HIERARCHICAL IMAGE REGISTRATION WITH AN ACTIVE CONTOUR-BASED ATLAS REGISTRATION MODEL

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ABSTRACT

This paper proposes to apply the non parametric atlas registration framework we have recently developed in [6]. This technique derived from the optical flow model and the active contour framework allows to base the registration of an anatomical atlas on selected structures. A well-suited application of our model is the non rigid registration of medical images based on a hierarchical atlas. This hierarchical registration approach that we have previously introduced in [7], aims to better exploit the spatial dependencies that exist between anatomical structures in an image matching process. Its basic idea is to first register the structures the most relevant to estimate the deformation in order to help the registration of secondary structures. This aims to reduce the risks of mismatching. Here, we propose to test our novel simultaneous registration and segmentation model on different types of medical image registration problems. Results show the advantages to combine our active contour-based registration framework with the structure-based hierarchical approach and highlight the importance of the registration order of the anatomical structures.

1. INTRODUCTION

Image registration techniques aim at establishing a point-to-point correspondence between two images. The registration problem is treated as an optimization problem. Its goal is to find the transformation (or spatial mapping) that will bring a moving image into alignment with a fixed image. In fact, registering two images consists to align their corresponding features. The class of features that can be extracted from the images to register corresponds to the feature space. The search space is defined by the parameters of the type of transformation selected to align the images.

Image registration problems are often solved hierarchically. Here we consider as hierarchical, the approaches that consist to reduce the registration problem in a simpler problem by limiting the feature space and/or the search space. The solution of this simpler problem is then used as initial condition for a more complex problem, i.e. with more image features to register and/or more parameters to optimize. Afterwards, the process is repeated until the original image resolution and/or number of parameters is reached. The hierarchical approach is mainly used to increase the ability of a registration algorithm to recover large differences between the moving image and the fixed image, to avoid to fall in a local minimum during the optimization of the transformation parameters (mismatching), or to speed up the registration process.

Common methods proposed so far to reduce the feature space generally consist to reduce the image resolution, often by a coarse to fine multiresolution approach [2], and/or to extract particular image features, as the contours, by image filtering [5]. In [7], we propose to reduce the feature space by selecting with a hierarchical atlas, the image objects to consider at each level of the registration process. The main objective of our approach is to exploit the spatial relationships that exist between neighboring regions in the registration task. In [7], we describe the hierarchical atlas as an image composed of several layers. Each layer contains a subset of the moving image objects. The hierarchical atlas is built in order that the position of the regions defined in one layer is depending on the position of the regions defined in the previous layer. The advantages of the image registration with a hierarchical atlas are twofold. First it allows to apply local matching constraints only on the objects that are relevant to establish a point-to-point correspondence. Then it reduces the risk to fall in a local minima by registering first the objects determining the position of other objects. However, this hierarchical image registration process is rather limited to applications where a reference image can categorize a range of images. It is thus well adapted to describe biological images due to the existing consistency between anatomical structures of same type. Atlas registration is already used in many medical applications such in surgical or radiation therapy planning, automatic labeling of anatomical structures or morphological and morphometrical studies to bring prior knowledge in a segmentation task.

The hierarchical image registration suits well to the non parametric atlas registration framework we have recently presented in [6]. This technique derived from the optical flow model and the active contour framework allows to base the registration of an atlas on selected structures. In this paper, we propose to evaluate our simultaneous segmentation and registration model on three different types of image registration problems. In particular, we will show the advantages of the hierarchical approach in our active contour-based atlas registration framework and highlight the importance of the registration order of the anatomical structures.

This paper is organized as follows. Firstly, in Section 2, we present an overview of our non parametric atlas registration framework introduced in [6]. Then, we describe how this framework can be improved by combining it with the hierarchical registration approach we have presented in [7]. After, in Section 3, we show the performance of our hierarchical registration model on 2D and 3D medical images. Finally, results are discussed and conclusions are drawn in Section 4.

