MEDICAL IMAGES REGISTRATION WITH A HIERARCHICAL ATLAS

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ABSTRACT

Atlas-based medical image segmentation is a well known method for including prior knowledge in medical image analysis. It requires as basic component the registration of an atlas with the image. In this paper, we introduce the concept of hierarchical atlas and show how to efficiently include it in a state-of-the-art non-rigid registration algorithm. We first present how to build a hierarchical atlas. Then we present the extension of a non-rigid registration algorithm, namely the B-spline Free Form Deformation (FFD), to a hierarchical version. The procedure includes first an affine registration to bring the atlas and the patient image in global correspondence. Then the non-rigid registration is performed layer by layer, i.e. registering the image with each layer of the hierarchical atlas, using the result of the registration of the previous layer as initial condition for the registration of the next layer. We show on 2D CT images that this approach gives better results than the non-rigid registration algorithm alone, in terms of registration accuracy.

1. INTRODUCTION

In this paper, we want to explore the integration of a registration method in segmentation of the neck structures in Computed Tomography (CT) images. The clinical aim is radiotherapy of the neck cancer. In a radiotherapy treatment, a source emits radiations which penetrate through the skin in the tumoral volume to be irradiated. To be both effective in cancerous tissues and respectful to healthy ones, the dose of radiation should vary according to the area. In the neck, 7 distinct spaces are counted out by specialists; for each space a specific intensity is required. In the traditional approach a alloy cover is constructed for each patient in order to protect some regions and thus minimize the destruction of healthy cells. Obviously, this technique is too restrictive in term of time and cost. According to the current state of the technique, the ultimate "high precision" technique is the Intensity Modulated Radiotherapy (IMRT) where the intensity of the radiation is modulated depending on the region. This requires thus a precise definition of the region of interest, *i.e.* a segmentation of the target image. Nevertheless, for tumors of the Head and Neck (H&N), the implementation in routine practice is facing significant obstacles. Indeed, besides the precise contouring of primary H&N tumors that is often difficult, the accurate, reproducible and time-efficient contouring of elective nodal risk regions represents an even greater challenge that is making the use of this technique uncommon. To cope with this problem, we propose to use an atlas of the neck area and to exploit it to segment the different regions of interest. Several atlas-based segmentation techniques have been proposed for medical applications. Their review is out of the scope of this paper. Let us only mention two of them directly related to this paper. In [1], Bach *et al.* present an atlas-based segmentation for pathological brain images and in a hierarchical point of view, Kapur *et al.* ([7]) adapt a registration algorithm for each level of a multi-level knee atlas. In the case of the neck, we must take into account the high local variability and complexity of the region, and therefore a localized registration is required. In the literature, we can find a large panel of registration methods. A general formulation of the problem that is often encountered consists in optimizing a functional F:

$$\arg\min_T F(\text{Image1}, \text{Image2}, T)$$

where T is the geometric transformation used to register one image with the other one.

The resolution of the formulation depends on one side on the choice of T and on the other side of the choice of F. Firstly, the choice of T determines the nature of the transformation and the number of degrees of freedom associated. For more local result, a non-rigid approach must be used. Several methods have been developed. Christensen and Miller [4] proposed for T a free deformation on the model of viscous fluid (similar to the Navier Stokes equations). By analogy with Maxwell's Demons, Thirion [13] has developed a diffusion model. Meyer *et al.* [9] have proposed an algorithm based on thin plates spline deformation. Following this idea, Rueckert [12] *et al.* have used B-splines associated to a multi-scale framework. Finally, in a similar scheme, Rhode *et al.* [11] apply radially symmetric basis functions which can be spatially adapted. In most of the methods, the parameters of T are iteratively computed such a way that the similarity measure F between both images is maximized. Different techniques for measuring this similarity have been developed. A widely used measure is the mutual information, or its derived form the normalized mutual information, which model the statistical relationship between the target image and the transformed image. The mutual information measure has been introduced in parallel by Collignon [5] and Viola [14]. [2], [3], [11], [12] and [9] take this criterion as the similarity measure (see [10] for a review on this topic). In this paper, we propose a variation of the atlas-based segmentation technique, by defining a hierarchical procedure to progressively register the atlas with the target image. As a demonstration, we will consider Computed Tomography(CT) images of the neck.

