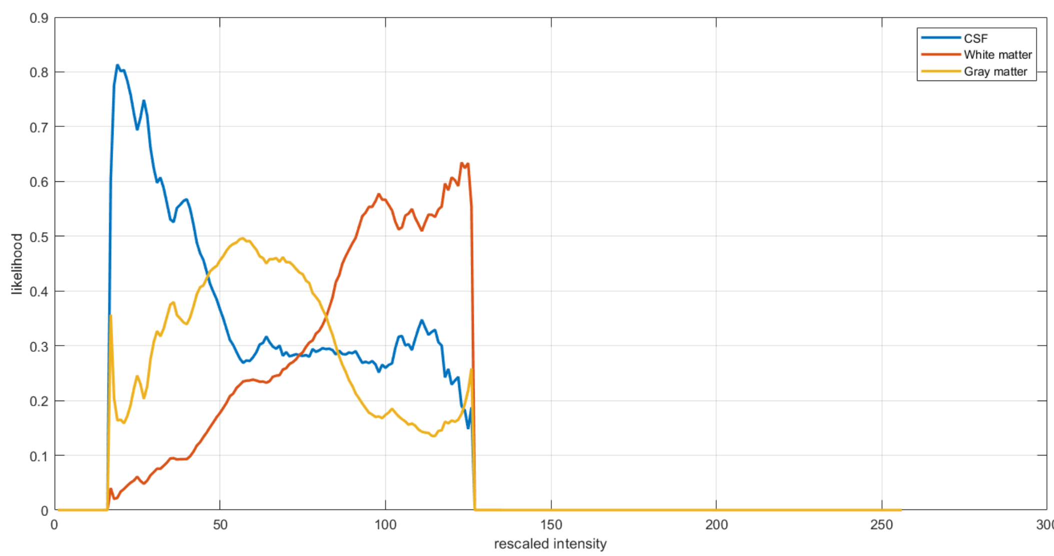
Moving Image name	**-NCC value**
1000	-0.957
1001	-0.962
1002	-0.917
1006	-0.960
1008	-0.971
1009	-0.966
1010	-0.968
1011	-0.967
1012	-0.965
1013	-0.953
1014	-0.962
1015	-0.959
1017	-0.965
1036	-0.949
Median	**-0.962**
Average	**-0.958**
Std	**0.0129**

Table 1: Metric values for registering the dataset to 1007

The idea of making the tissue model is to have probabilities that can be used for segmenting the tissues. At any vertical line, inside available intensities, the sum of probabilities is one, see Fig.6.



