Auto-contouring the Prostate for Online Adaptive Radiotherapy

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Abstract. Among all the organs under cancer treatment, prostate is a very important one in male pelvic region but very difficult to segment, due to the poor contrast of 3D CT images, invisible boundaries between the prostate and its neighboring organs (e.g. bladder, rectum), and artifacts produced by prostate seeds etc. Furthermore, the same patient's organ conditions (e.g. size, shape and location) can significantly change throughout the whole treatment course. In this paper, we propose a learning-based approach to deal with both inter-patient and intra-patient variation for auto-contouring the prostate in adaptive radiotherapy. In general, the method starts with learning population-based characteristics, and adaptively incorporate patient-specific knowledge as the same patient's subsequent treatment images become available. Specifically, we learn a population-based boundary classifier and a sparse shape dictionary based on a set of already contoured patients. For intra-patient treatment tasks, previously segmented prostates of the same patient are utilized to adaptively update the boundary classifier and sparse shape dictionary. The updating process is fully automatic and completely offline, which won't affect run-time efficiency. The proposed method has been extensively evaluated on 44 3D CT images of 11 patients, each with more than 3 daily treatment images. Our method produces superior performance over two other state-of-art auto-contouring methods, which is promising for online adaptive treatment planning.

1 Introduction

In radiotherapy procedures, a patient needs to take a series of 3D CT images for treatment planning, re-planning, online dose delivery throughout the whole treatment course. To create a new treatment plan, a physician often needs to contour the image from scratch. It is a time consuming task which often induces large inter/intra institutional variation. Ideally an automatic contouring method not only reduces contouring time for the physicians, but also improves the accuracy and consistency for treatment. Among all the organs under cancer treatment, prostate is a very important one in male pelvic region but very difficult to segment. Major challenges for inter-patient cases are the following: (1) low contrast of 3D CT images, which makes large portion of the prostate boundary invisible (Figure 1), (2) image artifacts produced by prostate seeds (Figure

1 (a) (c)), and (3) large area of gas/feces/coil filling in the rectum (Figure 1 (b)(d)(e)). For intra-patient cases, the same patient's organ condition may vary a lot at different treatment times (Figure 2) due to (1) size of volume changes in response to treatment, (2) relative position change between neighboring organs, (3) shape deformation due to filling state of neighboring organs (e.g. bladder or rectum). Therefore, the desired auto-contouring method should be capable of handling both inter-patient and intra-patient variations. Additionally, the online processing should be computationally light weighted to adapt to the fast pace of online treatment procedures.

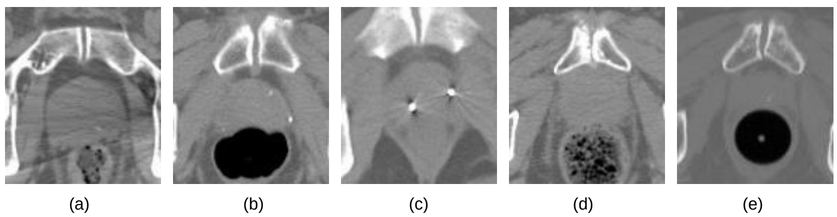

Fig. 1. Some prostate CT images from clinics: (a) an image with streaking artifacts, (b) a patient with large rectum gas, (c) a patient with seeds causing bright spots and streaking artifacts, (d) a patient with feces filling, (e) a patient with a rectum coil.

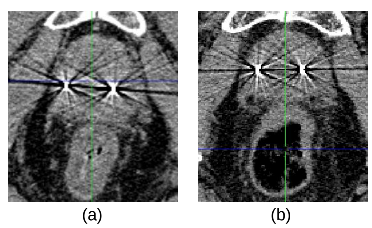

Fig. 2. An example of intra-patient variation of two images taken at different treatment times. (a) a patient's image at time t_1, (b) the same patient's image at time t_2.

