Towards an automatic delineation of lower abdomen structures for conformational radiotherapy based on CT images

J. Costa[†], H. Delingette[†], Jean Christophe DIAZ[‡], Dr. William WIBAULT[*], Dr. Ann EGELMEERS[◇].

[†]INRIA Sophia-Antipolis
2004 Route des Lucioles
06902 Route des Lucioles, BP 93

[‡] DOSISOFT S.A.
45 Av. Carnot
94230 Cachan

[*] Département de radiothérapie
Institut Gustave Roussy

[◇] Service de radiothŕapie
Hôpital Saint Joseph
Gilly - Belgique

e-mail : Jimena.Costa@sophia.inria.fr, Herve.Delingette@sophia.inria.fr

Abstract. The delineation of anatomical structures based on images of the lower abdomen in the frame of dose calculation for conformational radiotherapy is very complex to automatize. We present here the first results of a semi-automatic delineation of the bladder in tomodensitometric (CT) images. The method we have used is based on deformable templates whose deformation is guided by the image and by the user as well, in case the latter desires to correct the automatic delineation.
In order to validate our approach, we use a set of CT images that have been segmented by medical experts. These hand-made contours act in fact as ”ground truth”, allowing for an objective evaluation of the performance of our algorithm.

Abstract. La délinéation de structures anatomiques à partir d'images médicales du petit bassin reste une tâche très complexe à automatiser dans le cadre du calcul de dose en radiothérapie conformationelle. Nous présentons ici, les premiers résultats concernant la délinéation semi-automatique dans des images tomodensitométriques (Scanner X) de la vessie. La méthode utilisée repose sur des structures déformables dont la déformation est guidée par l'image, mais aussi par l'utilisateur s'il désire corriger la délinéation automatique.
Pour calibrer cet algorithme, nous utilisons un jeu de plusieurs images scanners qui ont été délinées par des experts médicaux. Ces contours tracés manuellement servent en effet de ”vérité terrain” permettant une évaluation objective de la performance de notre algorithme.

1 Introduction

Image segmentation denotes the technique of extraction of image structures (regions or objects) so that the outlines of these structures will coincide as accurately as possible with the physical 3D object outlines. Image segmentation is an essential step for many advanced imaging applications; accurate segmentation is required for volume determination, surgery and radiotherapy planning among others. In particular, accurate segmentation in conformational radiotherapy allows for a better conformation of the high-dose volume to the target volume, with normal tissue avoidance and the subsequent potential benefit of both reduced normal tissue toxicity and dose escalation to the tumour.

Image segmentation approaches may be performed in one of these ways:

Manual segmentation methods, which, given normal image resolution, usually suffer from potentially large inter- and intra-expert variability in the resulting delineations.

Fully automatic segmentation methods are usually not robust due to image complexity and the variety of image types and interpretation.

Semi-automatic segmentations methods combine the benefit of both manual and automatic segmentation techniques. Any remaining errors introduced by automatic segmentation methods may be corrected by manual editing. In this work, a method based on deformable templates is shown.

We present here a semi-automatic segmentation method. We approach the issue of boundary finding as a process of fitting a series of deformable templates to the contours of anatomical structures. We choose simplex meshes (introduced in [4]) to model the templates, owing to their fairly simple geometry, which facilitates the incorporation of deformation constraints. An initial simplex mesh undergoes both global and local deformations to fit the boundaries of a given anatomical structure in a set of tomodensitometric (CT) images, and the result can later be interactively modified and/or corrected by the user. We apply our method to the segmentation of the bladder, then comment on the results and finally present our conclusions and future work.

2 Materials

Our work was based on the following materials:

2.1 Images

We performed our tests on tomodensitometric (CT) images of the lower abdomen of 6 different patients.

2.2 Contours

We were provided with a set of 2D contours corresponding to each slice of the structures of interest. These contours have been hand-delineated by Dr. William Wibault, at the Gustave Roussy Institute, and Dr. Ann Egelmeers, at Saint Joseph Hospital (Belgium), who used Dosisoft software for that purpose.

2.3 Reconstruction

In order to validate our approach, we reconstructed 3D models of the series of 2D contours we had received (some examples can be seen in Figure 1). This process of reconstruction comprises the following stages:

(1) Choose the contours that correspond to the structure of interest.
(2) For each slice's contour, fill the background and foreground with different colors.
(3) Extract the isosurface that corresponds to the target structure (for example, the bladder) and store the resulting model.