2. METHOD

2.1 Active Contour-based Atlas Registration Model

The main source of inspiration of our joint registration and segmentation algorithm is the partial derivative equation (PDE)-based method proposed by Vemuri et al. in [12][1]. The formulation of their model is intuitively deduced from the general level set[2] evolution equation (1) introduced by Osher and Sethian in [9].

$$\frac{\partial \phi_d(x,t)}{\partial t} = \phi_{d,t}(x,t) = v(\phi_d(x,t))|\nabla \phi_d(x,t)|, \qquad (1)$$

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[1]There exists also a variational energy-based approach initiated by Yezzi et al. in [13]. We chose the PDE-based approach because it seems more flexible to solve joint registration and segmentation problems notably in the choice of the attractive and regularization terms composing the speed function.

[2]The level set method is the non parametric model of the active contour technique.

where v is the velocity of the flow or speed function that contains the local segmentation and contour regularization constraints and ϕ_d is the signed distance function often used to represent implicitly the active contour (AC) by its zero level. The original idea brought by Vemuri's model is to replace, in (1), ϕ_d by the intensity function of the image to register (the moving image). Thus, the level sets considered in the segmentation process correspond to the contours naturally present in the moving image, i.e. the curves of high image gradient. A dense deformation field is then generated by tracking the deformation of these level sets during the segmentation process. The main advantage of this model using the intensity function, is to register any type of contours (closed, open, connected or disconnected) unlike the signed distance function that can only model closed and disconnected contours. However, this advantage can also be a drawback. Since all the level sets of the reference image are considered, inconsistencies between both images, e.g. local intensity differences between both images or a lesion in the patient image, can lead to missregistration. Moreover, since this contour representation does not permit to select consistent contours or closed regions in the atlas, the Vemuri's model is limited to pixel-based segmentation forces only. That means that this model cannot use in the registration process typical segmentation forces of the AC framework such as boundary-based and region-based forces (see Section 2.1.3). Unlike [12], our registration model is able to use forces developed in the AC framework since it is based on the general level set approach [9]. Moreover, we propose to handle the registration of multiple regions by modeling the active contours with a label function.

2.1.1 Deformation Field Extraction

The general formulation of our model is derived from the tracking of the signed distance function motion with the optical flow (OF) approach [3]. The OF technique assumes that the brightness of the moving image, here the level set function ϕ_d, stays constant for small displacements and a short period of time:

$$\phi_d(x,t) = \phi_d(x+du, t+dt) \Rightarrow d\phi_d(x,t) = 0, \qquad (2)$$

where du is the instantaneous deformation vector field and $d\phi_d$ is the total derivative of ϕ_d. By using the chain rule, this optical flow constraint can be rewritten as the evolution equation of a vector flow:

$$\frac{\partial u(x,t)}{\partial t} = -\frac{\phi_{d,t}(x,t)}{|\bigtriangledown\phi_d(x,t)|}\frac{\bigtriangledown\phi_d(x,t)}{|\bigtriangledown\phi_d(x,t)|}, \qquad (3)$$

where $\phi_{d,t}$, given by (1), represents the variation of the level set function according to the desired forces such as supervised segmentation, shape prior knowledge or contour regularization. Thus, by introducing the evolution equation of the level set segmentation model (1) in (3), we obtain the following formula *merging the active contour segmentation framework with the image registration task*:

$$\frac{\partial u(x,t)}{\partial t} = -v(\phi_d(x,t))\frac{\bigtriangledown\phi_d(x,t)}{|\bigtriangledown\phi_d(x,t)|}. \qquad (4)$$

The level set function ϕ_d does not evolve with the usual finite difference scheme. Its position at time t is given by the deformation field $u(x,t)$ and the initial level set function $\phi_d(x,0)$ such that:

$$\phi_d(x,t) := \phi_d(x+u(x,t),0), \qquad (5)$$

with $\phi_d(x,0)$ is the initial active contour position. This ensures that the evolution of the level set function exactly corresponds to the current deformation. Introducing (5) in (4) yields to:

$$\frac{\partial u(x,t)}{\partial t} = -v(\phi_d(x+u(x,t),0))\frac{\bigtriangledown\phi_d(x+u(x,t),0)}{|\bigtriangledown\phi_d(x+u(x,t),0)|}. \qquad (6)$$

This equation corresponds to *the general formulation of our AC-based atlas registration model*. It defines a displacement vector (or

registration force) at each point of the level set function. The level set function models the contours of the objects selected in the atlas to drive its registration. We show in Sections 2.1.2 and 2.1.3 that a large variety of active contour segmentation models can be used in the registration process.