2. METHOD

2.1 Construction of the Atlas

Given a CT image of the neck, we define an atlas of this region (figure 1) by manual extraction of some structures of interest in a reference image. Next, we establish a hierarchical

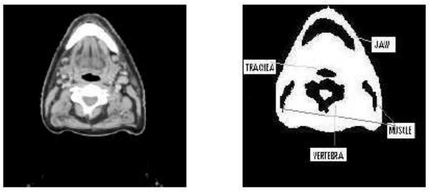

Figure 1: Left: Source image. Right: The atlas deduced from the source image

construction of our atlas, related to the degree of easiness of the segmentation problem. The first layer will be composed of the most visible structures and the last layer, obviously, of the less visible. Figure 2 illustrates the construction of the mask.

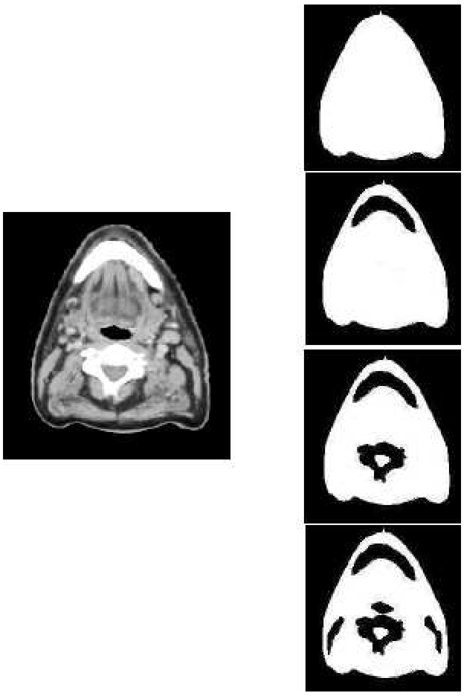

Figure 2: Left: Source image. Right: Successive atlas layer

2.2 Registration Technique

In order to find the best matching between the target image and the mask, we need to know the transformation that relates the coordinate space in an image A with the corresponding coordinate space in the other image B. Let us call T this registration transformation:

$$T : B \mapsto A$$
$$T(u_B) = u_A$$

In the following, A will denote the target image and B the source image.

2.2.1 Global part

As a pre-processing, we apply an affine transformation to the source image to put it in global correspondence with the target one. In 2D, this leads to the optimization of 6 parameters, describing the translation, rotation, scaling and shearing of the source image.

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \mathbf{T}_{rigid} \begin{bmatrix} x_B \\ y_B \\ 1 \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \quad (1)$$

2.2.2 Nonrigid registration using B-splines

For this part, we have chosen to use a state-of-the-art non-rigid registration techniques, based on B-Splines, following an approach similar to [12]. We want to remind the reader that the actual algorithm used here is not central in this paper. We just use it to illustrate our hierarchical approach, which is the main point that we want to present. Any good non-rigid algorithm can fit in this framework. For this type of registration, a control points grid is constructed in the source image. The goal is to find the best displacement of those control points which maps the source image landmark points to the target image using spline interpolation. B-Splines belong to the Free Form Deformations (FFD) class and are a powerful tool for modelling deformable model. Unlike the classical radial basis functions such as thin-plate Splines, B-Spline have finite support. It means that we will have only a local influence for each control point.

