Atlas based segmentation

Course Title: Medical Image Registration and Applications (MIRA)
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Objective(s):

- To perform rigid and non-rigid registration with elastix and tranformix.
- To develop an algorithm to build the probabilistic atlas from the registered images.
- To demonstrate the result of the final probabilistic atlas (intensities and label probabilities) and the tissue models for each tissue class.

Introduction:

Atlas-based segmentation is a commonly employed technique in the field of medical imaging for the purpose of segmenting images. The primary goal of this approach is to make use of existing knowledge about the structures that need to be segmented. This knowledge is typically derived from one or more reference images of the same structure, which have been previously annotated, often through manual annotation. These reference images are referred to as atlases, and they can be categorized into two main types: topological and probabilistic atlases. The information provided by the atlas is then integrated into a segmentation algorithm, such as the Expectation-Maximization method, to enhance the algorithm's performance.

Atlas:

An atlas is a combination of two elements: an intensity image, often referred to as the template, and its corresponding segmented image containing atlas labels. To segment images, they are initially aligned or registered to this template. Following the registration, the obtained transformation is then applied in reverse to the atlas labels. This reverse application leads to the creation of the segmentation outcome for the target image, constituting the entire process known as label propagation. The approach used for label propagation can vary based on the type of atlas utilized. The atlases can be categorized into two primary categories such as topological atlas and probabilistic atlas.

a) Topological Atlas Approach: The Topological Atlas approach, also known as a single-subject or deterministic atlas approach, relies on a single template intensity image and its corresponding ground truth to deduce the segmentation of an unlabeled image of the same structure. The choice of the single image can be either random or based on a similarity measure, where the image most similar to the target within the dataset is used as a reference. The target image is aligned with the template through registration, and the resulting segmentation is achieved by applying the inverse transformation of the registration process to the atlas labels.

b) Probabilistic Atlas Approach: Probabilistic atlases are created using multiple reference images, and they're typically used in methods that involve segmenting using multiple atlases. In this approach, the atlas is formed after aligning all the images in the dataset to a common reference image and transferring their labels to this shared registration space. The choice of the reference image during the alignment process can be either random or based on an error or similarity measure. The reference intensity image for the atlas can either be the same as the instance used as the reference image or it can be an average image obtained by blending all the aligned intensity images together. The labels in the atlas result from combining the transferred labels from all the images in the training set. There are two main techniques for merging these labels.

- Averaging Technique**:** This method involves calculating the average of the transferred labels for each class. This results in a membership probability map that indicates, for each voxel location, the likelihood of that voxel belonging to a particular region.

- Majority Voting Technique: In this approach, each voxel is assigned the label that appears most frequently at its location among the training set images.

Atlas Generation:

Creating a multi-atlas requires having multiple training images. We can either utilize all the images available in the dataset or choose a subset based on a metric, such as selecting the ones that closely resemble the target image the most. The process of constructing a multi-atlas typically involves three key steps:

1. *Registration Phase:* During this stage, a fixed image is chosen from the population, serving as a reference. All other images are then registered to this chosen image, aligning them in a common space.

2. *Label Propagation Step***:** In this phase, the transformation parameters acquired in the first step are applied to the corresponding labels for each instance. This process ensures that labels are moved to the registration space in accordance with the transformations applied to the images.

3. *Atlas Generation:* In the final step, the registered images are utilized to construct the atlas. The template for this atlas can either be the fixed image chosen for registration or the mean of all the images. The labels are derived by combining the propagated labels of the training images through methods such as averaging or majority voting, as previously mentioned.

Tissue Models:

Tissue models represent the conditional probabilities of voxel classes given their intensities, denoted as $p(\omega|x)$. These probabilities are derived by utilizing the ground truth label assignment for each volume. Subsequently, these tissue models can be employed for generating a brain segmentation solely based on intensities or for providing improved initialization in the Expectation Maximization algorithm.