(a) tissue-wise normalized histogram



(b) tissue model probabilities

Figure 6: Comparison between the normalized histogram and tissues models

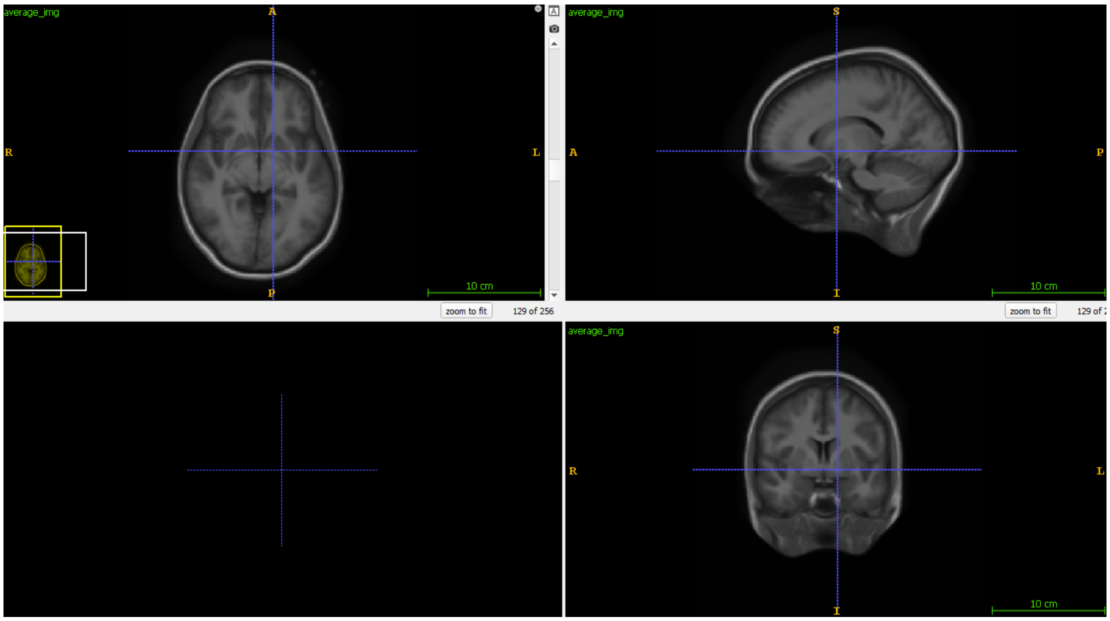


Figure 7: Axial slice = 129, sagittal, and coronal slices in the template image

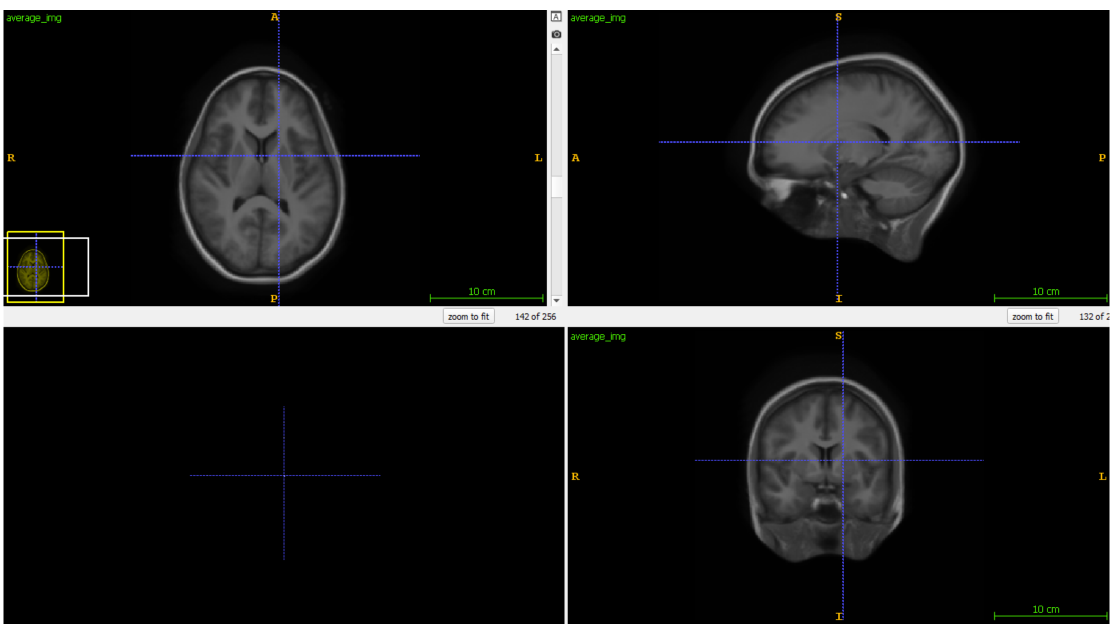


Figure 8: Axial slice = 142, sagittal, and coronal slices in the template image

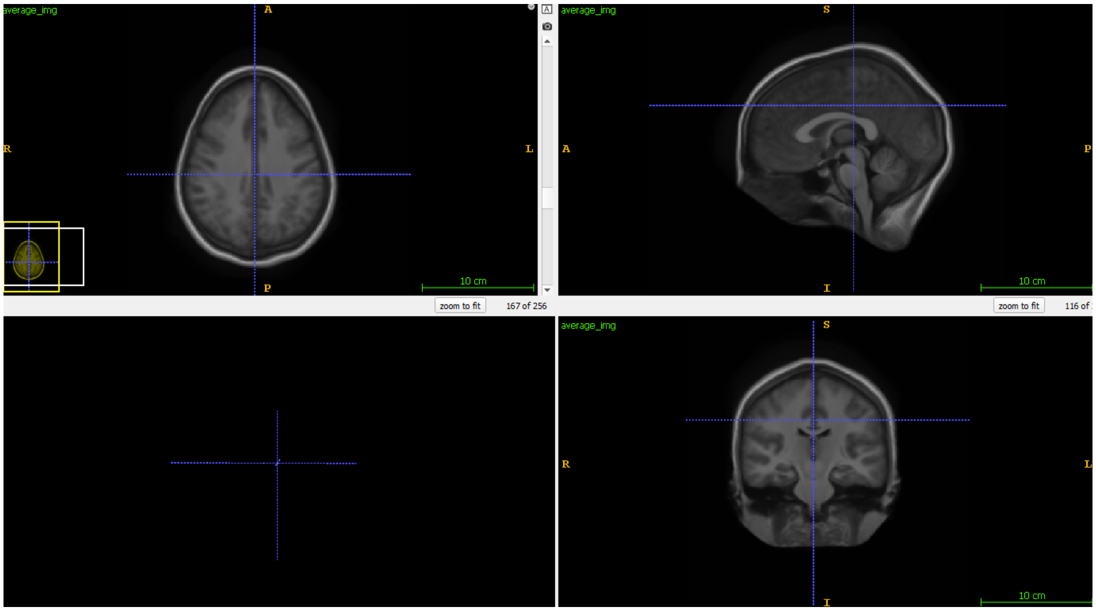


Figure 9: Axial slice = 167, sagittal, and coronal slices in the template image

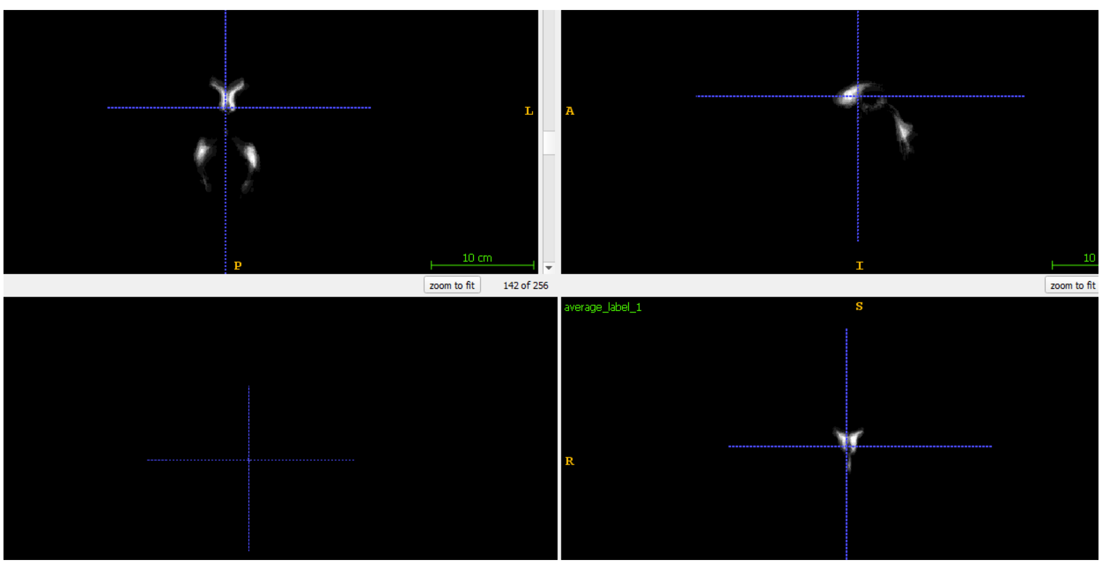


Figure 10: Axial=115, sagittal, and slices from the template label of CSF region

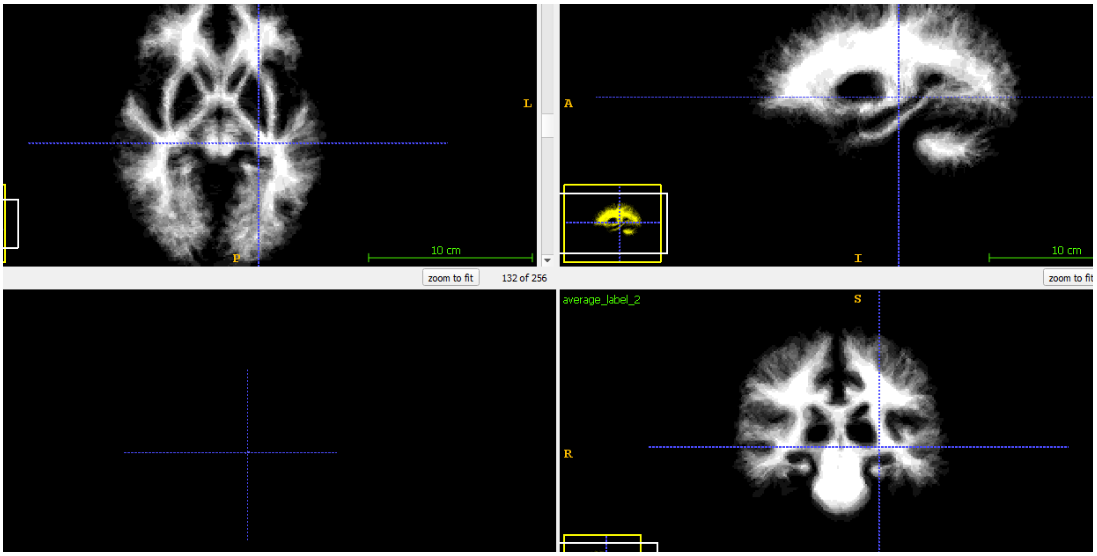


Figure 11: Axial slice = 132, from the template label of White matter (WM) region

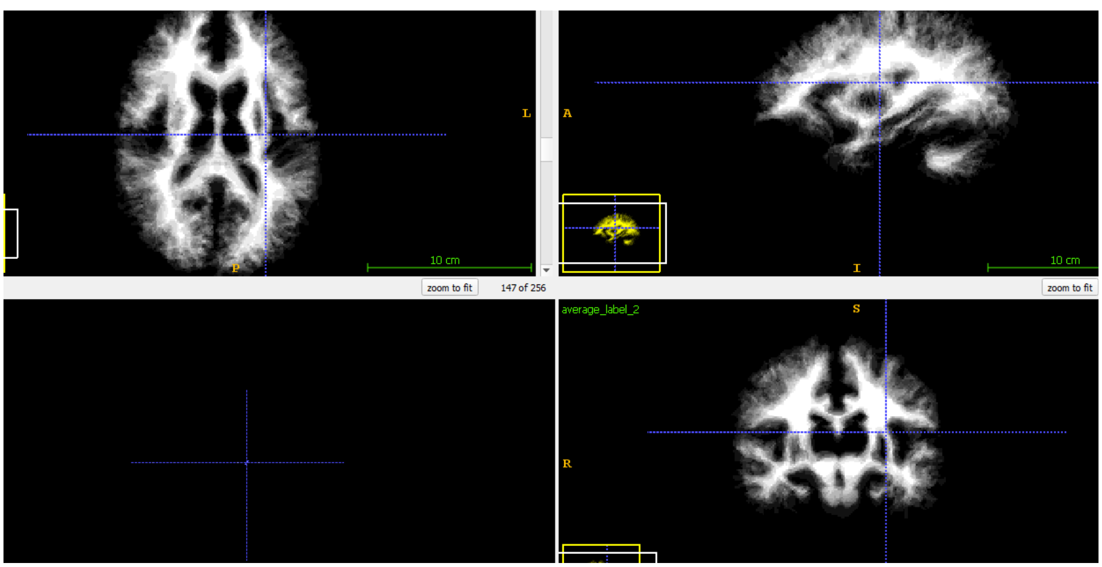


Figure 12: Axial = 147, sagittal, and coronal slices from the template label of White matter (WM) region

