

## Computer Vision and Imaging Extended [30241]

### Assessed Assignment

#### 1. Instructions

This is an individual assignment. You are required to submit a written report and your accompanying code. The report must be no more than THREE pages long including all graphs and tables. The report should be submitted as a PDF file via CANVAS (See Canvas for deadline).

Your assignment involves some implementation and some experimentation, plus the write up. All images to be processed are provided.

Your code/script should also be submitted as supplementary data (runnable code file, e.g. Jupyter Notebook or \*.py): Remember to follow good practice with structure, use of functions and adding of comments to your code. If the submitted code cannot give the reported results, the corresponding section will be considered fail.

Any text beyond the stated 3 pages will not be marked. There will be 5% penalty per day (or part of) for late submissions, up until the portal closes on Friday December 12th at midday when no more submissions will be accepted.

Your submitted assignment should:

- Be a maximum of 3 pages (A4)
- Have minimum margins (top/bottom/sides) of 2 cm
- Use Arial (narrow) font of 11
- Contain your student ID, and module code in the header
- Use Python for implementation

#### 2. The assignment:

Often, given a set of images, we are required to segment out regions/labels before further analysis of our data. For this task, you are given 10 consecutive 'axial' cross-sections of a publicly available MRI of a single human subject and are required to segment out 5 tissue layers. Specifically, you are provided a single file, 'Brain.mat' which contains T1 weighted MRI images (each slice has a dimension of 362\*434 pixel) with each z-slice being at 1 mm interval (spanning 10 mm), Figure 1. Additionally, a corresponding set of manually segmented labels is also provided for comparison and evaluation, Figure 2.

The ground-truth labels identify six regions in Figure 2:

- Label 0 = air
- Label 1 = skin/scalp
- Label 2 = skull
- Label 3 = cerebrospinal fluid (CSF)
- Label 4 = grey matter
- Label 5 = white matter