Implementation and Results:

In this lab work, we built a probabilistic atlas for brain tissue segmentation from scratch based on a training set of 15 brain MRI volumes. We used Python as a programming language. The lab task is implemented into several parts.

a) Registration: In the first part of the lab task, first we consider a fixed image from the dataset for the registration. We can select the fixed image based on some statistical information to be more specific. However, here we considered 1001.nii image as the fixed image while others were moving images. After that, we performed the affine and bspline registration using the elastix.exe and transformix.exe binary files along with affine and bspline registration parameters. The registration results are shown in the figure below.

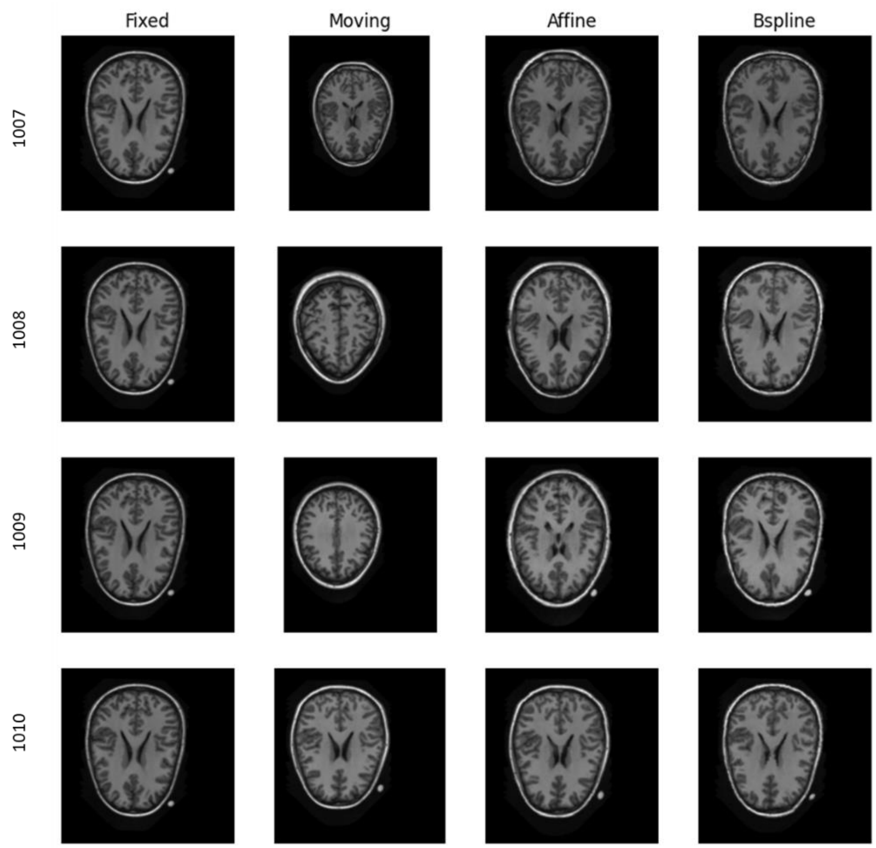

Fig.1: Fixed Image, Moving Images, Affine and Bspline Registered Images.

b) Atlas Generation: The template image is created by averaging the registered brain images. To form the probabilistic atlas, each propagated categorical label volume is split into four binary label volumes, one for each class. The average of the propagated labels for each tissue is then computed across all subjects, resulting in four membership probability maps: CSF, GM, WM, and Background. The majority voting atlas is derived by applying *argmax* to the concatenated array of probabilistic atlases. In simpler terms, each voxel is assigned to the tissue with the highest probability at that voxel's location in the probabilistic atlas. The following figures are shown the generated atlases from both the affine and bspline registration.

