Multi–Structure Atlas–Based Segmentation Using Anatomical Regions of Interest

Oscar Alfonso Jiménez del Toro[1] and Henning Müller[1,2]

[1]University of Applied Sciences Western Switzerland (HES–SO),
[2]University Hospitals and University of Geneva, Switzerland,

Abstract. The Visceral project organizes a benchmark on multiple anatomical structure segmentation. A training set is provided to the participants that includes a sample of the manual annotations of these structures. To evaluate different segmentation approaches a testing set of volumes must be segmented automatically in a limited period of time. A multi–atlas based segmentation approach is proposed. This technique can be implemented automatically and applied to different anatomical structures with a large enough training set. The addition of a hierarchical local alignment based on anatomical knowledge and local contrast is explained in the approach. An initial experiment to evaluate the impact of using a local allignment and its results show a higher overlap ($> 9.7\%$) of the structures measured with the Jaccard coefficient. The approach is an effective and easy to implement method that adjusts well to the Visceral benchmark.

Keywords: Visceral, Atlas–Based Segmentation, Image Registration

1 Introduction

The Visual Concept Extraction Challenge in Radiology (VISCERAL [1]) organizes two benchmarks on the processing of large–scale 3D radiology images [3]. For Benchmark 1 there is a multi–layered task focusing on the segmentation of 20 anatomical structures (e.g. lungs, kidneys, liver, etc.) in different imaging modalities. A training set of these structures is provided to the participants. It contains a small amount (7 volumes per modality) of the manual annotations of these structures done by radiologists. A testing set also composed of manual annotations will be used to evaluate and compare different automatic approaches currently used in image segmentation and landmark detection. Both Computed Tomography (CT) and Magnetic Resonance (MR) volumes are included in the dataset in contrast- and non contrast–enhanced images. The approaches must be fully automatic and scalable to process large amounts of data.

A multi–atlas based segmentation approach is proposed. This technique requires no interaction by the observer and has been evaluated with high accuracy and consistent reproducibility in individual anatomical structures [4, 2]. Since

[1] `http://www.visceral.eu`, as of 14 September 2013.

multiple structures have to be segmented per volume, a complementary approach using individual local masks as input for the registrations is implemented. We set up an initial experiment using part of the Visceral training set to mesure the impact of adding a local affine allignment based on the volume location of an anatomical structure (i.e. right lung). The results are provided as well as a brief discussion of the current work and future steps.

2 Methods

Image Registration: An atlas in this context includes a patient volume $V_A(x)$ and its label image of the structure created by manual annotation. The query volume $V_Q(x)$ is where the location of a structure is unknown. With image registration the spatial relationship between the target and atlas images is estimated:

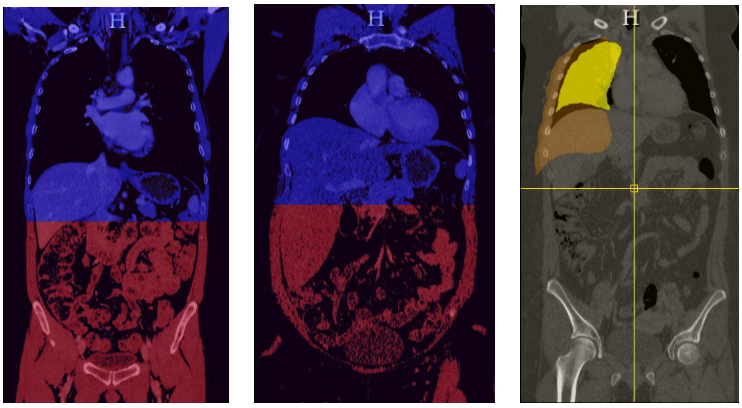
$$\hat{\mu} \quad = \quad \underset{\mu}{arg\ min}\ C(T_\mu; V_Q, V_A), \tag{1}$$

where C is a cost function of the parameterized coordinate transformation T_μ with a transformation parameter vector μ. The label image is transformed using the obtained coordinate transformation. The stochastic gradient descent optimizer [1] with a multi–resolution approach implemented in Elastix [2] is used for the registrations.

In a multi–atlas segmentation approach the labels obtained from the different registered atlases are fused resulting in a single label. The advantage of using many atlases is explained by the removal of local errors if the majority of obtained labels agree on a per–voxel classification [4]. The implementation of a majority voting approach [4] is considered for this approach, but more complex label fusion methods such as STAPLE [5] can also be applied.

Multi–structure segmentation approach: Anatomical variability is a common obstacle for a successful atlas–based segmentation. Since multiple structures are meant to be segmented in the Visceral benchmark 1, the anatomical variability of each structure can influence in the location of the others. Therefore, using anatomical regions of interest (ROI) to guide the registrations for each structure individually are proposed. These local masks are created based on *a priori* knowledge of the anatomical location of the structures involved and its local contrast in each particular modality.