2.1.2 Label Function Representation

The signed distance function representation ϕ_d can be used with any type of forces derived from the active contour framework (see Section 2.1.3). However, this representation can model two regions only. As we said, the intensity function representation proposed by Vemuri et al. in [12] can model any type of contours but it can only be used with pixel-based registration forces. To cope with these limitations, we propose to represent the active contours selected in the atlas by a label function ϕ_L[3]. This label function permits to define an arbitrary number of regions as follows: $\phi_L : x \in \Omega_k \rightarrow \phi_L(x) = k, k \in [1,..,n]$ if $x \in \Omega_k$, where Ω_k is the kth labeled region and n is the number of regions. In this representation, active contours are modeled by the discontinuities of ϕ_L. The main advantage of the label function representation is to distinguish n regions by using only one function. However, this representation does not contain the polarity information (information indicating the inside and the outside of a modeled region) necessary to compute the region-based forces of the AC segmentation framework. Thus, we introduced in the general formulation of our model (7) a function $S(x) \in \{-1,0,1\}$ in order to generate the polarity information. The objective of this function is to adapt the orientation of the gradient $\bigtriangledown\phi_L$ based on local label values such that it always gives the polarity of the current region, i.e. $S(x)\bigtriangledown\phi_L$ is always oriented from the inside to the outside of the region (see [6] for more details on our model). With the label function representation, the general formulation of our registration model (7) becomes:

$$\frac{\partial u(x,t)}{\partial t} = -S(x)v(\phi_L(x+u(x,t),0))\frac{\bigtriangledown\phi_L(x+u(x,t),0)}{|\bigtriangledown\phi_L(x+u(x,t),0)|}. \qquad (7)$$

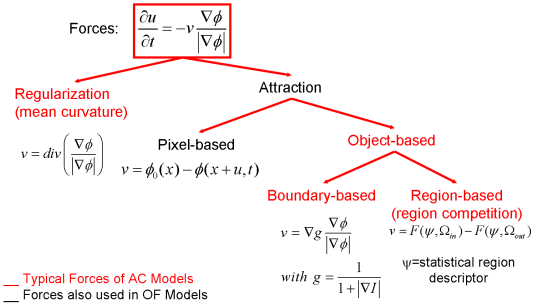### 2.1.3 Registration / Segmentation Forces

Figure 1: Classification of the AC forces according to their effect in a contour matching process.

Figure 1 summarizes the different types of forces coming from the AC segmentation framework that can still be used in the registration process. The most used *regularization force* of the AC framework is the mean curvature force. This force smoothes the level sets by minimizing their length. They can be applied on any type of contour representation. The *pixel-based forces* are based on the smallest image feature, the pixel value. They allow the local registration of the whole moving image domain or selected regions. Pixel-based forces are the typical segmentation forces of the OF

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[3]We note that in the active contours segmentation framework, the idea of using labels to perform a multiphase segmentation has recently been presented (see for instance [8]). The difference with our work is that this representation has been proposed for particular variational energy-models and we present a scheme for any type of PDE-based models.