We work with 3D segmentation instead of 2D because, as we will explain in the following sections, a set of slice by slice contours can lead to an irregular and unrealistic 3D delineation.

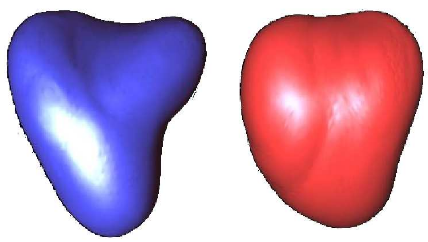

Fig. 1. Some of the reconstructed 3D models from a set of 2D contours of the bladder.

3 Method

3.1 Motivation - Manual Structure Delineation

Because of the difficulty to accurately and reliably delineate structures in medical images, this task has traditionally been assigned to human operators. However, given the improvements achieved over the past years by imaging tools (commercial MR scanners now routinely resolve images at millimetric resolution, digital cameras can convert histological sections into million-pixel images) the manual segmentation phase has become an intensive and time-consuming task. A trained operator typically has to go through around 80 256x256 images, slice by slice, to extract the contours of the target structures, one after the other. This manual editing is not only tedious but particularly prone to errors, as assessed by various intra or inter-operator variability studies ([2], [9], [6] and others).

Manual editing thus suffers from many drawbacks:

– The results are often difficult if not impossible to reproduce. Even experienced operators display significant variability with respect to their own previous delineation for difficult structures, (see Figure 2).
– For 3-D delineation, editing tools usually display 3D data in the form of a 3 synchronized, 2D orthogonal views (sagittal, coronal and axial) onto which the operator draws the contour of the target structure. The output data therefore consists of a series of 2D contours from which a continuous 3D surface has to be extracted. This is a non-trivial post-processing task, itself prone to errors. Moreover, since the operator has to mentally reconstruct the 3D shape of the structure from a series of 2D views, inter-slice inconsistencies and bumps are inevitable. More robust segmentation methods can usually be derived from true 3D structure models in that they can ensure globally smoother and more coherent surfaces across slices.

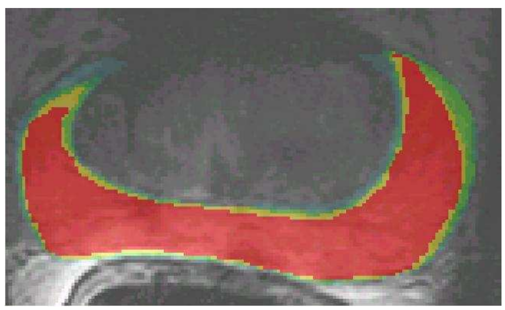

Fig. 2. Variability in the delineation of the peripheral zone of the prostate in 5 repeated segmentations by the same expert. The various colors in the prostate boundary indicate the 5 different delineations that were performed.

3.2 Deformable Templates

Many deformable surface representations have been proposed for model-based segmentation of medical images ([8]). Among existing representations, we use the discrete simplex meshes ([3], [5]) for their simple geometry and their ability to define shape constraints in a computationally efficient manner.

Simplex Meshes Simplex meshes are discrete model representations (set of vertices and edges) with prescribed vertex connectivity. They are curves or surfaces that evolve in a 2-D or 3-D space to get to delimit an anatomical (or pathological) structure. To encode the structure surfaces, we use 2-simplex meshes: each vertex is then connected to exactly three neighbors (see Figure 3). This inherent geometric simplicity greatly eases the imposition of constraints to bias the segmentation process. Additionally, ”zones” (subsets of vertices with their associated edges) can be defined on the simple meshes to further specify the constraints. We have focused on devising a segmentation system where maximum use is made of the available medical expertise, concerning the shape of the structures, their appearence, etc.

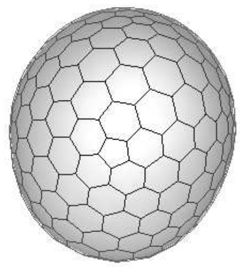

Fig. 3. A simplex mesh. In this case, it is the average mesh of all the reconstructed 3D models of the bladder, and is used as the initial mesh in our segmentations.

Deformable models are thus a recipient that stores a priori information about the geometry and the apparence of anatomical structures.