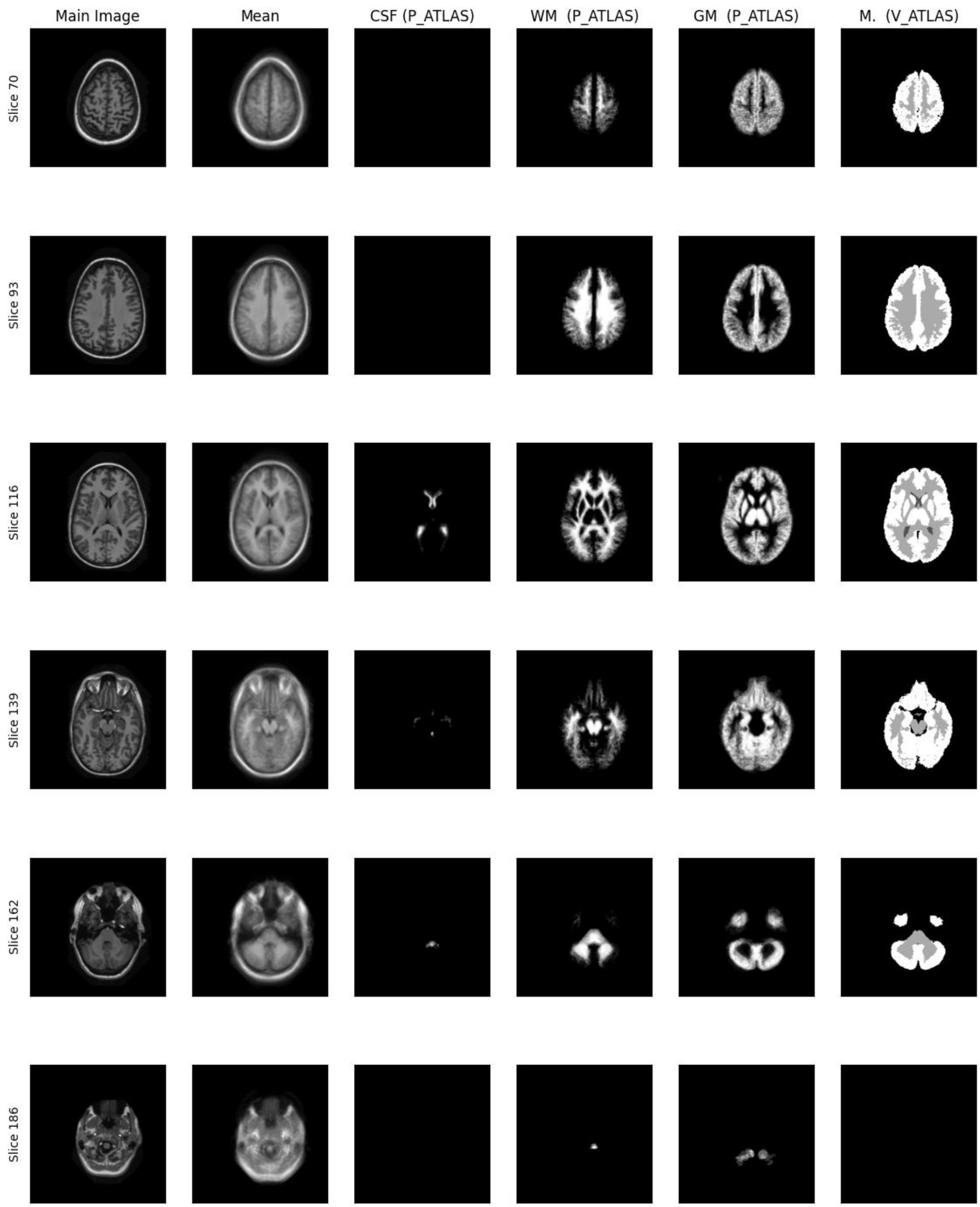

Fig. 2: Generated atlas from the affine registration

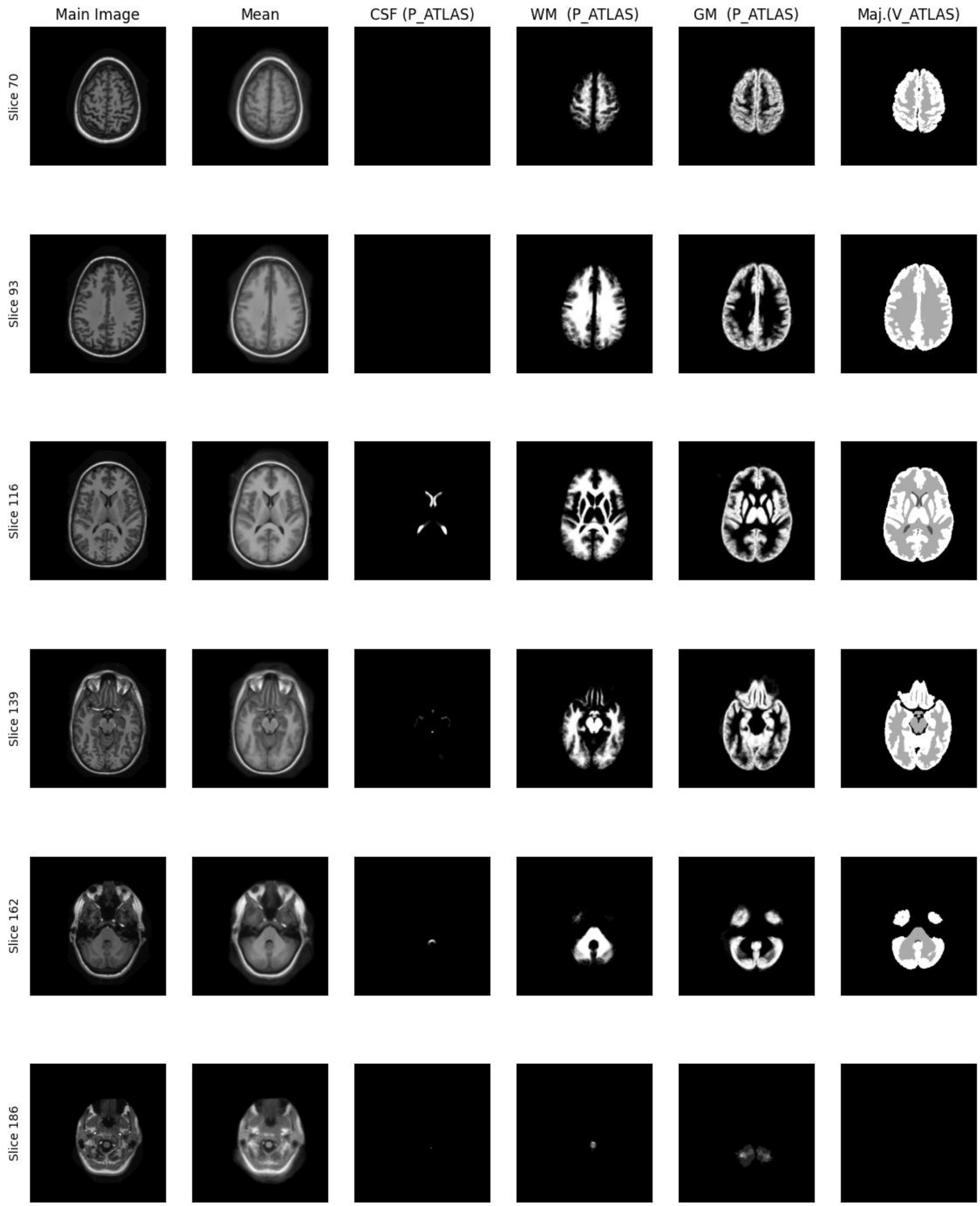

Fig. 2: Generated atlas from the bspline registration

c) Tissue Model: After propagating the labels for each volume, we can create the likelihoods (conditional probabilities) for each voxel, denoted as $p(x|w_k)$, representing the likelihood of a voxel intensity x given a tissue class w_k. The resulting probability density function is obtained by normalizing the histograms based on the total number of samples used. Once the probability density function is established, the posterior probability is derived using Bayes' rule (1), assuming a non-informative prior.

$$p(w_k|x) = \frac{p(x|w_k)\, p(w_k)}{\sum_k p(x|w_k)\, p(w_k)} \quad (1)$$

The expression simplifies when the prior probability $p(w_k)$ is uniform across all classes, resulting in an element-wise division of the obtained likelihoods by the sum of the likelihoods for all classes.

$$p(w_k|x) = \frac{p(x|w_k)}{\sum_k p(x|w_k)} \quad (2)$$

In this lab work, after constructing the atlases, tissue models were built using two approaches. Both methods involved computing the histogram of voxel intensities under the desired tissue mask for all cases in the atlases collection. The distinction between the approaches lies in their use of tissue masks. Using the Atlas, tissue regions for each image in the dataset are defined by the majority voting atlas in the registered space. On the other hand, using the Labels, tissue intensities for each image in the dataset are determined by the propagated labels in the registered image.