A hierarchical set up is defined starting with the structures that have a higher local contrast in the training set (e.g. lungs). These structures provide the initial allignments and segmentations that will guide the remaining segmentations for the smaller and harder to detect structures. Once the initial structure is segmented a new ROI in the query volume is defined for the following structure and so on. For a start, the method would perform a multi–atlas based segmentation approach for the lungs, since they have high local contrast and are located in the superior part of the anatomical volumes. We use the upper half of the atlases and query image as the initial mask to guide the registrations. The output segmentation is used to define the ROI for the spleen, which is located below the lung. The mask includes the lower part of the lungs and the upper half of the lower part of the volumes where the spleen should be located. The definite creation of the masks for each modality and each structure is still a work in progress and needs to be defined and evaluated.



(a) (b) (c)

Fig. 1. Anatomical variability. The coronal views of three different volumes (a,b,c) included in the dataset are shown. Images (a) and (b) are coloured in two different regions (blue upper part and red lower part) using half of the slices in the Z direction of the volumes. Image (a) has bigger size lungs than image (b) but a smaller liver. Once both atlases are registered using global affine registration to image (c), image (b) has a better overlap in the right lung (yellow lung in (c)) than patient (a) (orange lung in (c)). If the same output transformation is used for the liver, then patient (a) will probably not have the best segmentation output for the liver, which is limited in its superior anatomical part by the lung

3 Initial Experiments and Results

To measure the impact of an initial local registration against a global allignment an experiment with the manual annotations from the Visceral training set was performed. Seven contrast–enhanced thorax and abdomen CT images included in the Visual Concept Extraction Challenge in Radiology training set (Visceral [2]) were used to evaluate our approach. These CT scans were acquired from patients with malignant lymphoma. They have a field of view from below the skull base to the pelvis. The scans have a resolution of $0.604x0.604$ to $0.793x0.793$ mm and in–between plane resolution ≥ 3 mm.

[2] `http://www.visceral.eu`, as of 14 September 2013.

A leave–one–out cross validation approach was applied to measure the Jaccard coefficient of the right lung manual annotations after only using affine registration. The Jaccard coefficient is a spatial overlap metric where no overlap is equal to 0 and a perfect overlap is equal to 1. We choose the lung because is an organ with high local contrast and it influences the location of many of the structures in the abdomen. In our approach to the Visceral dataset, this organ works as an initial reference for the other structures to be segmented.

We registered the images using only a global affine alligment. Independently, an affine registration using a mask for the superior half of the image in the reference plane includes a priori knowledge of the location the lungs in the volumes. The resulting segmentations of both approaches were compared to the manual annotations of the structure provided in the training set.

Using a mask for the superior part of the volumes gave an overall increase of 9.7% in the average Jaccard of all the volumes registered. Both the highest score for the best individual atlas and for the worst atlas had an increase in the Jaccard coefficient in all the compared volumes.

Table 1. Global vs. local. The average Jaccard coefficients computed after a single affine registration for all the CT contrast–enhanced volumes are shown. For the global registration no mask was used. For the local registration a mask is created using the superior half of the images in the Z direction. The superior half was used to incorporate the anatomical location of the lungs which are located in the upper half of the anatomical volumes. They are addressed as the first anatomical structure to be segmented because of their high local contrast and bigger size compared to the other structures in the dataset. The average highest and average lowest Jaccards coefficients for a single atlas are also provided. A local allignment provides better overlap than a global allignment

	Average	Highest	Lowest
Global	0.517 ± 3.6	0.67	0.33
Local	$\mathbf{0.568 \pm 3.9}$	**0.72**	**0.39**

4 Discussions and Conclusions

The results from our initial experiments support the usage of local masks for structures with high contrast to improve the initial affine registration of individual structures. An initial alligment with a better overlap provides higher certainty to the following non–rigid registration and eventual label fusion. Since affine registrations are less time consuming than non–rigid registrations, they can be added to find these initial ROIs. The ROIs can be redefined for new structures using the transforms provided by the local registrations of the previous structures as input.

Using masks obtained from these initial ROIs forces the atlas segmentations to circumscribe to a particular anatomical area in the query volumes. The definitive hierarchical sequencing of the segmentations and creation of the ROIs for each structure remains undefined. More experiments are needed to asses a hierarchical order for the individual structure segmentations. Still, the method allows for further improvement in each of the registration steps for both the affine and non-rigid registrations. Label fusion is also a part of the method that could be refined once the final registrations are obtained.

In conclusion, these are the initial steps and evaluations for a multi–structure segmentation approach using multi–atlas based segmentation. By adding an anatomical location and image contrast *a priori* knowledge better outcomes are obtained individually for each of the segmented structures.

Acknowledgments This work was supported by the EU/FP7 through VISCERAL (318068).

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