Initial model - An average mesh In order to aid in the segmentation process, we wished to use an initial model that was as close as possible to the structure of interest (in our case, the bladder). Given the high variability of this anatomical structure, we decided to base our initialization on the 3D models we reconstructed from the 2D contours we had been provided with. For that purpose, and once a 3D mesh was constructed from each set of 2D contours for each bladder, we computed an average mesh taking all of them into account, and used this mesh as the initial approximation to the segmentation solution.

Computation of Simplex Mesh parameters using Fuzzy K Means The Fuzzy K Means algorithm is a clustering algorithm which classifies input data according to a set of characteristics (as described in [7], [1], [10], and many others). In our case, we were interested in obtaining a set of classes that roughly separated the structures of interest (i.e., the bladder) from the other structures in our CT images. Thus we could obtain intensity ranges in which our structures of interest reside, and use these ranges to guide our deformable model.

In our approach, we have used the resulting classification of the Fuzzy K Means algorithm to automatically establish a range of intensities for the bladder's upper portion, lower portion and exterior part, and we have used these results to guide the evolution of our simplex meshes.

Evolution of Simplex Meshes Once the average mesh has been computed and its parameters have been established, we must define the laws that govern its deformation.

In our case, the evolution of the model is guided by the simultaneous optimization of two criteria. The first one is a measure of the geometric regularity of the model, using for example local curvature measures. The second one measures the distance of each mesh vertex to the closest apparent boundary of the structure of interest in the image. These methods are very effective. Our initial model (see Figure 3)is an average of 6 hand-made segmentations, which is initialized in an approximative manner around the region of interest. The model then evolves from this initial position to automatically improve the fit to the boundary of the region to be detected.

A reasonable expectation for the accuracy of the algorithm is that it be no worse than what is manually achievable.

The evolution of deformable models is generally based on the hypothesis that the contours that delimit the sought structures correspond to a global or local minimum of an energy function. We propose an evolution scheme that allows to better control the deformations of the model, and thus permits a less accurate initialization of the model and the segmentation of noisy data, thanks to a hierarchical deformation scheme.

We use a ”coarse to fine” approach to combine a global deformation procedure that limits the model shape variations and a local deformation component to match small shape variations (see [10]).

Global deformations: This type of deformation takes into account every vertex of the model, thus making the deformation less sensitive to noise, but, if used alone, it may be too constrained to allow for a sufficient variation of the model in order to reconstruct the data in a satisfying way.

Local deformations: Here, the modifications of the surface take place locally at each vertex of the deformable model, and only a limited neighbourhood of that vertex is considered. These deformations allow for very localised variations in the surface and therefore the potential segmentation of noise present in the data. The model gets close to the data, but it has a very poor geometric quality.

We use a hierarchical approach that progressively increases the number of degrees of freedom of the transformation. This approach results in a global positioning of the model over the bladder image in the first place, and a progressive refinement and adaptation to smaller variations in the structure (local deformation).

3.3 Hierarchical approach

Among the anatomical structures of the lower abdomen, we chose to start by segmenting the bladder, which can be found quite clearly in the tomodensitometric images. We will continue with the other, more ”evident” structures of the lower abdomen (rectum, femoral heads, etc.), and then, by computing the statistical relationship of their position with respect to that of less visible strucures (such as the prostate), we will expect to be able to segment the latter, even if their visibility is limited.

3.4 Segmentation of the bladder

The bladder is an organ that presents a very high variability in size, shape, color (see Figure 5) and contrast among different patients, and even within the same patient at different times of the day. It can be seen as an almost spherical structure of good contrast, such as in Figure 6, or as a structure of low contrast, as in Figure 9, and even as a structure of inhomogenous gray level, with two marked regions (the lower and upper portions, such as in Figure 4).

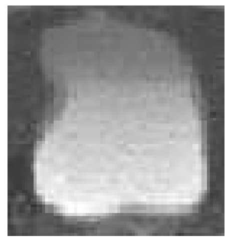

Fig. 4. In this image, the bladder shows a marked intensity variation between its lower and upper portions.

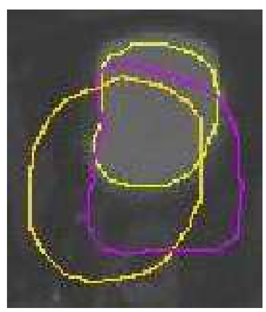

Fig. 5. Variations in shape and size of the bladder of different patients.

