ECE4250 - Class Project Information

April 4, 2020

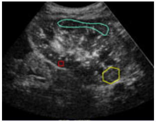
Class Project

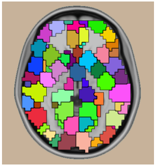
- Project grade:
  - 5% milestone 1 (April 13)
  - 10% milestone 2 (May 4)
  - 15% final report (May 15)
  - 5% Valid Competition Submission (by May 14)
  - 5% bonus: Competition Performance

What is an image?

- An image is a function from spatial (2D or 3D) coordinates to a continuous range of scalar (grayscale) or vector (e.g., color) values
- It is often represented on a discrete (pixel/voxel) grid
- Pixel values (intensities) are often physical measurements
- However, pixel intensities alone provide little context (biological, anatomical, pathological, etc.)

Terminology: Image Segmentation

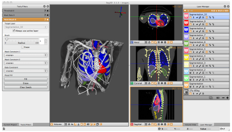




- Segmentation is one way of providing context
- Identify a region of interest (ROI)
- Partition the image into regions (sometimes called parcellation)
- Assign (e.g., anatomical, functional, pathology) labels to voxels

Image Source:
http://www.healthcare.philips.com
www.nitrc.org

Manual segmentation



- Refers to a human performing the task (e.g., delineate an ROI on an image)
- Requires some interface software (e.g., Seg3D)
- Often requires expert
- Crowdsourcing is a possibility
- Expensive (costs time, money, expertise)
- Low reliability (across experts, sessions, sites)

Image Source: www.sci.utah.edu

Automatic segmentation

- Learn relationship between image intensities and segmentation labels
- Goal: high accuracy and reliability
- Advantage: Fast, cheap
- Fully automatic (no intervention) or semi-automatic (e.g., quality control, guidance)

Assessing accuracy and reliability

- Accuracy: agreement with some "gold standard" (often manual segmentation)
- Reliability: agreement between two segmentation results on scans from same case
- Indirect assessment via impact on downstream analysis (e.g., group difference)

Assessing accuracy and reliability

Given two segmentation maps, metrics of agreement are often based on overlap scores

- Jaccard overlap: Intersection over Union
- Dice Coefficient: $\frac{2S \cap T}{|s| + |T|}$

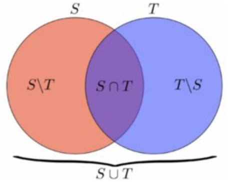


Image registration

- Problem Statement: Let I_1 and I_2 be the target (fixed) image and source (moving image) respectively. They both show the same objects but with a different field of view or resolution.
- In the example shown below, the goal is to find T such that (x, y) in I_2 maps to $(x^{'}, y^{'})$ in I_1.

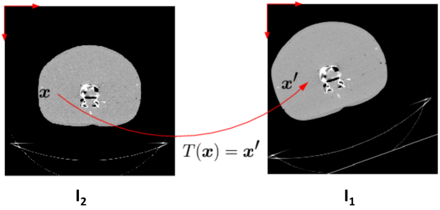


Image Source: https://www.creatis.insa-lyon.fr/ srit/tete/ 2012_master_eeap_si_m5.pdf

Image Registration

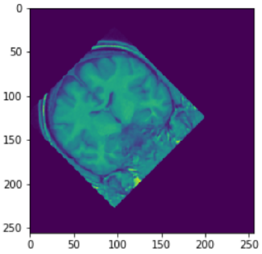
- Take pixel index (i, j) – the pixel with same index in another image is likely at a different "location"
- Establish common coordinate system
- Spatial alignment
- Mathematical formulation:

$$\hat{T} = \arg\max_{T \in \mathcal{T}} \mathcal{S}(I_1, I_2 \circ T)$$

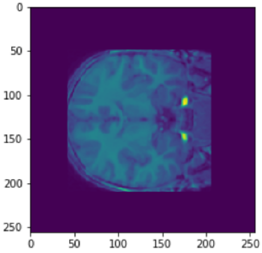
T : (x,y) $\rightarrow$ (x$'$, y')
I_1 Fixed image
I_2 Moving image
S denotes the similarity measure

Image Registration

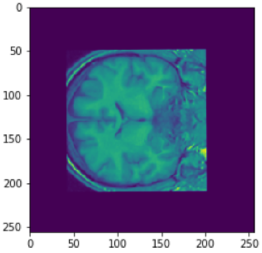
Application: Compare two or more subjects for a given modality



Subject 1 (Moving image)



Subject 2 (Fixed image)



Subject 1 (Registered to Fixed image)