model. In AC model, these forces are rather used to include intensity or shape prior knowledge in a segmentation process. These forces can match any type of contours (closed or open) and can also be used with any type of representation. However, they are very sensitive to image noise and are limited to recover small deformations. The *object-based forces* can register image regions. If we apply an object-based force on each point of a signed distance function, every level set will collapse to the closest target contour in the target image. So, they need to be computed only on the zero level set of the signed distance function ϕ_d or around the interface of the labeled function ϕ_L. Finally, *region-based forces* are very efficient forces of the AC framework because they are much less sensitive to noise than the *boundary-based forces*. They can also perform supervised segmentation, i.e. they can use prior knowledge extracted from a reference image. For the atlas-based applications we address in this paper, we use a registration force based on mean priors that is inspired by the unsupervised region-based segmentation model proposed by Chan and Vese [4]. This force is derived from the following energy designed to be minimal when the mean of a region Ω defined in the target image by the evolving level set function is close to the mean of the corresponding region in the reference image: $E = \int_{\Omega_{in}} |I(x) - \mu_{in}^{prior}|^2 dx + \int_{\Omega_{out}} |I(x) - \mu_{out}^{prior}|^2 dx$, where Ω_{in} is the image area inside the contour and Ω_{out} is the image area outside the contour, μ_{prior} is the prior mean of a given region extracted from a reference image (the atlas) and I is the intensity function of the image to segment. The corresponding speed function is: $v = (I(x) - \mu_{in}^{prior})^2 + (I(x) - \mu_{out}^{prior})^2$. This mean-based force assumes that corresponding regions between the reference and the target images have similar means[4]. Note that μ^{prior} does not evolve during the registration process. Hence it is computed once on the reference image in a pre-process step. At each iteration, the displacement computed on the active contour is extended to the whole image by linear diffusion. Then, the transformation is constrained to be bijective with the technique proposed by Thirion in [11]. Finally, the registration process is speeded up with a multi-resolution approach.

The main advantage of our active contour-based atlas registration model is that it allows to base the registration of an atlas on selected objects. Registering particular objects of an image will inevitably influence the position of their surrounding objects due to the dense deformation field interpolation. To take benefit of this spatial dependance in the atlas registration process, we propose in the next section to combine our atlas registration model with the hierarchical atlas registration approach we have previously introduced in [7].

2.2 Hierarchical Atlas Registration Approach

Figure 2 illustrates the AC-based registration process integrating the hierarchical approach. To register a moving image to a fixed image, the usual method begins to align globally the images with a parametric registration algorithm. This first step allows with a few degrees of freedom to put both images in the same position and thus to bring their corresponding contours closer. In this work, we have used an affine registration algorithm. Then, a registration algorithm according much more degrees of freedom to its transformation is used to recover the possible variabilities that we can have between both images especially if they come from different patients. The hierarchical approach we have proposed in [7] permits to perform this second step progressively by limiting the number of anatomical structures to register. The first layer of the hierarchy contains a subset of structures that are the most relevant to compute the deformation field. The resulting deformation field is then used as initial condition for the registration of the next layer of the hierarchy. This next layer includes the next most relevant structures to register but also the contours of the first layer in order to keep a constraint on their registration. Afterwards, the process is repeated until the n layers defined in the hierarchial atlas are registered. The goal is that the registration of the structures of one hierarchical layer helps the segmentation of the structures of the next ones as in the usual process the global registration helps the local registration. In the result part, we will see that the order in the structures registration is important for the good convergence of the matching process.

In [7], we have used a mutual information-based BSplines algorithm similar to the method proposed by Rueckert et al. in [10] to register each layers of the hierarchical atlas to the target image. In this paper, we propose to use the region-based forces of our novel active contour-based atlas registration model to register the objects defined in the hierarchical atlas. The advantage of our novel algorithm is that it is more flexible than the BSplines algorithm to include local constraints in the registration process. First, it is specially designed to base the registration on structures selected by an atlas. Then, we will see in Section 3.1) that it can also model without any special scheme, a tumor growth in an atlas. In order to also consider in the registration process the variation of textures of the image objects or open contours, we propose to perform the final step of the hierarchical registration process with the most local registration forces of our atlas registration framework, the pixel-based forces. Pixel-based forces can be computed on the whole image domain if the atlas is consistent with the fixed image[5] or only on selected regions.

In this paper, the hierarchical approach will be especially used to combine in a registration process the advantages of the region-based forces and the pixel-based forces of our active-contour-based framework.
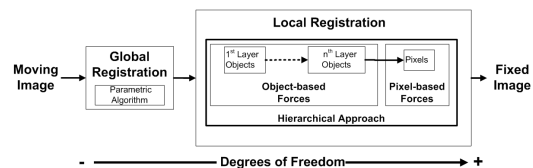

Figure 2: Active contour-based atlas registration process integrating the hierarchical approach.