To account for the potential variations in the gray levels of the upper and lower portions of some of the bladder images, we have divided our mesh also into an upper and lower halves, so that each portion can evolve independently, guided by different intensity parameters.

The parameters (intensity ranges) for both portions, and for the background as well, were computed using the Fuzzy K Means algorithm. Since the resolution of the CT images is quite good, the Fuzzy K Means algorithm can be expeted to show (and in fact it does) a very good convergence rate.

The images were pre-processed with a gaussian filter to decrease the noise level.

The initial model was computed as the average of the 3D models which were reconstructed from the sets of 2D hand-made bladder contours provided by the experts.

Once the parameters for the region-based algorithm had been calculated, we initialized our average model of the bladder and began the rigid transformations that globally placed the mesh as accurately as possible over the bladder found in the CT. As we mentioned before, this step makes the whole procedure less prone to the influence of noisy data and outlier points.

After this step, the mesh progressively began to undergo more local deformations, which allowed it to adapt itself to smaller variations in the data.

4 Preliminary results

We present here the results of two segmentation processes.

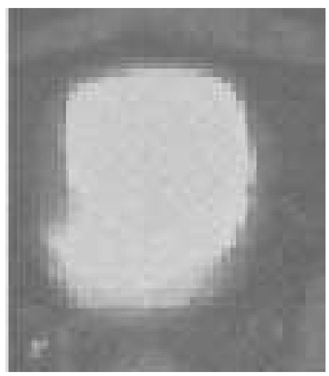

Fig. 6. The first bladder example. In this image, the bladder has a homogenous intensity in its interior.

As can be seen in Figure 6, the bladder has a uniform color and also has an interesting contrast with respect to its background. It was segmented using the algorithm described in the previous section, and the same laws of motion were applied to both the upper and the lower portion of the simplex mesh. Figure 7 shows the image's histogram. The resulting segmentation can be seen in Figure 8; it has a high accuracy and is readily at the level of a hand-made segmentation by an expert.

The second bladder is shown in Figure 9. This is clearly not a very well contrasted image, and, furthermore, the bladder shows different gray levels at its top and bottom portions. However, our segmentation algorithm performed well, as can be seen in Figure 10 as compared to the manually segmented result.

Concerning bladders which showed greater variations between their upper and lower portions, the deformable model had sometimes trouble adapting to both regions at a time, and fitted very well one of the portions but failed to fit the other portion in a satisfying manner.

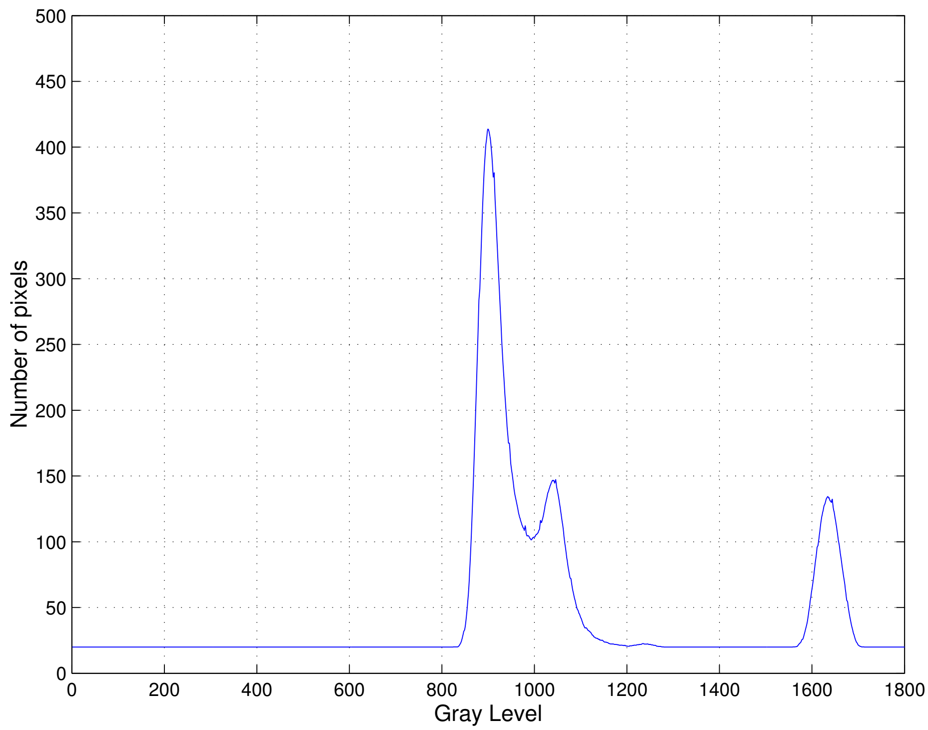

Fig. 7. The (smoothed) histogram for the first example. We can see 3 peaks: from left to right, they represent the outer background of the bladder (dark), the upper portion of the bladder (slightly lighter), and the lower portion together with the bones (the lightest structures in the image).