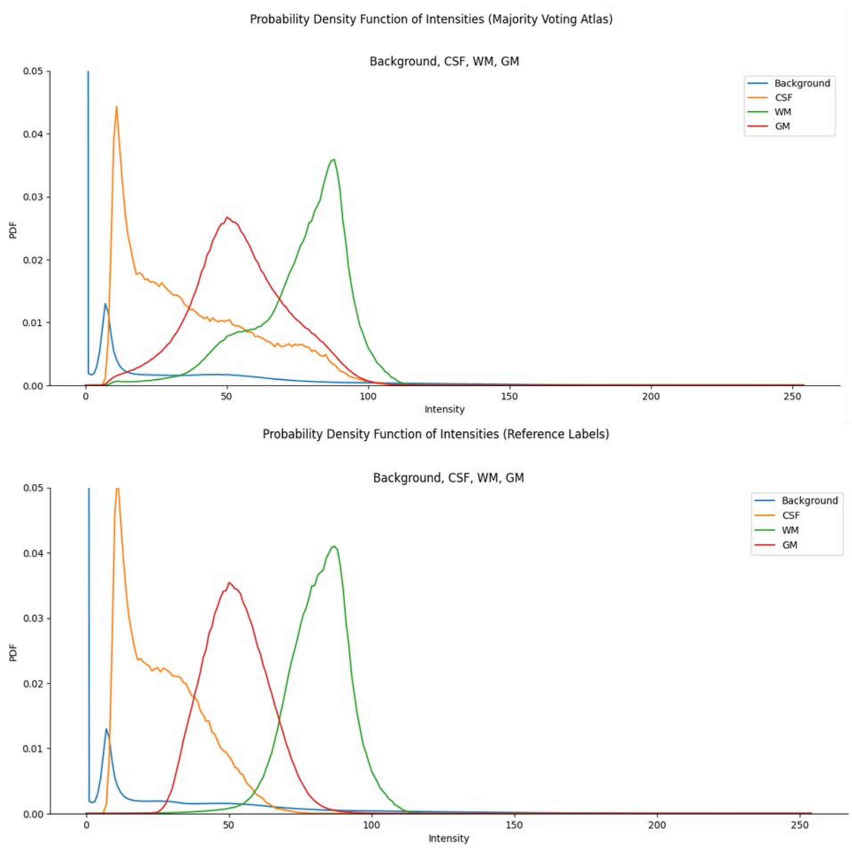

Fig. 3: Probability density function of intensities for affine registration with majority voting atlas and reference labels.