3. RESULTS

3.1 Atlas Registration on a Brain MR Image with Tumor

Figure 3 shows preliminary results obtained in a tumor growth application. This experiment aims to illustrate the effect of the region-based registration forces and its usefulness in an hierarchical atlas registration process. The atlas and the patient images are respectively shown in Figures 3(a) and 3(b). These images correspond to 2D slices extracted from 3D brain MR images. We note that the patient image contains a tumor not present in the atlas. A one-voxel seed (shown by a red point) has been inserted inside the atlas to model a tumor growth. The difference between the tumor growth model we have previously presented in [1], is that this seed simply corresponds to the initial position of an active contour and not to a special tumor growth model. With this method, the pre-segmentation of the patient tumor is not require as with our previous method because the active contour is going to segment the tumor of the patient image during the registration process. The contours copied on all these images are contours selected in the atlas (the head in green, the brain in yellow, the ventricles in blue and the tumor in red). Our active contour-based algorithm permits to select the atlas contours that will drive its registration. In this case, the registration was performed following the registration of the head contour and the tumor growth. The rest of the image just follows the deformation interpolated from the displacement of the selected contours. Figure 3(c) shows the segmentation result obtained after

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[4]Possible intensity differences between both images can be reduced in a pre-process step by histogram matching.

[5]Here, we consider two images as consistent if there exist a point to point correspondence between each objects of both images.

the region-based registration of the external contour of the head and the tumor. Figure 3(d) shows the computed deformation field. We can see that the registration of the selected green and red contours has brought the yellow and blue contours closer to their target contours. This object-based registration points out the spatial dependance that exists between anatomical structures. This is this spatial dependance that we would like to exploit in the image registration. However, as we have only based the registration process on selected contours of interest, the probability of registration errors increases more we are far from these contours. To cope with this limitation, we propose for the next medical application to use region-based and pixel-based forces and to combine both these forces with the hierarchical approach.
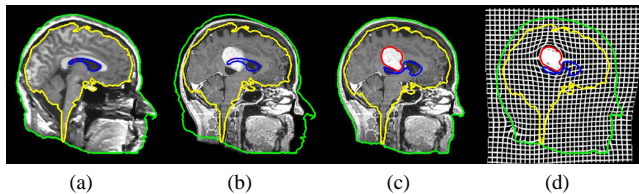

(a)　(b)　(c)　(d)

Figure 3: Active contour-based registration of an atlas on a brain MR images presenting a large occupying tumor. a) Intensity atlas with objects of interest (the head in green, the brain in yellow, the ventricles in blue, and the tumor one-voxel seed in red). b) Atlas contours superimposed to the patient image. c) Results of the joint segmentation and registration driven by the external contour of the head and the tumor contour. d) Computed deformation field.

3.2 Compensation of Intra-Operative Brain Shift

Image-guided surgery aims at bringing pre-operative information to the surgeon during the procedure. Most often, this involves registering pre-operative images with the patient in the operative room. A number of methods have been developed for this purpose. Until late 80's, these have involved rigid body registration techniques. Although rigid body techniques have proven clinically useful, it has been shown that brain deforms during the surgical procedure. The main factors causing this deformation include the loss of cerebrospinal fluid (CSF), the injection of anaesthetic agents, and the actions of the neurosurgeon (such as resection and retraction). When this is the case, rigid body transformations are not sufficient to register accurately pre- and intra-operative information. These deformations can significantly diminish the accuracy of neuronavigation systems. Therefore, it is of great importance to be able to quantify and correct these deformations by updating preoperative imaging during surgery.

