HL2027 PROJECT 2 REPORT

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INTRODUCTION

In context of surgery planning, finding a specific tissue or organ in MRI images can be an important step to assess the condition of the patient. Segmentation of body organ in MRI images is important factor to make sure that the organ/tissue is quickly located and distinguished with surrounding tissues/organs. Atlas-based segmentation is of many segmentation methods, by using a set of mask model to determine which detected organ belongs to. Moreover, one can use classifier to predict which slice of the MRI images that contain the appearance of a certain tissue/organ. By finding them instantly and easily, the patient assessment can be less time-consuming. This would make MRI observation easier for the medical staff. In this project experiment, we try to utilize atlas-based segmentation to determine which bone is the hip bone. And with a separated experiment, we also try to use a classifier to find a femur head along MRI image slices.

BASIC THEORY

Registration : Calculating suitable transformation map to align two or more images into a same coordinate space. Linear registration involves translation, rotation, scaling, and shear transformations. Non-linear or non-rigid transformation utilizes uneven transformation field which allows local warping of positions.

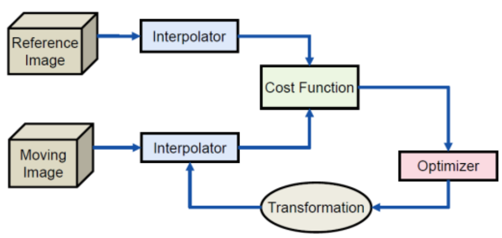

Figure 1. Chart showing basic registration operation

Cost Functions : A function to show a degree of similarity between the transformed image and the reference image, as shown in Eq[1].

$$E(u) = \int_{\omega} \; Data\ term + Reg.term \;\; d\omega \; = \int_{\omega} D\big(I_R, T(I_M, u)\big) + \lambda R(u)\, d\omega \qquad \text{Eq[1]}$$

The data term can be defined by multiple ways, such as:

- Sum of squared differences :

$$D\big(I_1, I_2\big) = \int_{\omega} \|I_1 - I_2\|^2 \, d\omega \qquad \text{Eq[2]}$$

- Mutual information :

The main idea is to maximize the joint entropy of both reference and moving image.

$$MI = Entropy\ of\ R + Entropy\ of\ M - Joint\ Entropy$$

$$MI = \int_{\Re} p_R log(p_R) dr + \int_{\Re} p_M log(p_M) dm - \int_{\Re} p_{RM} log(p_{RM}) dr\ dm \qquad \text{Eq[3]}$$

Similarity measure : To measure whether or not the segmentation method actually works, similarity measure is implemented. Examples of similarity measurement method are :

- Dice coefficient:

$$QS = \frac{2|A \cap B|}{|A|+|B|} \qquad \text{Eq[4]}$$

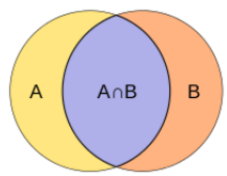

Figure 2. Area overlap between two circle

- Hausdorff Distance :

HD(X,Y) = max(h(X,Y), h(X,Y)) Eq[5]

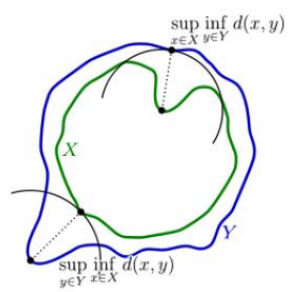

Figure 3. Hausdorff distance calculation

Optimization : In Fig. 1 , we can see that optimizer is needed to perform registration. Optimizer is used to make the transformation operations more efficient. An example of optimizer algorithm is gradient descent, which iterates cost function calculation until it reaches minimum value.

Atlas-based segmentation : By using a mask created from the label created from medical expert, one can store labels from multiple samples. The stored manual labels are then extrapolated to the new image to segment certain organ or tissue with similar statistical model characteristics. The registration operation is required to align atlas image to the new image.