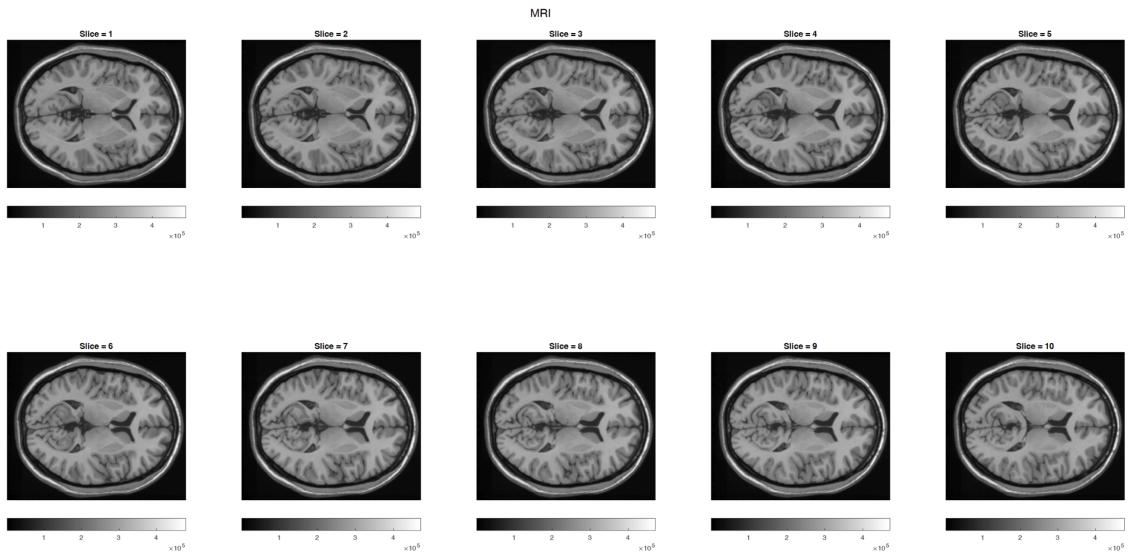


Figure 1: T1 weighted MRI data at 10 consecutive slices

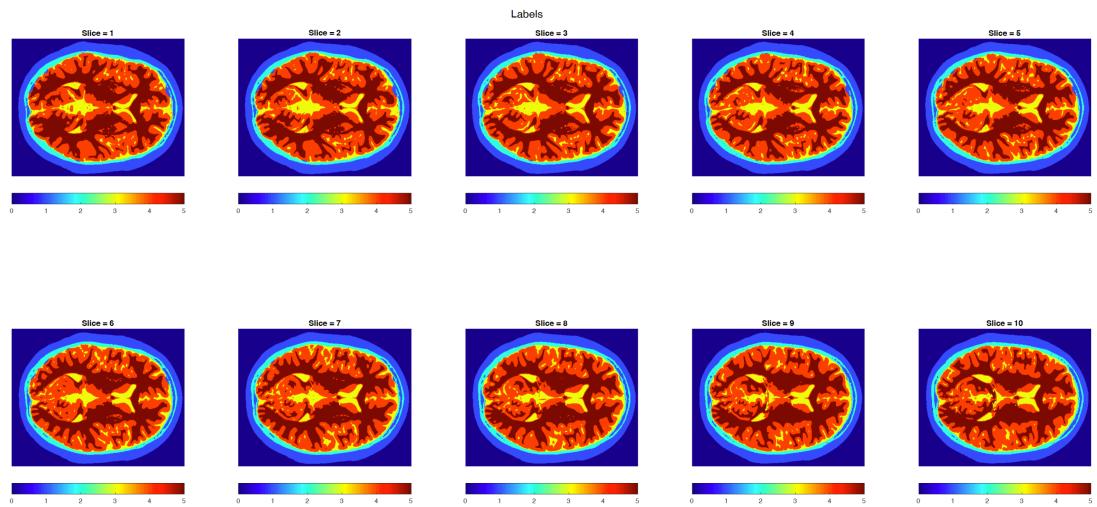


Figure 2: Segmented 'labelled' regions of the T1 weighted data in Figure 1

### Loading .mat files in Python:

To load the data in Python, you may use `scipy.io.loadmat`. For example:

```
from scipy.io import loadmat
data = loadmat('Brain.mat')
T1 = data['T1']
label = data['label']
```

### **Task 1: 2D tissue segmentation [10 Marks]**

Design and implement two or more two-dimensional tissue segmentation algorithms and apply exactly the same processing pipeline to every slice in the dataset. You may combine multiple techniques, and you are encouraged to draw on material covered in the module. If you choose to use a method not formally taught in class, your report should briefly explain how it works and how you implemented it.

### **Task 2: Result evaluation [5 Marks]**

Compare your segmented results for each algorithm to the ground-truth label provided. Justify and explain the metric used to assess accuracy. Based on your evaluation and results, highlight the best algorithm to be used.

### **Task 3: Advanced 3D tissue segmentation [10 Marks]**

For this final task, you are asked to develop a segmentation approach that operates on the MRI data as a 3D volume rather than as independent 2D slices. The aim is to explore whether using information across slices can improve consistency and accuracy compared to the slice-by-slice methods from Task 1.

You are free to choose the strategy, but your method should remain conceptually aligned with the segmentation techniques covered in class. A valid approach may involve applying a chosen technique directly to the full volume, extending a 2D method to encourage agreement between neighbouring slices, or incorporating a simple form of 3D post-processing after an initial slice-wise segmentation.

You may wish to consider that threshold-based methods, Otsu's method, and K-means clustering can all be applied to the entire 3D dataset rather than slice by slice. You might also find it helpful to think about simple ways of enforcing coherence across slices, (e.g. smoothing or majority-label operations in 3D space). This task does not require or expect any form of deep learning, neural networks, 3D U-Nets, or advanced machine-learning segmentation frameworks. The emphasis is on extending the ideas already introduced in the module into a three-dimensional setting using straightforward methods.

After implementing your approach, evaluate the results using the same metric you adopted in Task 2 and reflect on whether incorporating 3D information offered any clear advantage.

### **Final notes**

Write an experimental report of THREE pages detailing the experiments you have carried out. Follow the standard scientific structure: begin with a short aim, then describe the methods you implemented, present your results concisely, and conclude with a summary of which detector performed best for the images and why.

Remember, credit will be given where there are details and reasoning. If you use any techniques not introduced in the lectures, ensure that their key elements are explained succinctly so that the marker can evaluate your work.