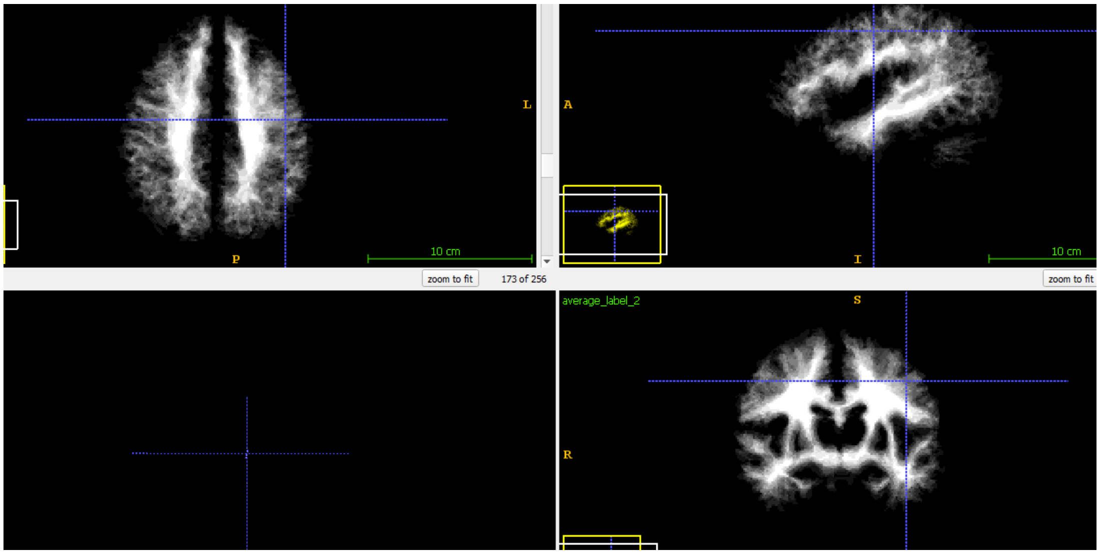


Figure 13: Axial = 173, sagittal, and coronal slices from the template label of White matter (WM) region

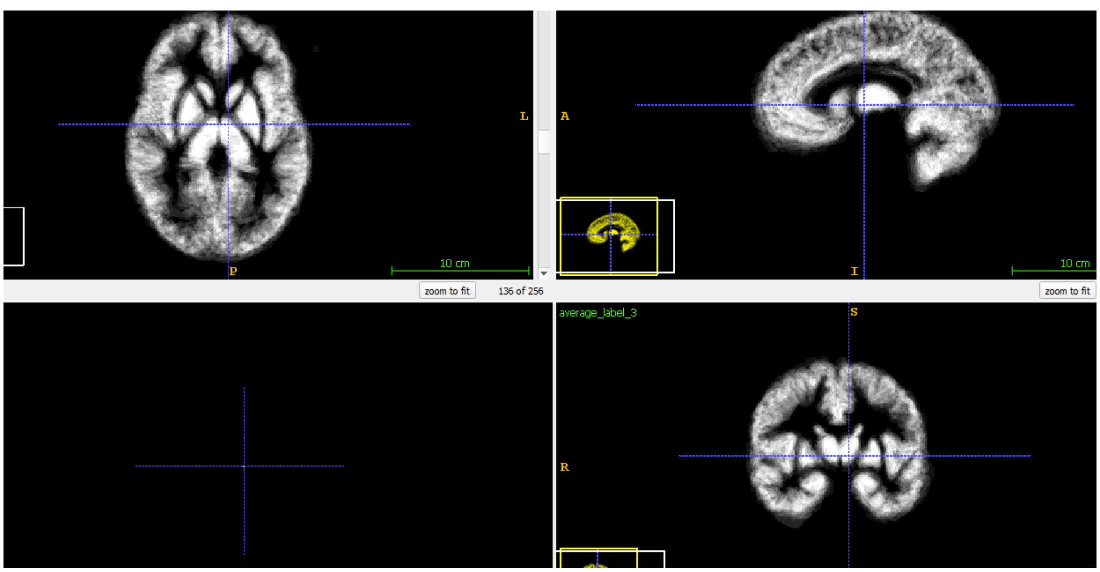


Figure 14: Axial slice = 136 of average label 3 (Gray matter)

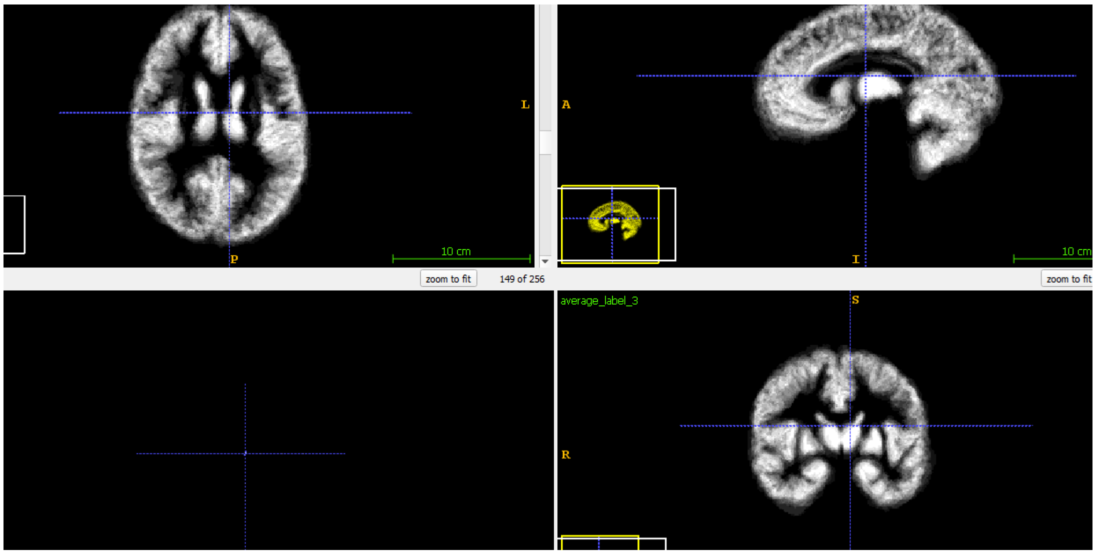


Figure 15: Axial slice = 149 of average label 3 (Gray matter)

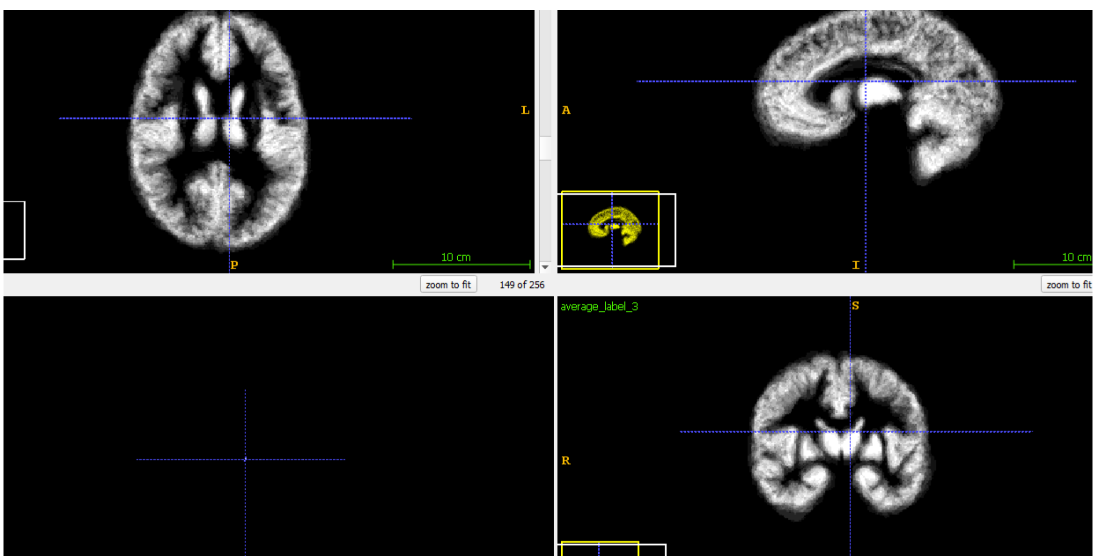


Figure 16: Axial slice = 171 of average label 3 (Gray matter)

References

[1] K. Stefen, and S. Marius, "elastix the manual," September 4, 2015.