Let now define our B-Spline-based FFD. $= \{(x,y) \mid 0 \leq x < X, 0 \leq y < Y\}$ is the rectangular domain containing the region to be transformed and a $n_x \times n_y$ mesh of control points $_{i,j}$. Using the B-spline interpolation, we define the local transformation by :

$$T_{local}(x,y) = \sum_{l=0}^{3} \sum_{m=0}^{3} {}_l(u) \; {}_m(v) \; {}_{i+l,j+m} \quad (2)$$

where $i = \lfloor \frac{x}{n_x} \rfloor - 1$, $j = \lfloor \frac{y}{n_y} \rfloor - 1$, $u = \frac{x}{n_x} - \lfloor \frac{x}{n_x} \rfloor$, $v = \frac{y}{n_y} - \lfloor \frac{y}{n_y} \rfloor$ and $_l$ represents the l-*th* basis function of the B-splines:

$$\begin{aligned} {}_0(s) &= (1-s)^3/6 \\ {}_1(s) &= (3s^3 - 6s^2 + 4)/6 \\ {}_2(s) &= (-3s^3 + 3s^2 + 3s + 1)/6 \\ {}_3(s) &= s^3/6 \end{aligned} \quad (3)$$

where $0 \leq s < 1$.

After the affine and the B-spline transformation, the final deformation field is given by:

$$u' = u + T_{local}(u) \quad (4)$$

where $u = (x,y)$ is issued from the affine transformation.

With the basis functions, the weight of the contribution of each control point in $T_{local}(x,y)$ is estimated. Thus, the control points displacement determines the local transformation. The next step is to find this displacement by optimizing a similarity measure.

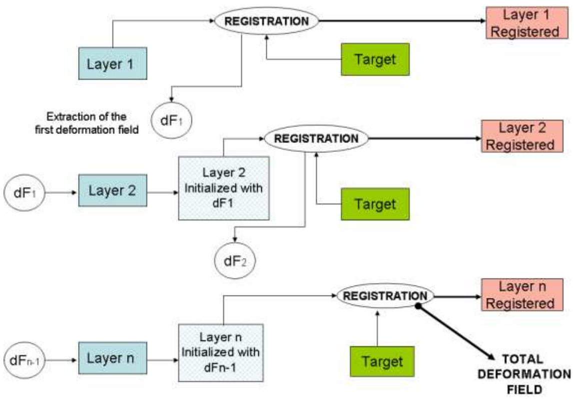

Figure 3: Summary of our hierarchical atlas based registration algorithm

2.2.3 *Similarity criterion: Mutual Information*

In the registration process, the choice of the metric system of similarity has significant effects. The similarity criterion will measure the quality of the alignment between the target and the source image. As it has been said, since in our application the target image come form a CT scanner and the source image is a binary image, the similarity criterion must take in account the multimodal nature of those images. Therefore we have chosen to use Mutual Information (MI), which measures statistical dependance between two images. Mutual information is defined in terms of entropy:

$$H(A) = -\sum_a p_A(a) \log p_A(a) \qquad (5)$$

One form of mutual information is:

$$MI(A,B) = H(A) + H(B) - H(A,B) \qquad (6)$$

where $H(A)$, $H(B)$ denote the marginal entropies of A, B and $H(A,B)$ denotes the joint entropy of two random variables. The joint entropy measured from the joint histogram must be minimized in order to maximize the mutual information. We have used the Mattes *et al.* [8] implementation for the MI computation.

2.3 Hierarchical atlas-based registration

Using the algorithm described previously, we wish to register successively each layer of our atlas with the target image. In this aim, the FFD registration is applied for each layer. Our strategy is to treat each layer's registration as a sequential process. Concretely, the deformation field of the layer i will initialize the deformation field of layer $i+1$. Thus, each deformation field is a part of the hierarchical scheme where the highest level corresponds to the last transformation. Figure 3 describes the steps of the hierarchical registration. Furthermore, the hierarchical scheme allows a coarse-to-fine approach for the registration.