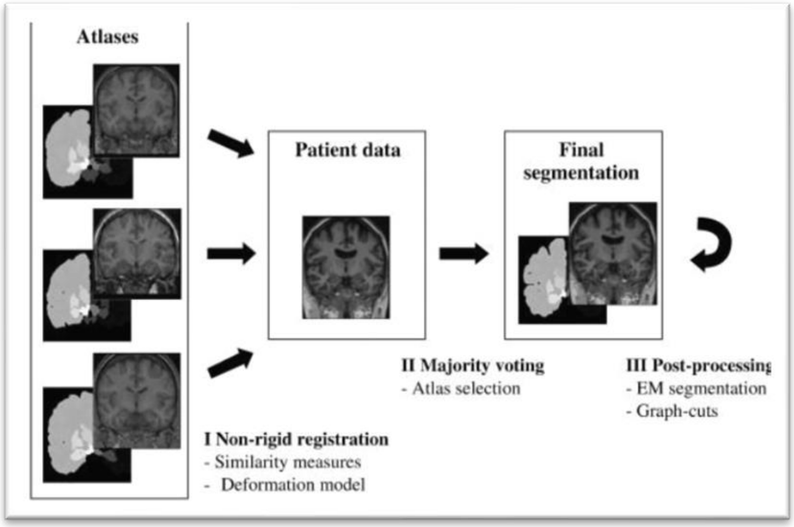

Figure 4. Basic of atlas-based segmentation.

Support Vector Machine (SVM) : SVM is a supervised machine learning algorithm for classification. It utilizes a hyperplane to separate between different cluster of datasets.

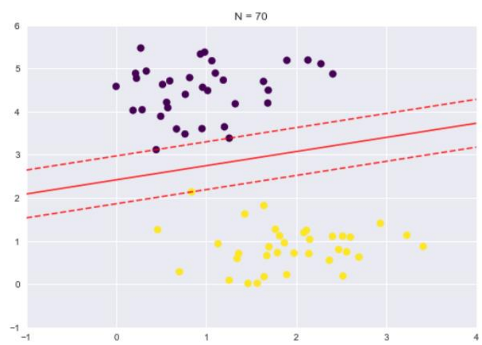

Figure 5. Example of datasets separation using SVM.

SOLUTION STRATEGIES

Atlas-based segmentation

Ground truths are produced from manual labelling by experts, for three set of MRI images. The ground truths consist of left femur, right femur, left hip, right hip, and sacrum bones. Atlas models are created by our own, using Mialab software to semi-automatically generate the atlas mask and ITK-SNAP to make minor corrections on the semi-automatic masks.

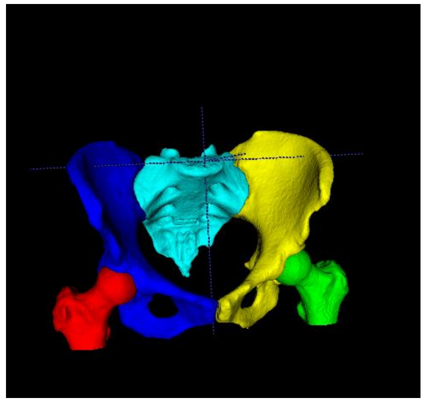

Figure 6. Label/mask created by the expert as ground truth.

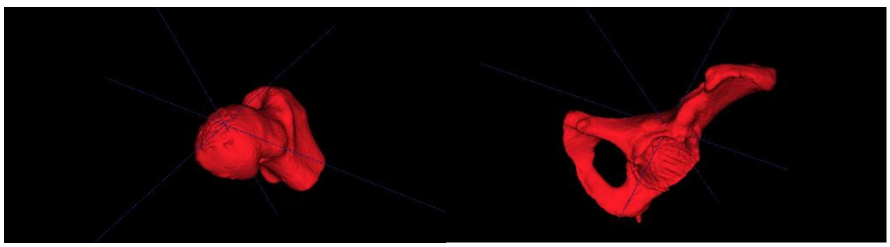

Figure 7. 3D imaging examples of left femur (left) and left hip (right) from the atlas we made.