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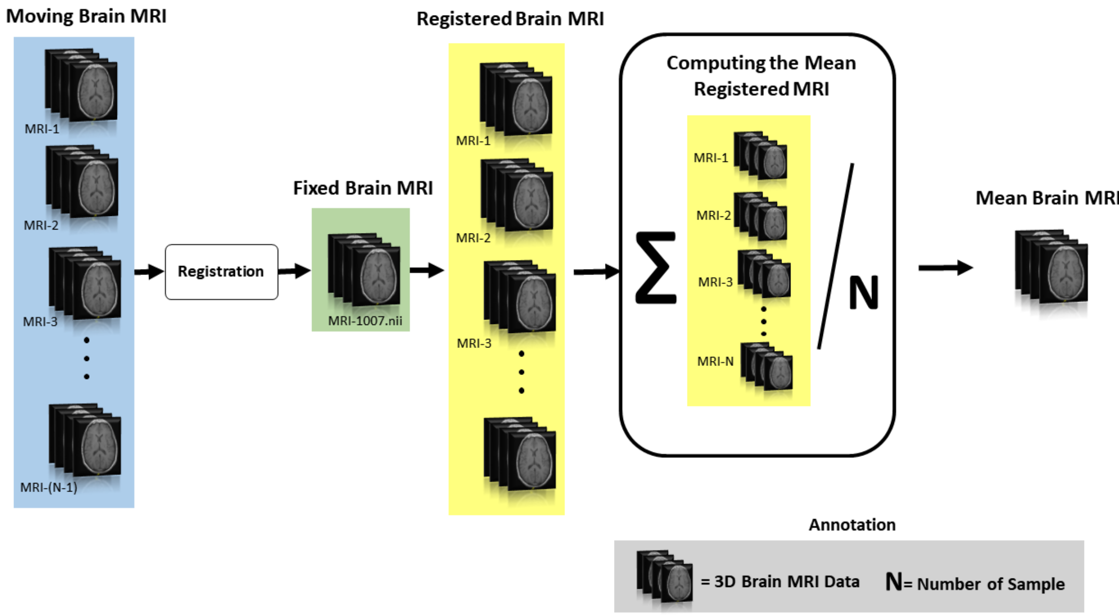

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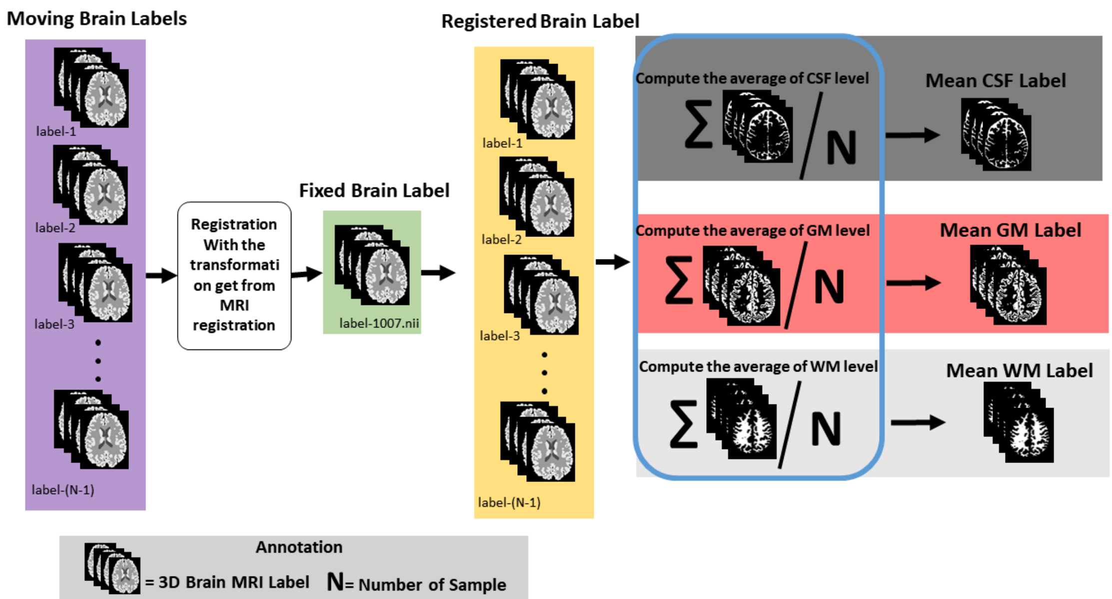

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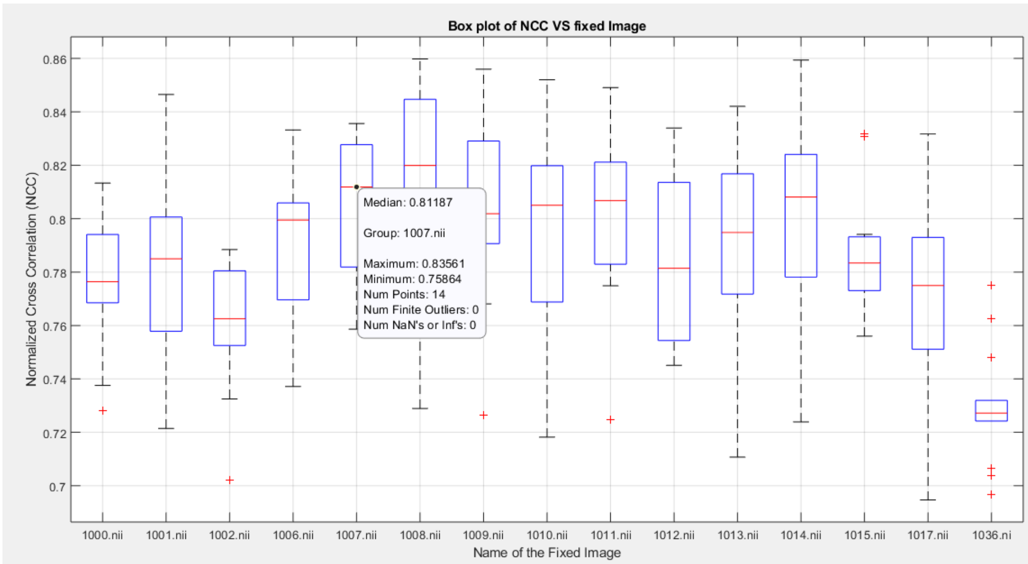

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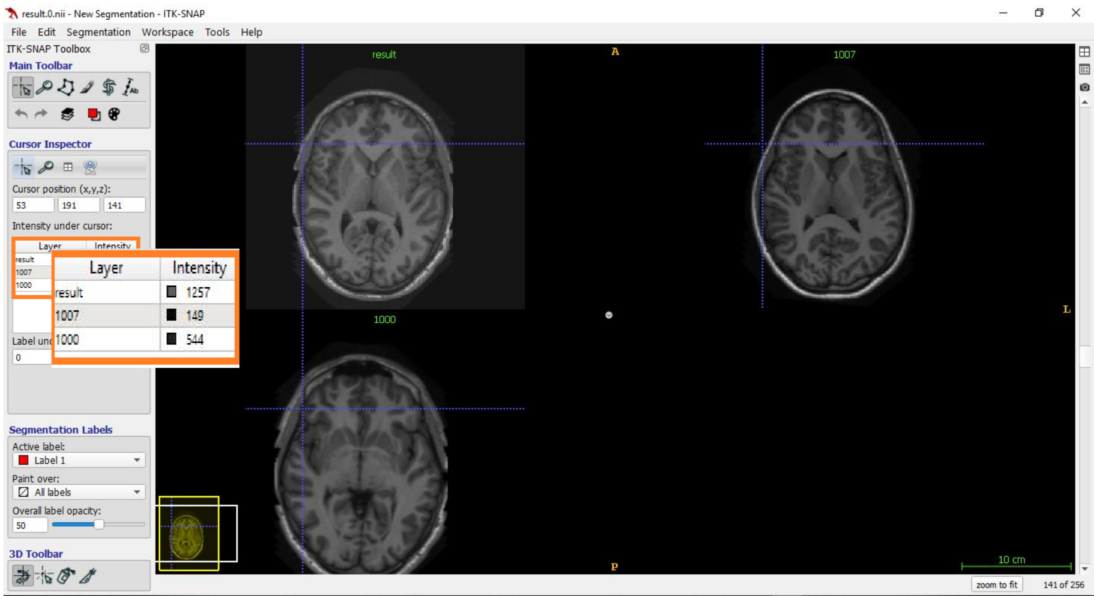

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In this case, the major difference is that the transformation here is `BSplineTransformation`. Fig. 5 shows a comparison with Fig.4.