Image Registration

Another application: Multi-modal image registration

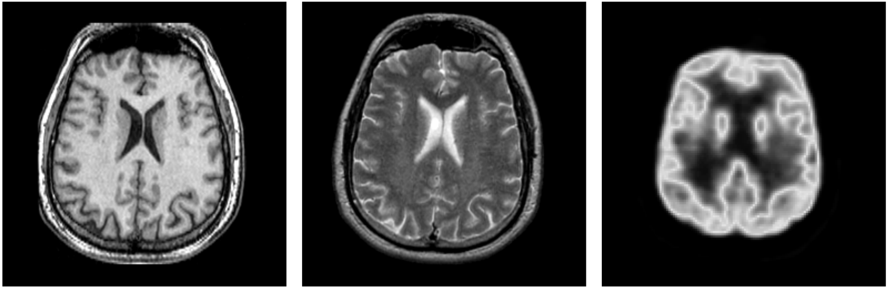


Image Registration

A registration algorithm has three components

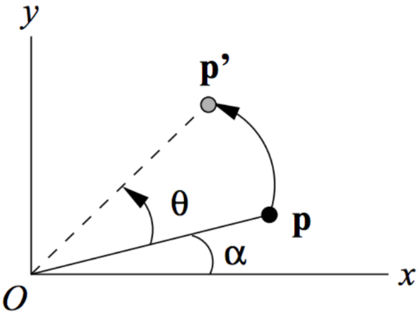
- Deformation model: e.g., rigid, affine, nonlinear
- Similarity function: e.g., sum of squared intensity differences
- Optimization method: e.g., iterative methods

$$\hat{T} = \arg\max_{T \in \mathcal{T}} \mathcal{S}(I_1, I_2 \circ T)$$

Global transformations: Rotation

Coordinates are rotated by angle θ.

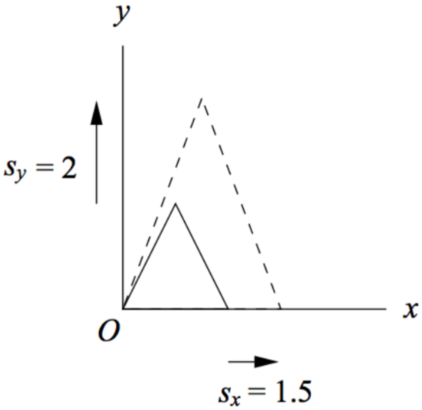
$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} cos\theta & -sin\theta \\ sin\theta & cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$



Global transformations: Scaling

Coordinates are multiplied by scalars.

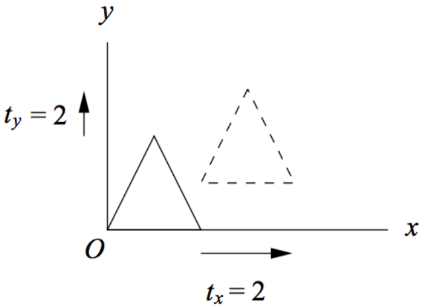
$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} s_x & 0 \\ 0 & s_y \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$



Global transformations: Translation

Coordinates are shifted by scalars.

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} t_1 \\ t_2 \end{bmatrix}$$



Can you express it as a matrix multiplication operation?

Solution: We need homogeneous coordinate system!

Special case: Only rotations, global scaling and translations

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = s \begin{bmatrix} cos\theta & -sin\theta \\ sin\theta & cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} t_1 \\ t_2 \end{bmatrix}$$

In homogeneous coordinates, this would translate to

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} scos\theta & -ssin\theta & t_1 \\ ssin\theta & scos\theta & t_2 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

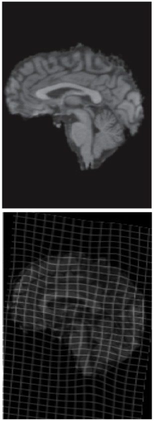
Affine Transformation

A general case

Any affine transformation can be expressed as the following:

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} a & b & t_x \\ c & d & t_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Image Transformation



- $T : \Omega_A \subset \mathbb{R}^2 \rightarrow \Omega_I \subset \mathbb{R}^2$
- $I : \Omega_I \subset \mathbb{R}^2 \rightarrow [0, 255]$
- $I \circ T : \Omega_A \rightarrow [0, 255]$

Intensity based similarity

Similarity criterion is a central ingredient of image registration

- Sum of squared difference (SSD) (Dissimilarity!)

$$S(P,Q) = -D(P,Q) = -\sum_x \sum_y (P(x,y) - Q(x,y))^2$$

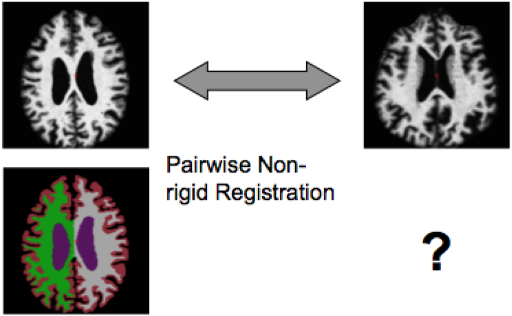
- Cross-correlation

$$S(P,Q) = \frac{\sum_x \sum_y (P(x,y) - \overline{P})(Q(x,y) - \overline{Q})}{\sqrt{\sum_x \sum_y (P(x,y) - \overline{P})^2 \sum_x \sum_y (Q(x,y) - \overline{Q})^2}}$$