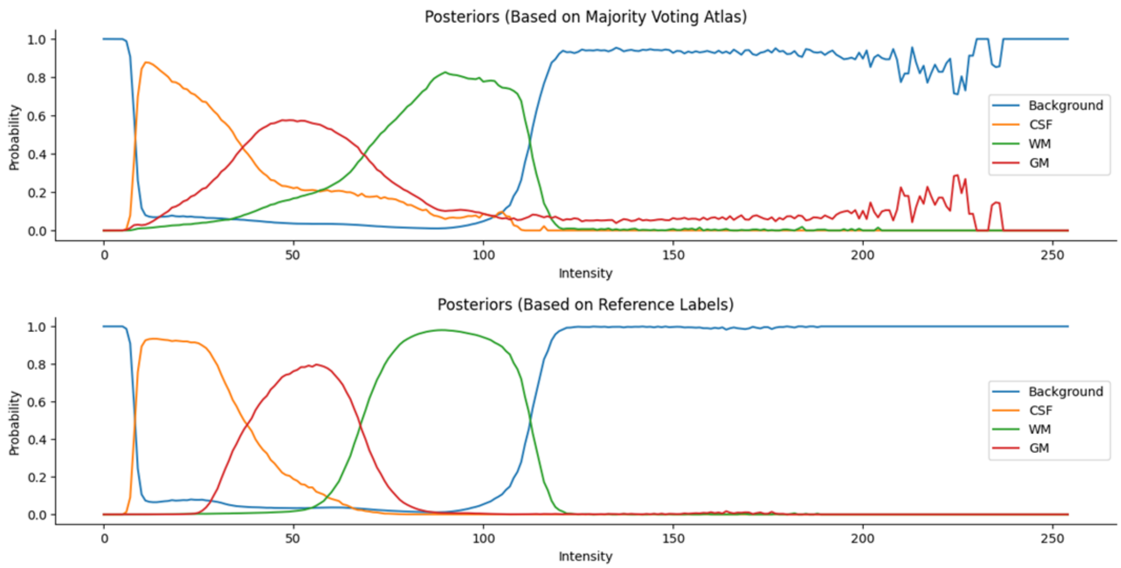

Fig. 4: Posterior probabilities obtained using affine registration and the majority voting atlas and reference labels.

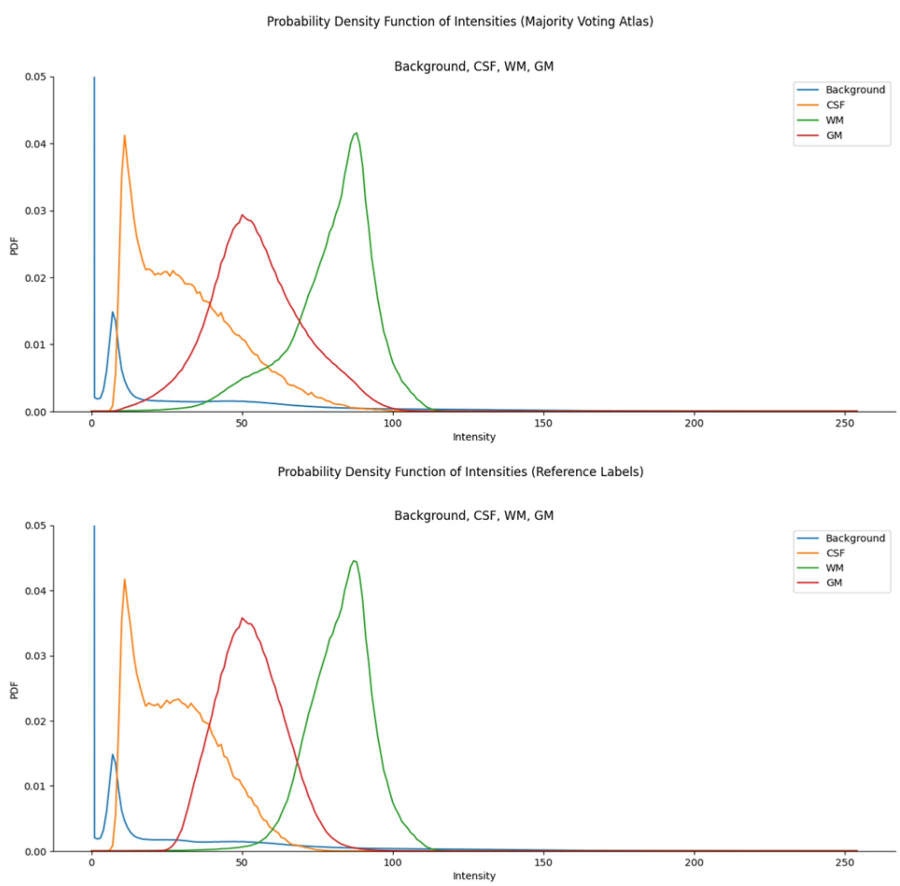

Fig. 5: Probability density function of intensities for bspline registration with majority voting atlas and reference labels.