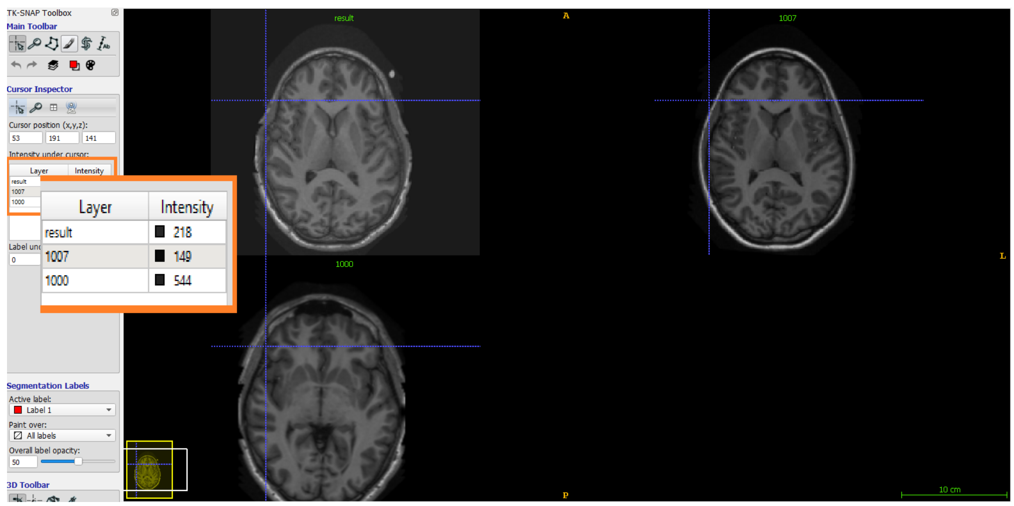


Figure 5: Using BSpline Transformation, the axial slice 141 becomes more similar to the fixed one

From Fig.5, it is obvious that point (53,191) in both the registered and fixed image is on the skull with closer intensities that using the affine transformation.

2.4.1 Transformation:BSplineTransform

The B-spline nonrigid transformation is defined by a uniform grid of control points. This grid is defined by the spacing between the grid nodes[1].Following line dine the transformation

```
(ResampleInterpolator "FinalBSplineInterpolator")
```

according to [1] most of the literature used cubic B-spline which ic is the 3rd order B-spline. following line was used to define the 3d order B-spline.

(FinalBSplineInterpolationOrder 3)

Initial and Final registration elastix's parameter files were shown below.

Elastix Parameter File

Initial Registration (Affine)
`(Registration "MultiResolutionRegistration")`
`(Metric "AdvancedNormalizedCorrelation")`
`(ImageSampler "RandomCoordinate")`
`(Interpolator "LinearInterpolator")`
`(ResampleInterpolator "FinalBSplineInterpolator")`
`(Resampler "DefaultResampler")`
`(Transform "AffineTransform")`
`(Optimizer "AdaptiveStochasticGradientDescent")`
`(FixedImagePyramid "FixedSmoothingImagePyramid")`
`(MovingImagePyramid "MovingSmoothingImagePyramid")`
`(NewSamplesEveryIteration "true")`
`(NumberOfResolutions 5)`
`(FinalBSplineInterpolationOrder 3)`
`(AutomaticScalesEstimation "true")`
`(ASGDParameterEstimationMethod "DisplacementDistribution")`
`(FixedInternalImagePixelType "float")`
`(MovingInternalImagePixelType "float")`
`(HowToCombineTransforms "Compose")`
`(ResultImageFormat "nii")`

2.5 Atlas Template and Labels

After applying the algorithm described in the previous two sections, the representative template and transformed (three) labels are available to play with. Fig. 7, Fig. 8, and Fig. 9 show a few slices of the template image. Figures 10, 11, 12, 13, 14, 15, 16 show different slices from average labels.

Final Registration (B-spline)
`(Registration "MultiResolutionRegistration")`
`(Metric "AdvancedNormalizedCorrelation")`
`(ImageSampler "RandomCoordinate")`
`(Interpolator "LinearInterpolator")`
`(ResampleInterpolator "FinalBSplineInterpolator")`
`(Resampler "DefaultResampler")`
`(Transform "BSplineTransform")`
`(Optimizer "AdaptiveStochasticGradientDescent")`
`(FixedImagePyramid "FixedSmoothingImagePyramid")`
`(MovingImagePyramid "MovingSmoothingImagePyramid")`
`(NewSamplesEveryIteration "true")`
`(NumberOfResolutions 5)`
`(FinalBSplineInterpolationOrder 3)`
`(AutomaticScalesEstimation "true")`
`(ASGDParameterEstimationMethod "DisplacementDistribution")`
`(FixedInternalImagePixelType "float")`
`(MovingInternalImagePixelType "float")`
`(HowToCombineTransforms "Compose")`
`(ResultImageFormat "nii")`

3 Results and Discussion

To evaluate the results, two ways were used: quantitative (Normalized Cross Correlation) and qualitative (by looking at results on ITK-snap). First, let's look at the NCC values for registering the dataset to image 1007, in other words, 1007 is fixed image and all others are moving. Table 1 shows the values with the average and standard deviation at the end. Those results were taken from `elastix` log files for the final registration (`BSplaineTransformation`) and last iteration and resolution. By comparing values for the boxplot shown in Fig.3 for 1007 as fixed and the median shown in Table 1, the benefit of using `BSplineTransformation` becomes clear.

3.1 Registered Tissue Models

To have a look at the distributions of pixels after registration, alg. 1 was followed.

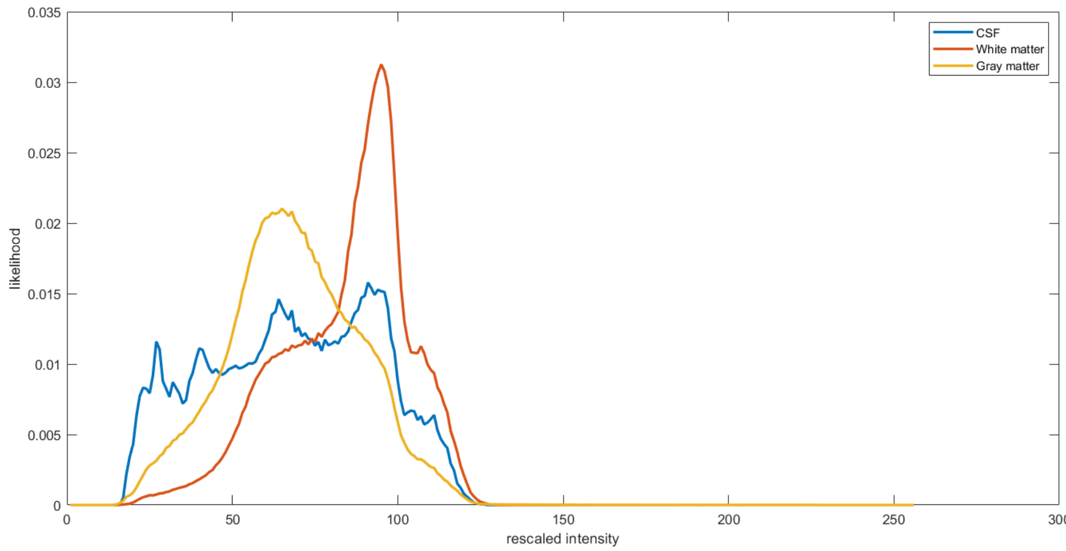
Algorithm 1 Tissue model calculation

1: rescale the image to have a predefined range [0,N]
2: extract regions pixels (R_{CSF}, R_{WM}, R_{GM})
3: $H_1 = Normalized\_Histogram(R_{CSF}, N+1)$; //N+1 bins
4: $H_2 = Normalized\_Histogram(R_{WM}, N+1)$
5: $H_3 = Normalized\_Histogram(R_{GM}, N+1)$
6: $H_j(i) = H_j(i)/\sum_{j=1}^{3} H_j(i);\ i = 0, 1, 2, \ldots, N$