Intuitively, the contouring process can be made easier by considering the same patient's previous contours as prior knowledge/reference. However, currently when designing a new plan or during treatment, physicians usually do not utilize the same patient's previous plans. Even when previous plans are used, they are incorporated by registration to map the previous contours to the current image. One common method is rigid registration. This method only provides a few degrees of freedom. Thus, the registered contours may not be precise. Deformable registration [1][2][3][4] may be employed to improve the accuracy by calculating non-linear organ deformations. In general, the accuracy of the contours may depend on the number of reference images (atlases) used [4]. There is, however, an increased computational cost proportional to the number of reference images (atlases), which makes it difficult to use for online adaptive planning. Alternatively, a few machine learning based methods [5][6][7] tried to use context information [5] or several layers of feature abstraction [7] to make the prostate region more discriminative for segmentation. They either focused on inter-patient segmentation or intra-patient segmentation. In [7], the authors evaluated those methods for prostate segmentation on MRI images and produced promising results.

In this paper, we propose a unified learning-based framework to accommodate both inter-patient and intra-patient variations for adaptive radiotherapy. In particular, a population-based boundary classifier and a population-based sparse shape dictionary can be trained. The trained boundary classifier and the sparse shape dictionary can then be used to perform auto-contouring in a patient's planning image. As more treatment images are collected, the system may automatically update the boundary classifier and the sparse shape dictionary to incorporate patient-specific information. Once a new treatment image is received, the system may perform auto-contouring of the interested organ on the fly. One advantage of this approach is its high accuracy. In the online auto-contouring stage, the method is able to achieve a mean Dice value of 0.93 for the prostate. Another advantage of this approach is its ability to handle extremely low quality 3D CT images (e.g., Figure 12), since consistent artifacts/low quality can be learned as part of the patient-specific knowledge. Additionally, this method is computationally very fast when applying to a new scan. Because the learning process of previous scans is completely off-line, which can be done any time when the machine is vacant. Online auto-contouring takes the same amount of time no matter how many previous images were used for training. This is an advantage over deformable registration methods with multiple atlases, in which case the amount of auto-contouring time increases with the number of atlases used. The proposed learning-based prostate segmentation method has been extensively evaluated on 44 images of 11 patients, each with more than 3 daily treatment 3D CT images. It produces superior performance over two other state-of-the-art segmentation methods. The learning framework is very accurate and fast with the flexibility of working on any quality images, which is well designed for online adaptive radiotherapy in clinics.

In section 2, we will discuss the methodology in detail. In section 3, enormous experimental results are given, which is followed by section 4 conclusions.

2 Methodology

Figure 3 shows the flowchart of this learning-based system. The top part shows the components for off-line training/updating, while the bottom part shows the online auto-contouring components. Algorithm flow involved in off-line training/updating is marked with red arrows. Algorithm flow involved in online

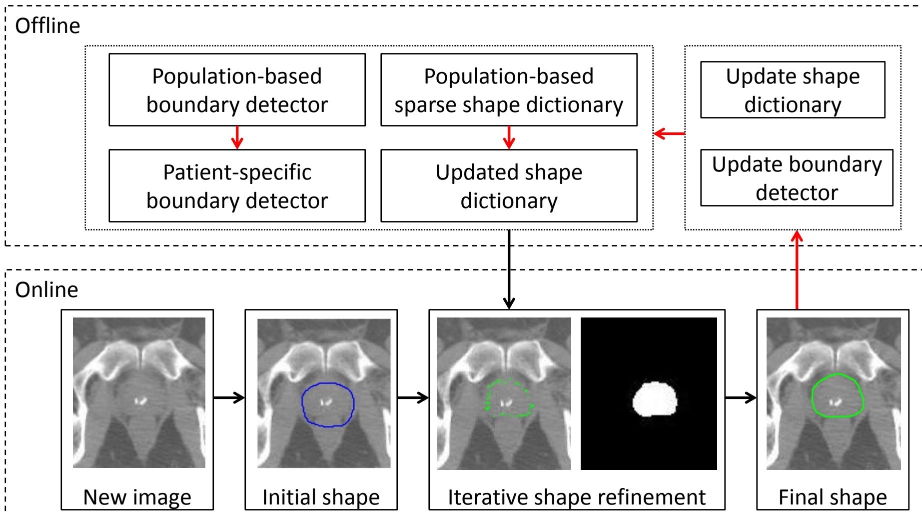

Fig. 3. Algorithm flowchart. Algorithm flow involved in off-line training/updating is marked with red arrows. Algorithm flow involved in online auto-contouring process is marked with black arrows.