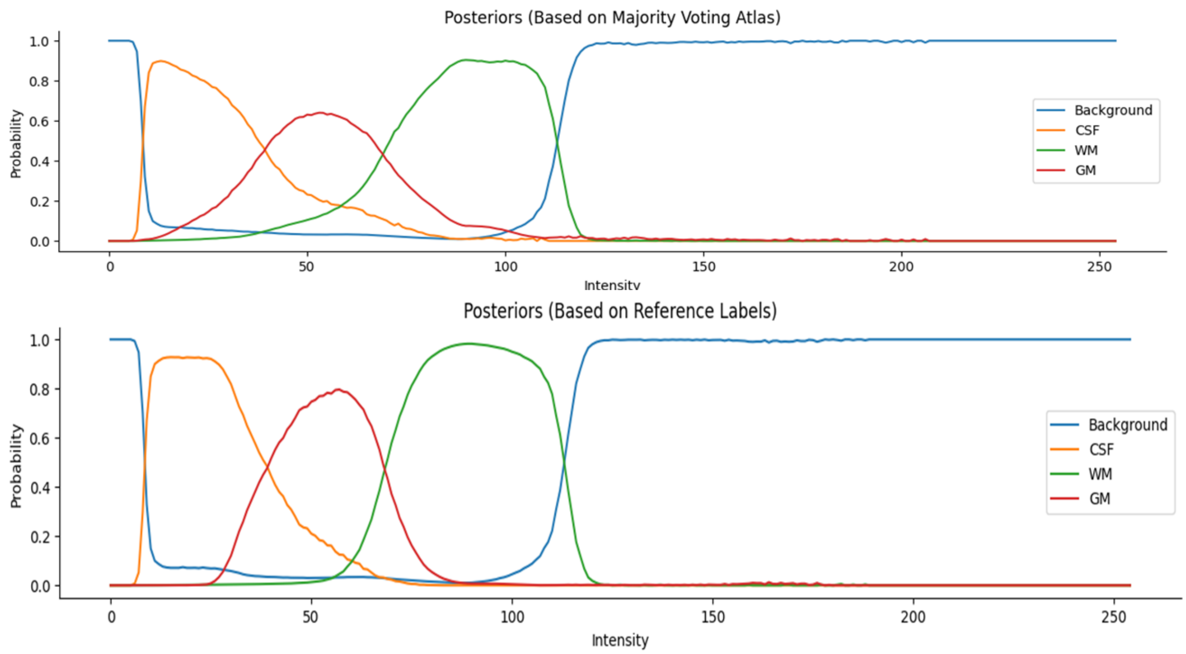

Fig. 6: Posterior probabilities obtained using bspline registration and the majority voting atlas and reference labels.

Finally, it can be said that the bspline (non-rigid) registration performed better than the affine (rigid) transformation technique. This observation was confirmed after an inspection of the average Mutual Information between the fixed and registered images. The results of the comparison can be seen in the following boxplot where we can clearly see that using the bspline transformation parameters provides better results than affine.

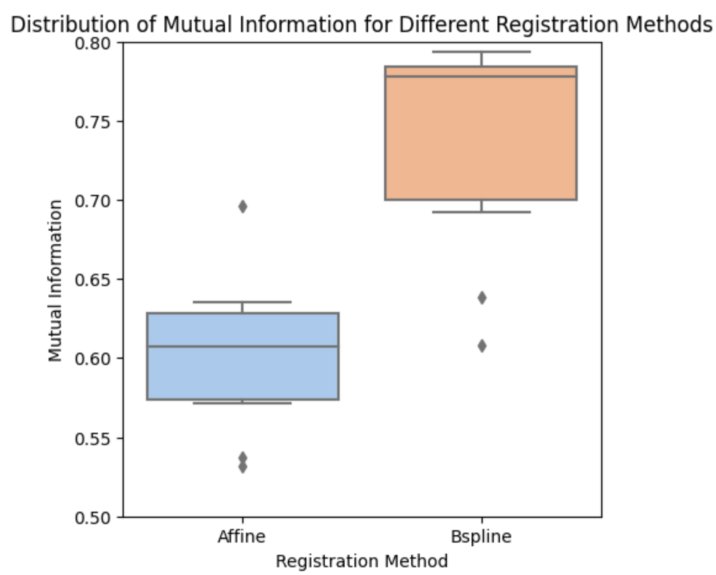

Fig. 7: Registration mutual information between affine and bspline.