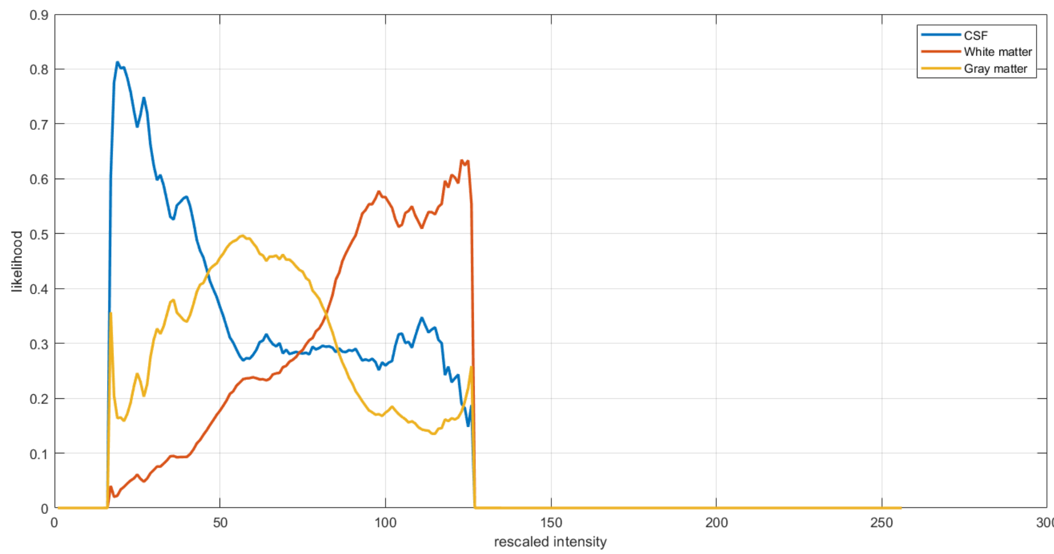
Moving Image name	**-NCC value**
1000	-0.957
1001	-0.962
1002	-0.917
1006	-0.960
1008	-0.971
1009	-0.966
1010	-0.968
1011	-0.967
1012	-0.965
1013	-0.953
1014	-0.962
1015	-0.959
1017	-0.965
1036	-0.949
Median	**-0.962**
Average	**-0.958**
Std	**0.0129**

Table 1: Metric values for registering the dataset to 1007

The idea of making the tissue model is to have probabilities that can be used for segmenting the tissues. At any vertical line, inside available intensities, the sum of probabilities is one, see Fig.6.