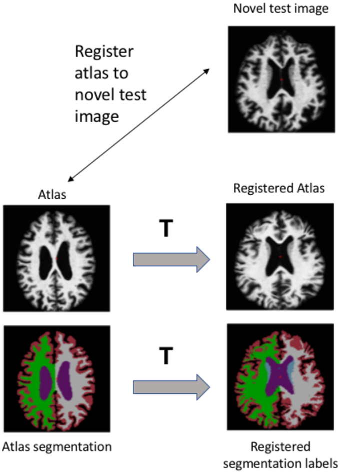
Template-based segmentation

- Given a single training image with segmentation – called template or an atlas
- Register the template image with novel image
- Use registration result to transfer labels over to novel image space

Template-based segmentation II



Template-based segmentation III



Project Components

- Brain MRI Registration
- Automatic template-based segmentation

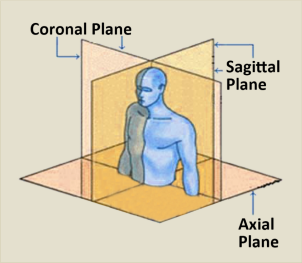
Dataset

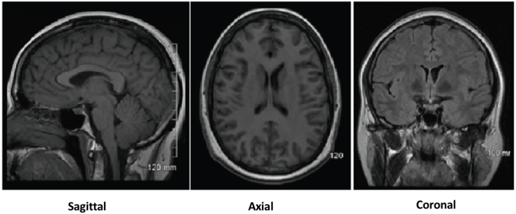
- You are given T1-weighted brain MRI volumes
- In total there are 17 subjects (6 training + 2 validation + 9 testing)
- Each subject has a single MRI scan
- These scans have been manually segmented into anatomical regions of interests
- You will receive the manual segmentations for the training and validations subjects
- All data are provided in ANALYZE format: http://imaging.mrc-cbu.cam.ac.uk/imaging/FormatAnalyze
- You may use nibabel for Python to read the files

Milestone 1

- Load the MRI volumes
- Determine the pixel spacing and slice thickness of each loaded volume
- Extract, visualize, and save middle coronal slices for all training+validation cases, including the MRIs and segmentations

Brain MRI


Coronal Plane
Sagittal Plane
Axial Plane


120 mm
120
100 mr
Sagittal
Axial
Coronal

Milestone 2

Part 1: Implement 4-parameter affine registration for aligning two 2D images (translation, rotation, global scaling)

- Write a function that takes in an input (moving) image, 4 transformation parameters (global scale, rotation, and translations along two axes) and output (fixed image) grid size, and computes the output (moved) image.
- a loss function that takes three inputs: a length-4 vector of geometric transformation parameters, a fixed image, and a moving image. The output should be equal to the sum of squared differences between the geometrically transformed moved image and the fixed image.
- an optimization module that minimizes the loss function for a given input image pair (fixed and moving). You can use the scipy.optimize module for this.

Part 2: Using registration tool for automatic segmentation

- Use your registration tool to resample each training image (moving) onto each validation image (fixed) (i.e., you need to run 12 registration instances). Visualize some slices of these results. You need to show that your registration works - i.e., plot results for before the registration and after the registration.
- Apply the registration results (optimal transformations) to resample the manual segmentations of each training subject onto the validation subject grids
- For every pixel on validation subject grid, compute the most frequent training label. This is called majority voting based label fusion. You can implement any tie-break strategy you want. This is a crude segmentation of the validation subjects.

Milestone 2

Part 3: Evaluating the segmentation results

- Write a function that computes the Jaccard overlap index for a given region of interest (ROI) between an input manual segmentation and an automatic segmentation. The Jaccard index is defined as the ratio between the area of the intersection and the area of the union, where the intersection and union are defined with respect to the manual segmentation and an automatic segmentation.
- Compute the Jaccard index for your automatic validation subject segmentations. Only consider following regions of interest (both left and right): Cerebral-White-Matter and Cerebral-Cortex.

Final Report and Competition

Goal: Implement better registration or label fusion strategies to improve segmentation results. / Possible directions include:

- Using a 6-parameter affine transformation or non-linear deformation model to get better registration than affine transformations
- Computing a weighted fusion approach where the training subjects (atlases) are weighed differently based on similarity between intensity values

Optimize the model on validation subjects. Use this model to compute automatic segmentations of all the test subject mid-coronal slices.