For this application, our model was tested to compensate the intra-operative brainshift between two intraoperative 0.5 Tesla MR brain images[6] (image size: 256x256x60, voxel size: 0.9375x0.9375x2.5 mm^3). Both these images have been aligned with an affine registration algorithm to account for patient movement within the magnet. Figure 4(a) shows a coronal view of the moving image. The contours of the target image have been copied in green on this Figure in order to visualize the deformation due to the brain shift. One can very well observe the brain shift in the direction of the earth's gravity, as well as the shrinking of the lateral ventricles. The registration processes described below was performed with 3 resolutions. The computing time is in average 50 minutes (120 iterations per resolution)[7].

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[7]The times given in this paper are related to a computer with the following characteristics: Intel(R) Pentium(R), 4 CPU, 2.8 GHz, 1.00 GB of Ram.

First we have tested our simultaneous registration and segmentation algorithm by applying region-based forces on the external contour of the brain and lateral ventricles for the 2 coarsest scales and pixel-based forces on the whole image volume for the highest scale. Figure 4(b) shows the results with the region-based forces. We can see that these forces have permit to reduce significantly the deformation due to the brain shift (see the lateral ventricles shown by the red arrow) and that the registration errors increase more we are far from the contours considered to drive the registration (see the internal sulci shown by the yellow arrow). Figure 4(c) shows the final result after the pixel-based registration. The deformation of the internal sulci is now also compensated (see yellow arrow). Figure 4(d) shows the whole computed deformation.
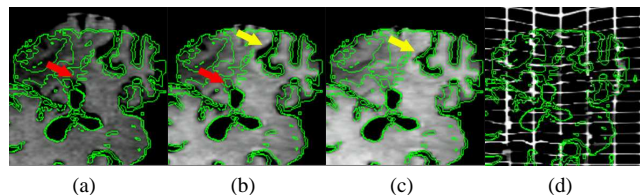

(a)　(b)　(c)　(d)

Figure 4: Registration combining region-based and pixel-based forces (Target contours in green). a) Initial difference. b) Region-based registration. c) Region-based and pixel-based registration. d) Computed deformation.

We have then compared the registration results by using pixel-based forces only, region-based forces only or by combining region-based and pixel-based forces with the hierarchical approach. Figure 5(a) shows an axial view of the registration obtained with pixel-based forces for the 3 resolutions. Figure 5(a) shows the registration obtained with region-based forces for the 3 resolutions. Figure 5(b) shows the registration obtained with the region-based and pixel-based forces combined with the hierarchical approach. After that, we have measured the registration errors of these registration by using landmarks. Figure 5(d) shows in red the landmarks that we have manually selected in the source image and in green the landmarks that we have manually selected in the target image. Note that the landmarks 1 to 3 have been selected on the cortical surface. The landmarks 4 and 5 on the ventricles, the landmarks 6 and 7 on internal sulci and the landmark 8 on the border of the edema. The eventual errors due to the manual selection of these landmarks have to be taken into account in the analysis of these quantitative results.
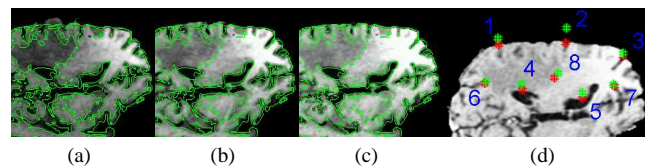

(a)　(b)　(c)　(d)

Figure 5: Comparison between pixel-based registration, region-based registration and, combined region-based and pixel-based registration. a) Pixel-based. b) Region-based. c) Combined region-based and pixel-based. d) Landmarks points superposed to the target image. Source landmarks in green. Target landmarks in red.

Table 1 presents for each landmark, the measurements of the Euclidean distances between the deformed moving landmarks and the target landmarks. These distances are given in *mm*. This table indicates in its first line the initial distances between the source and target landmarks. The following rows show the final distance obtained after applying the registration forces indicated on the left of the table.

From these results we can draw the following conclusions:

Table 1: Distances in *mm* between the deformed source landmarks after the region-based registration and the landmarks manually placed on the target image.