(a) tissue-wise normalized histogram



(b) tissue model probabilities

Figure 6: Comparison between the normalized histogram and tissues models

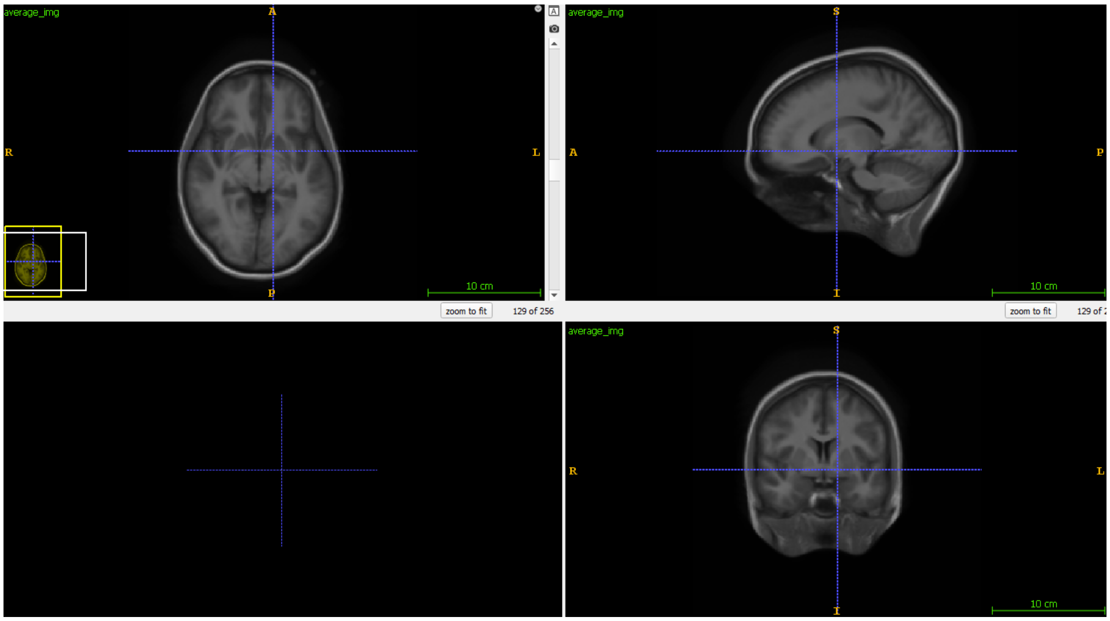


Figure 7: Axial slice = 129, sagittal, and coronal slices in the template image

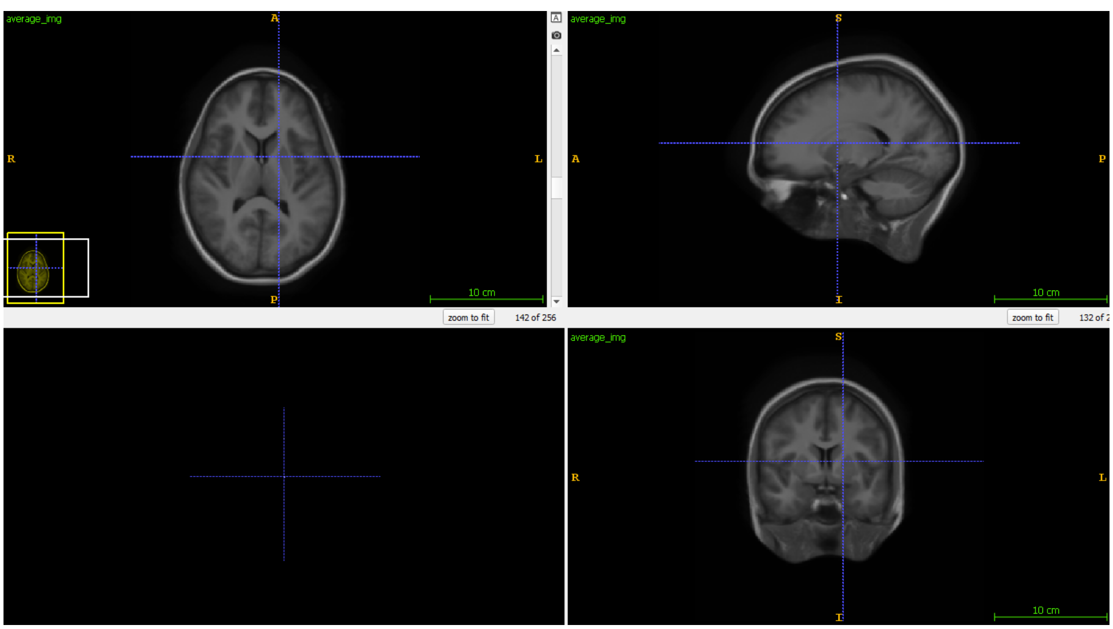


Figure 8: Axial slice = 142, sagittal, and coronal slices in the template image

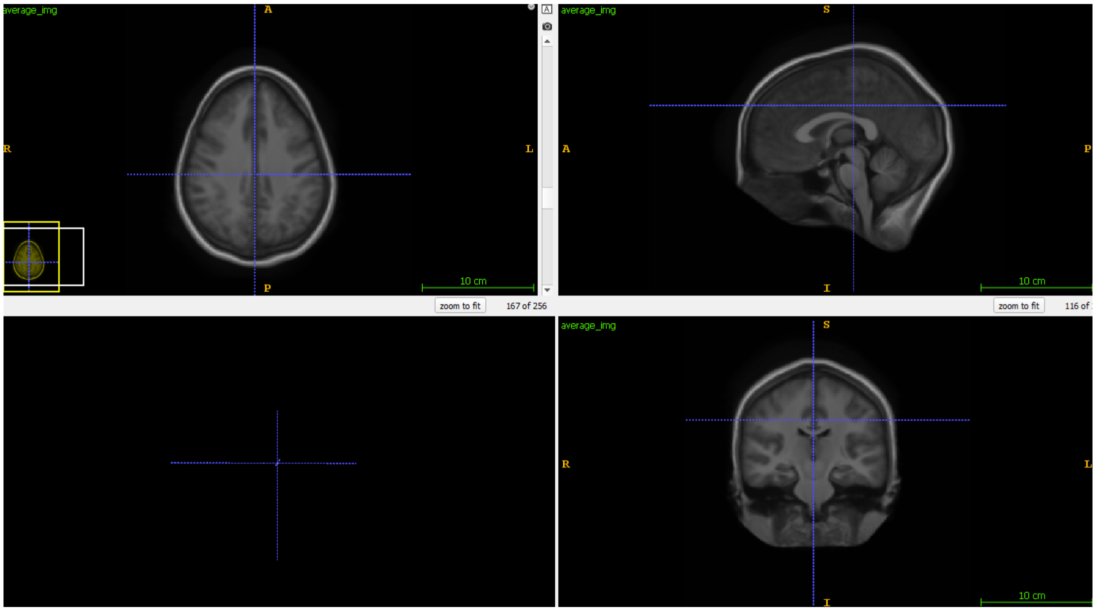


Figure 9: Axial slice = 167, sagittal, and coronal slices in the template image

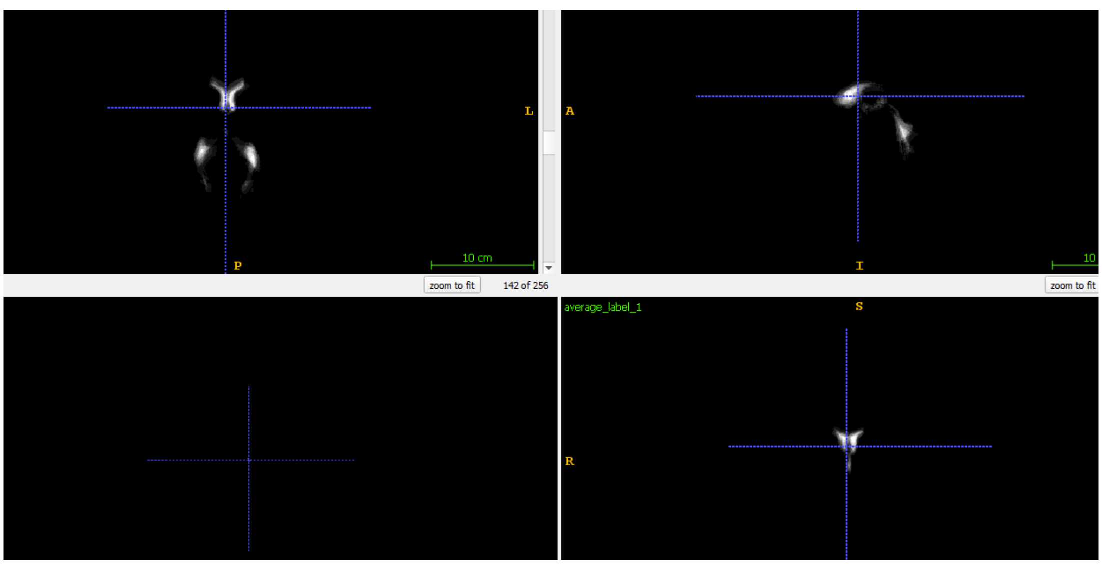


Figure 10: Axial=115, sagittal, and slices from the template label of CSF region

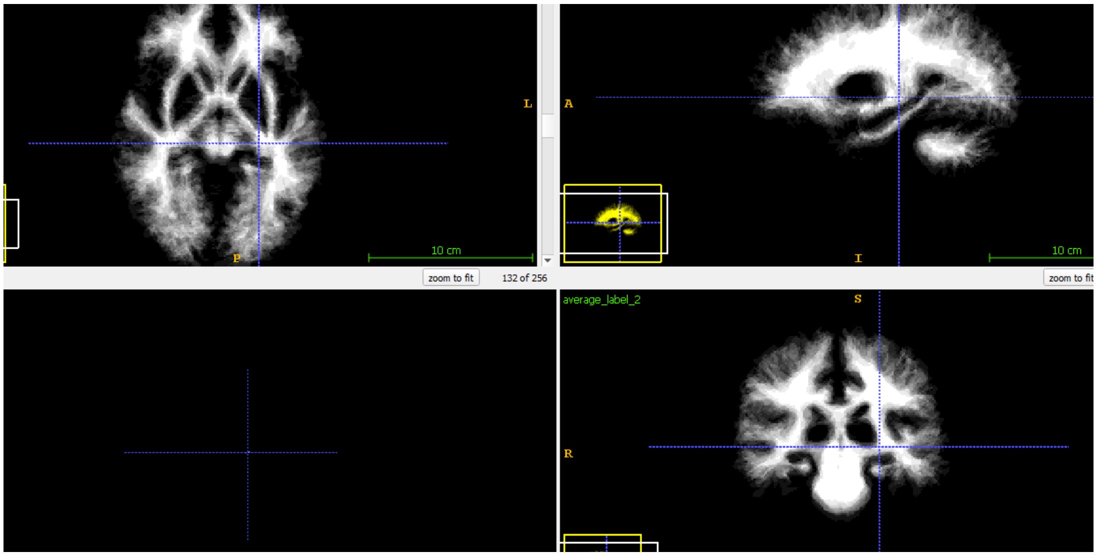


Figure 11: Axial slice = 132, from the template label of White matter (WM) region

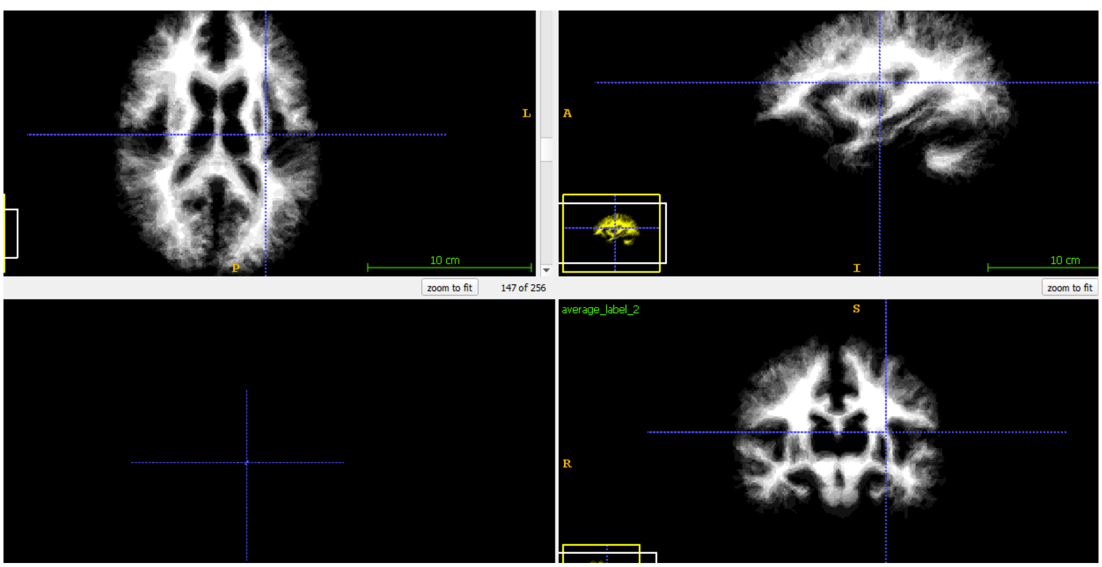


Figure 12: Axial = 147, sagittal, and coronal slices from the template label of White matter (WM) region