3. RESULTS

Using 2D images CT scans of the two patients neck region, we first apply a global registration using an affine transformation. From this result, we perform our tests. In this section, we compare the results of our algorithm with a state-of-the-art approach. In this case, we use the B-Spline multiresolution framework of Rueckert *et al.*[12] in which the resolution of the grid control points increases with the image resolution. Figure 4 gives the different results of registration. The first image in the left side is the superposition of the target image and the contour of the initial mask. The image on the middle shows the result after the registration in a multiresolution framework and the last image shows the results obtained with our algorithm. We note a difference of the registration in the external structure and in the smaller structures. In particulary the jaw has better registration results with our technique.

We assess the registration quality by measuring the distance between a set of landmark points of the source image transformed and the correspondent set in the target image. First, 7 points of interest are pointed manually on the target image and second the corresponded points are marked on the source image (figure 5). The Euclidean distance (equation 7) is used

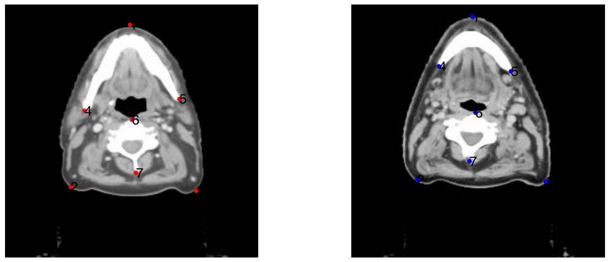

Figure 5: Corresponding landmarks on the target and source images

as the error estimator between the landmark point u_i' and the manually selected point u_{B_i} in the source image.

$$d = \|u_{B_i} - u_i'\| \qquad (7)$$

This estimation error is applied to the two registrations modality. Table 1 presents results of our measures. d_{init} is the error before the registration, d_{NRM} the error after a multiresolution non rigid registration and d_{NRHA} the error after the non rigid hierarchical atlas-based registration.

Table 1:

Landmarks	d_{init}	d_{NRM}	d_{NRHA}
1	9.06	8.01	2.69
2	8.06	2.19	2.81
3	6.00	5.96	1.91
4	7.21	5.46	5.09
5	10.63	7.28	4.58
6	8.06	5.11	2.08
7	31.76	26.22	24.07
Mean	11.54	8.60	3.73

4. CONCLUSION AND FUTURE WORK

In this paper, we have proposed a new framework for Free Form registration, illustrated in the case of B-Splines based registration. The registration by successive layers allows better local deformation. We have compared our technique with

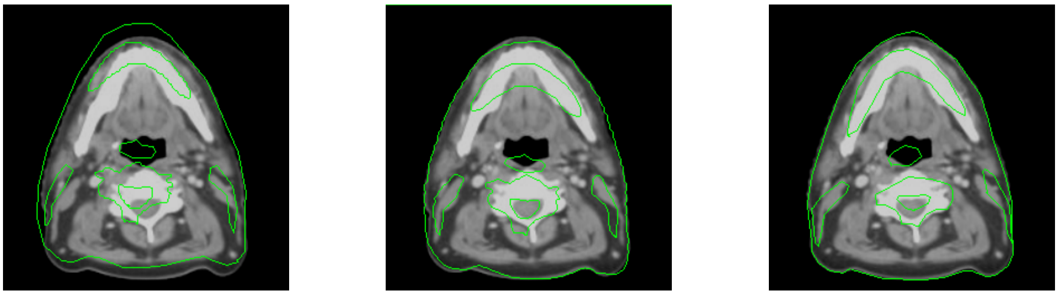

Figure 4: Results. From left to right, initialization of the atlas, atlas after applying FFD multiresolution registration, atlas after applying our FFD hierarchical framework

the well know technique of free form multiresolution registration. The results have shown that a hierarchical atlas captures more precisely the contours of interest. The registration made is a preliminary step before segmenting each area associated to a label. Future works will focus first on working on 3D images and on the automatization of the atlas construction.

5. ACKNOWLEDGEMENTS

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