Once we have created the atlas, we can implement atlas-based segmentation for a given image. As stated before it started with the registration of the target image to the images of the atlas. Two strategies were employed: a linear registration and a non-linear registration. The linear registration was performed using a linear interpolator, mutual information as metrics and gradient descent for the optimization process. The non-linear segmentation used the demons method. Then the transforms obtained from registration are applied on the masks of the atlas and a combined mask is created from this by majority voting. This mask is now the estimated segmentation on the structure of the target image by our pipeline.

Classification

The objective of this classification problem was to predict the probability of appearance of the femur head in given image's z-slices. We decided to train a Support Vector Machine classifier with three train images using a RBF kernel. The labels (appearance of the femur head or not) for these train images were assigned manually by observing them slice by slice. Three strategies were used to feed the classifier. First we used the simplest feature among all: the position of each slice. Because all the images analysed don't have the same number of slices we used a normalised position instead. As a second strategy we tried to extract some meaningful features from the images, both regarding intensity values and geometry. We chose for each slice the maximum intensity value, the location of the center of mass of the intensities, the normalised position of the slices again, and after binarizing the images with an appropriate threshold the total perimeter of all the objects present in the slice. Finally, as third strategy and because it is not easy to imagine relevant features for this particular problem, we used as features the intensity value of each pixel of the slice, then reshaped as a one dimension vector.

FINDINGS FROM THE EXPERIMENTS

Atlas-based segmentation

Note: Unfortunately and for reasons we could not find we were not able to get workable results from our non-linear registration implementation. In addition to being very time consuming it also creates important memory allocation issues when used on our laptop, making difficult the tests, even on subsampled images.

The accuracy of our atlas-based segmentation is analysed through the two indicators introduced above: the dice coefficient and the Hausdorff distance. The analysis with the linear registration method was performed on hip bones and femur bones, each time by working on the left-hand side and the right-hand side separately. The results are summarized in table 1 and 2.

The first thing to observe is that according to the chosen metrics the segmentations are not very accurate. This can be explained by the fact that linear registration especially for 3D images is not a very accurate method. Another factor could be that our atlas is only composed of three quite different images, which might not be enough. If we look at particular results, image 42 seems to be the one that has been segmented the most successfully and image 41 appears to be the worst segmentation. This can be explained by the relative bigger similarity of image 42 with the atlas images, leading to more accurate registration.

Regarding the difference between hip and femur results, it seems that we obtained better results with femur. The explanation is the lower complexity of the femur shape in comparison with hip bones. This has two effects: the registration is better in the area of the femur and our manually created mask (atlas creation) are better and intrinsically closer to the ground truth.

Finally one can question the relevance of using the Hausdorff distance as a metrics here. In fact knowing that the registration will not be very accurate it is not very interesting to consider a metrics that is very sensitive to outliers as this one. Here the dice coefficient is much more relevant and if a geometrical metrics is wanted it might be more relevant to use only the 90^{th} percentile of the Hausdorff distance instead.

Table 1. Segmentation result measurement in hip bone

Results hip:	Image 40		Image 41		Image 42	
	Left bone	Right bone	Left bone	Right bone	Left bone	Right bone
Dice	0.51	0.53	0.51	0.41	0.61	0.53
Hausdorff	37.63	38.28	33.36	34.37	25.02	31.76

Table 2. Segmentation result measurement in femur bone

Results femur:	Image 40		Image 41		Image 42	
	Left bone	Right bone	Left bone	Right bone	Left bone	Right bone
Dice	0.67	0.61	0.60	0.57	0.58	0.58
Hausdorff	23.37	30.82	34.12	34.57	44.38	37.68

Classification

The results for the first strategy of classification are good (Figure n+1) as we could expect. It is very easy to classify the appearance of the femur head using only the position of the labels in the train data. As expected also we observe that the probability of appearance is lower close to the decision boundary and reach a maximum in the middle. After checking the estimated maxima actually contain the femur head in the tested images. These results have to be criticized: we have not actually used a feature of the images to train the classifier, more a feature of the scanner or at least of the way the images are produced (we can imagine images obtained with a slightly different protocol and the classifier would not be efficient anymore).