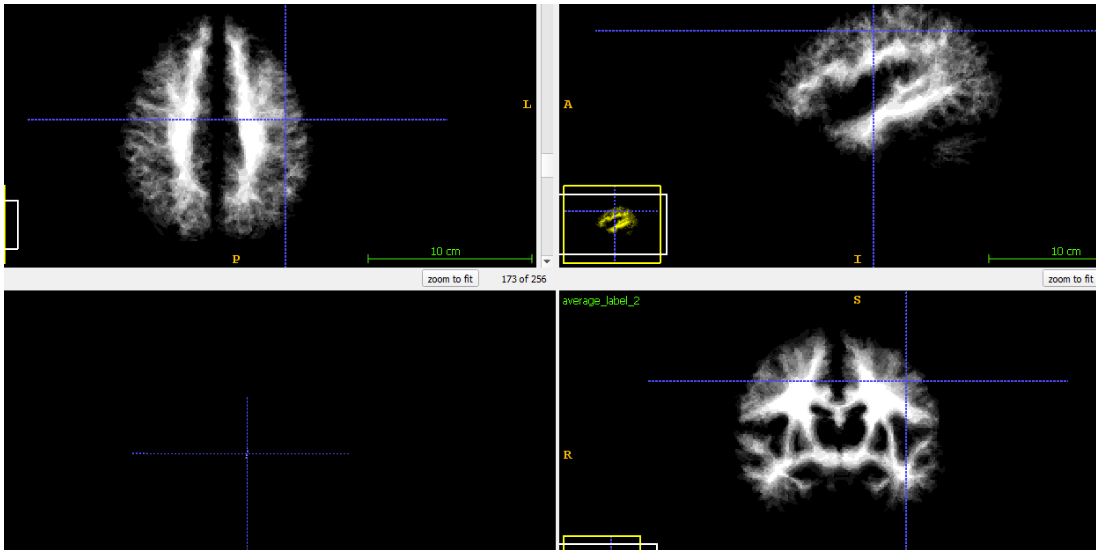


Figure 13: Axial = 173, sagittal, and coronal slices from the template label of White matter (WM) region

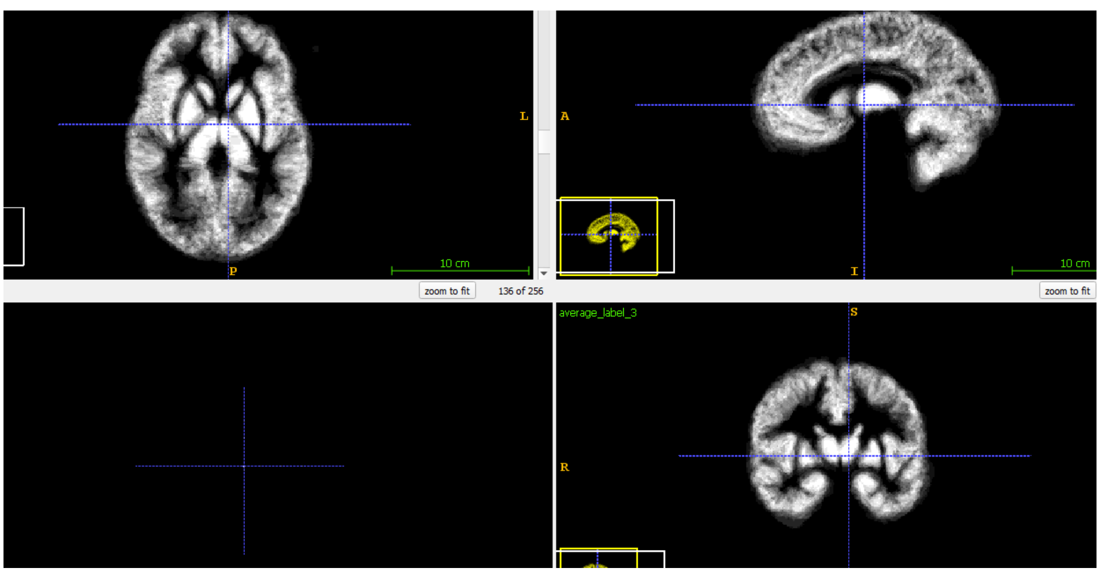


Figure 14: Axial slice = 136 of average label 3 (Gray matter)

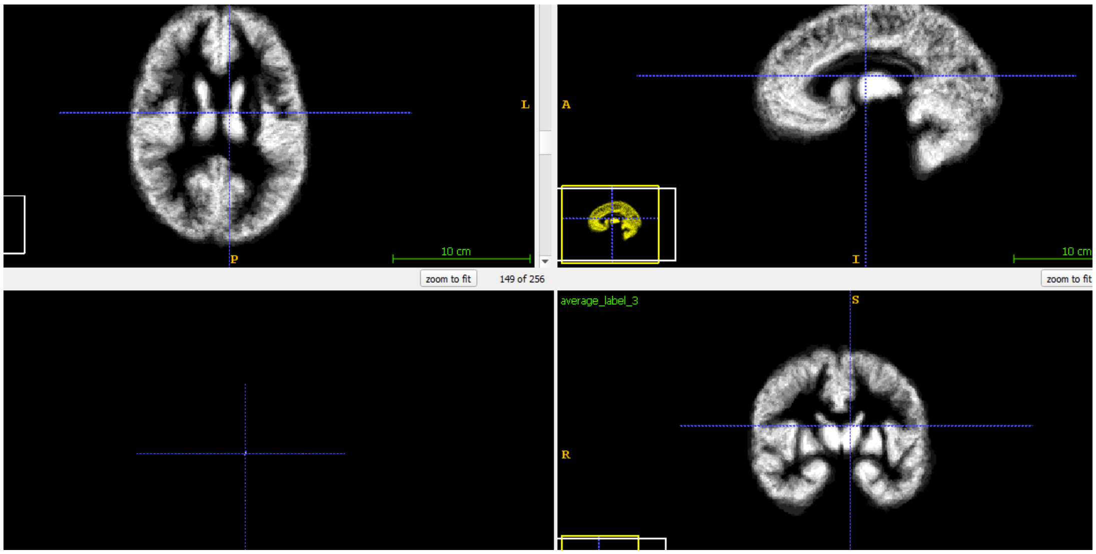


Figure 15: Axial slice = 149 of average label 3 (Gray matter)

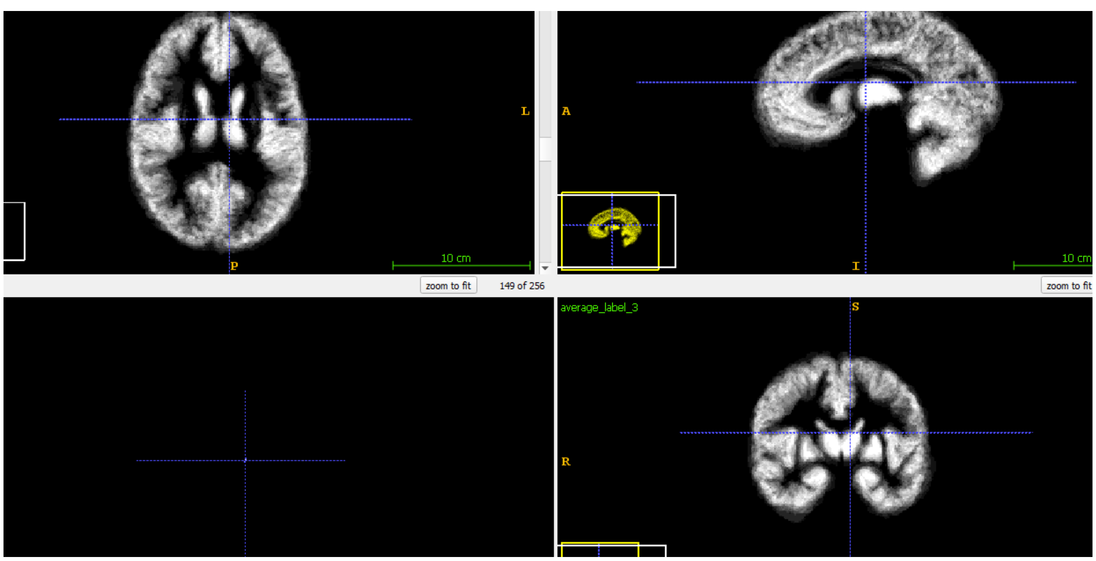


Figure 16: Axial slice = 171 of average label 3 (Gray matter)

References

[1] K. Stefen, and S. Marius, "elastix the manual," September 4, 2015.