	Cortical Surface			Ventricles		Internal Sulci		Eud. Border
#	1	2	3	4	5	6	7	8
Init.	5.12	11.20	1.86	3.78	4.39	2.24	2.39	4.48
Pixel	4.28	7.92	1.71	3.32	2.20	1.18	1.18	2.11
Region	1.18	3.26	1.59	1.71	3.33	2.02	2.11	2.49
Region + Pixel	1.18	3.26	1.33	2.45	2.45	1.71	1.71	2.26

- Table 1 shows that the region-based forces have allowed to reduce significantly the differences between landmarks even far away from the contours selected to drive the registration.
- We note a clear difference between the pixel-based registration and the combined region-based and pixel-based registration for the landmarks located in the middle of the shifted cortical surface, i.e. the landmarks number 1 and 2. The brain shift has been better recovered by applying a region-based registration before the pixel-based registration.

3.3 Neck CT Images

In this application, we have studied the type of structures we need to register first to follow the concept of the hierarchical approach. For this experiment we have used two 3D neck CT images. The original size of these images are 512x512x62 with a pixel size of 0.9375x0.9375x4.0 *mm*. To reduce the computation time, we have subsampled and cropped these images to a size 120x150x28 (pixel size 1.875x1.875x8 *mm*). The first column of Figure 6(a) shows the initial difference between both images. The gray level image is the moving image. The contours drawn on the panels correspond to the target contours. The red contours are the contours of the target bones and the yellow contours are the contours of the external contour of the target neck. We note that the contours of both images are initially quite well superposed. The red arrow shows a notable difference between the registration results.
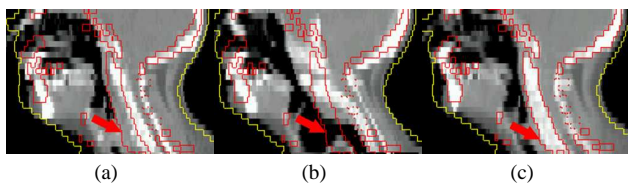

(a)　　　　　(b)　　　　　(c)

Figure 6: Registration order in the hierarchical approach. a) Initial difference. b) External contour-based registration. c) Bone-based registration.

For this experiment, we have performed two types of region-based registration. In the first type, the image registration is driven by the external contour of the neck. In the second type, we chose the hardest tissue of the neck, the bones, to drive the registration. The goal is to see how the other structures of the neck follow the registration of the selected structures. The computing time for both these registrations is in average 15 minutes (40 iterations without using a multi-resolution approach). Figure 6(b) shows the result of the external contour-based registration. Figure 6(c) shows the result of the bones-based registration. The effect obtained with both these registrations are discussed below.

External Contour-based Registration Even if the initial differences between the external contour of the atlas and the patient image was initially quite small (see Figure 6(a)), we note that their registration has provoked large changes in the position of the internal structures. This is notably the case for the position of the vertebra and the trachea. The contours of both these structures are become less well aligned than the initial position they had after the affine registration. Thus, this registration does not follow the hierarchical approach. **Bone-based Registration** In Figure 6(c), we can see that the alignment of the bones has brought the surrounding

structures closer to their target contours. This time the registration respects the hierarchical approach.

4. CONCLUSIONS

The main advantage of the atlas registration framework we have recently developed in [6] is that it allows to base the registration of an atlas on selected structures thanks to the region-based segmentation forces coming from the Active Contour (AC) method. Registering selected structures of a medical image will predictably influence the position of their surrounding objects due to the dense deformation field interpolation. To take benefit of this spatial dependance in the atlas registration process, we have proposed in this paper to combine our simultaneous segmentation and registration model with the hierarchical image registration approach we have previously introduced in [7]. Such structure-based hierarchical registration approach implies to study the existing dependencies between anatomical structures of a medical image and to determine which structures have to be registered first. Here, we have showed that a tumor growth in an atlas can bring the surrounding structures closer to their target contours, that the region-based forces derived from the AC framework can be useful to recover an intra-operative brain shift, that the hierarchical approach permits to combine the advantages of the region-based and pixel-based forces in a registration process and that the hardest structures as bones have to be registered first in an atlas. An interesting future work on the hierarchical atlas registration approach would be to study the dependance in position between anatomical structures in different types of medical image in order to better exploit this prior knowledge in atlas registration.

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