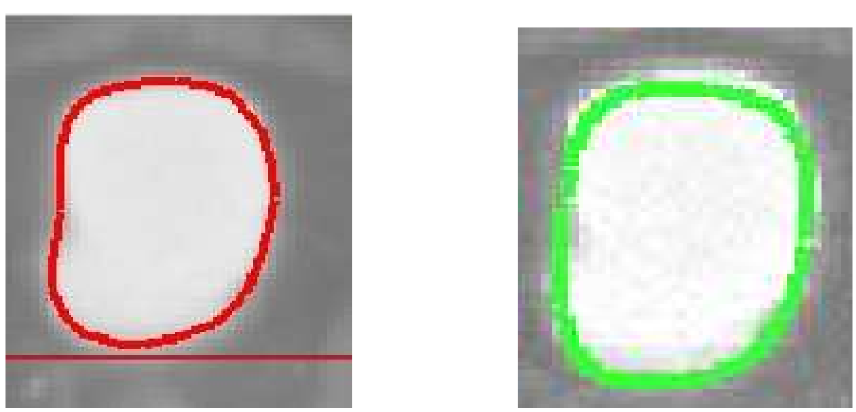

Fig. 8. The resulting segmentation for the first bladder image (left), and the hand-made segmentation by an expert.

Fig. 9. The second bladder example. As we see, there is a considerable lack of contrast, which would make the manual delineation very difficult.

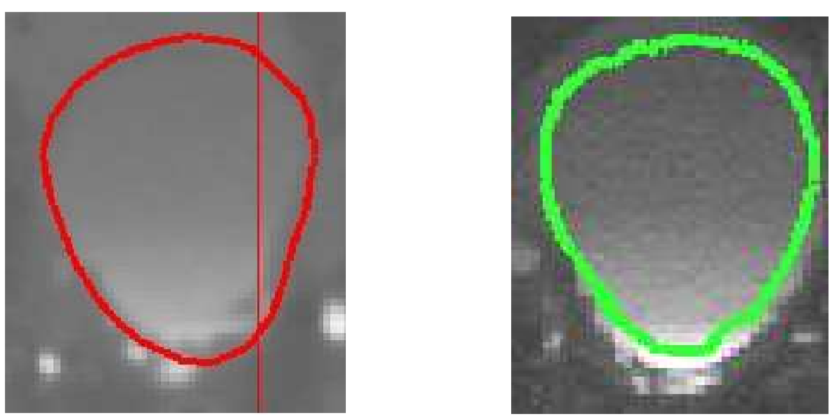

Fig. 10. The resulting segmentation for the second bladder image (left) and the hand-made segmentation by an expert

5 Conclusion and future work

In this paper we have shown that segmentation of bladder in tomodensitometric images can be performed using deformable surfaces. The model provides enough intrinsic (shape) and extrinsic (grey-level range) prior knowledge on the data, to constrain the deformations properly even in the presence of poorly contrasted or noisy images. We are now focusing on improving the model for the cases in which the contrast between the different portions of the bladder is high. We will then continue to segment the different structures near the prostate (femoral heads, rectum) that can be well detected and provide statistical information about the position of the prostate.

Prior smoothing of the image reduces the noise level and improves the region detection. The Fuzzy K Means algorithm provides a good base for the computation of intensity parameters for the model. The average model of the bladder proved to be an effective initialization for the algorithm. The model-based segmentation enables an accurate delineation of the bladder, comparable to hand made segmentation by an expert.

Although further work will be done concerning the adaptability of the model to images in which the bladder's interior shows high variability in its intensity, simplex meshes have shown to be a promising approach to address the issue of bladder segmentation. We are encouraged to test this method's performance in the segmentation of other structures of the lower abdomen as well.

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