This is why we used the second and third strategies to train the classifier. However these methods give uniform probability distributions as results for the appearance of the femur head (Figure n+2 and n+3). Our theory is that the features we tried to use (maximum intensity, center of mass, perimeter of objects, pixel intensity values) are somehow not able to discriminate a slice with or without the femur head. Further investigation should be done to determine relevant features that could actually train the classifier. Another improvement could be to use a decision tree instead of a Support Vector Machine classifier, able to sort the features by order of relevance and to lead to better results.

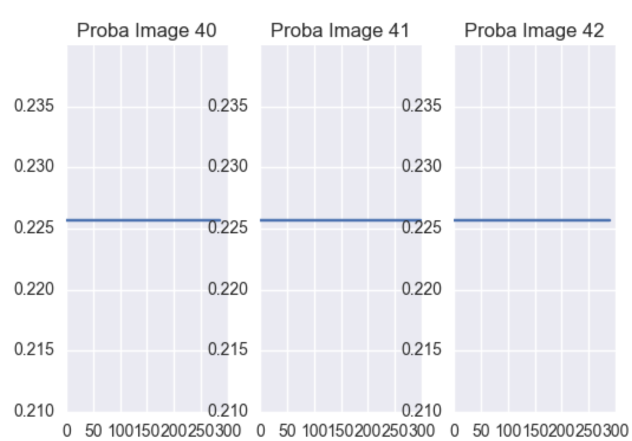

Figure 8 : Probability distribution using pixels intensity values as features

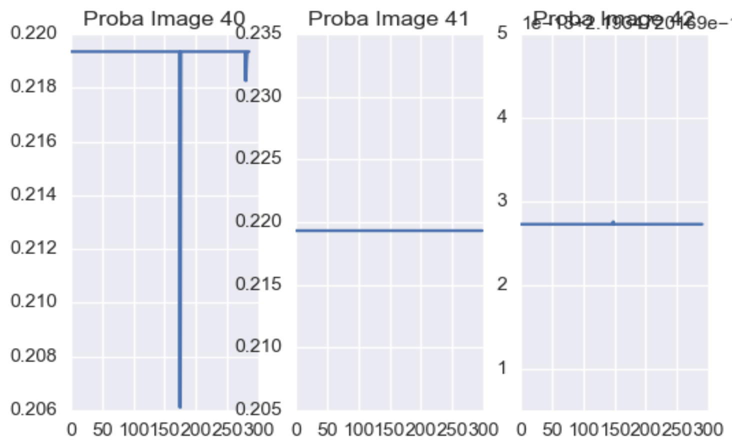

Figure 9 : Probability distribution using max, perimeter, center of mass and slice position as features

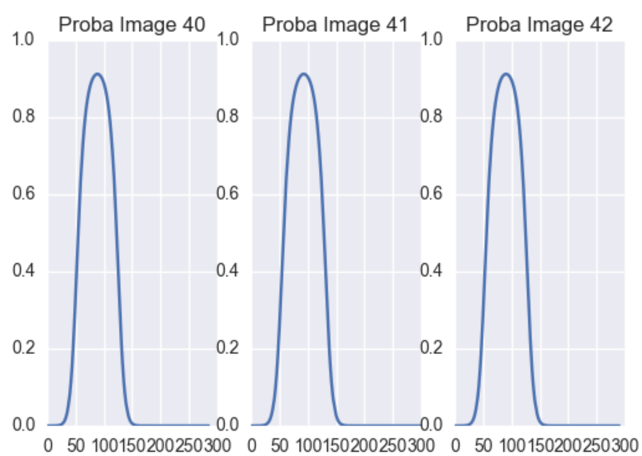

Figure 10 : Probability distribution using only normalized slices position as feature

FINAL CONCLUSION

In this project we performed two important tasks of medical imaging: atlas-based segmentation and classification. Results from these tasks help clinicians in many ways such as diagnosis or surgery. For the purpose of the project we focused on showing meaningful results even if the accuracy is not always good. This accuracy really depends on the quality of the atlas creation and of the registration. In order to improve it, non-linear registration should be performed. Regarding classification our analysis emphasised the need of extracting relevant features to efficiently train a classifier.

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