auto-contouring process is marked with black arrows. Details regarding each component are discussed in the following:

2.1 Population-based Boundary Classifier

In order to detect the boundary surface of the prostate for a new image, we first train a population-based boundary classifier. For each of the voxels being detected, the job of the classifier is to make a decision as to whether the current voxel "is" or "is not" on the boundary. From a set of patients' images, we collect positive and negative samples according to the manual contours provided by experts. Boundary voxels on the contours are selected as positive samples, while voxels far away from the contour are selected as negative samples. For each training sample, rotation invariant 3D steerable features [8] are extracted and stored as a feature vector. We use the random forest algorithm [9] to train the boundary classifier on the collected samples. During online contouring stage, we use the Demons [2] method with a single atlas to get the initial contour. For each voxel on the surface of the initial contour, we apply boundary classification in a neighborhood along the normal direction. The boundary classifier will return a probability value for each voxel being searched. Then we select the one with the highest probability as the new boundary location.

2.2 Population-based Sparse Shape Refinement

The detected 3D boundary from the boundary classifier is very noisy. Thus a shape model is needed here to constrain the solution space. Among all the recently promoted shape models, the sparse shape model [10][11][12][13] is known to be able to handle complex shape variations, model non-Gaussian errors and preserve local detailed information of the input image, which well fits our needs. So we adopt this model to refine the detected boundary. Specifically, we first construct a sparse shape dictionary from a set of patients. Once we have a new input boundary shape, we use the dictionary as the shape prior to refine the shape. In particular, it selects a sparse set of 3D shapes in the shape dictionary and composes them together to represent the input shape. This model leverages two sparsity observations of the input shape instance: (1) the input shape can be approximately represented by a sparse linear combination of shapes in the shape dictionary; (2) parts of the input shape may contain gross errors but such errors are sparse. For each refinement iteration, the algorithm minimizes the following optimization function:

$$\arg min_{x,e,\beta} \left\| T(v_S, \beta) - SDx - Se \right\|_2^2 + \gamma_1 \left\| x \right\|_1 + \gamma_2 \left\| e \right\|_1 \tag{1}$$

Where v_S is a subset of points on the input shape, D is the shape dictionary that represents all training shapes, $T(v_S, \beta)$ is a global transformation operator with parameter β, which aligns the input shape to the same space of D. x denotes the weighting coefficients of the linear combination, and e is a vector that models the large residual errors. S is a binary diagonal matrix which indicates if a certain point is in the subset v_S. Here, in our implementation, each input boundary shape is represented by a 3D mesh with 4096 surface points. Each surface point is represented by its three dimensional coordinates. The solved shape is then sent back to the boundary detectors for another round of shape refinement (Figure 3). The iterative process stops once 1) it reaches a certain number of iterations or 2) it reaches a certain minimal residual error.

2.3 Adapting Patient-specific Information

Once a new treatment image is collected, it is necessary to update the boundary classifier and the sparse shape dictionary accordingly to incorporate patient-specific information. To update the boundary classifier, we collect training samples from a certain number of the same patient's previously treated images (n = 3 in our implementation). If a patient doesn't have as many treatment images available yet, we then compare the structure similarities betwwen the current image and the pool of images from all the patients, and select the most similar ones. We use the method in [14] to handle this image retrieval task. Only the selected images are used for training the new boundary classifier. The updating process is off-line and doesn't require human intervention.

While updating the boundary classifier is quite efficient since not many images are required for training, updating the sparse shape dictionary is a completely different story. To handle large shape variation even from the same patient, we want a general shape dictionary that can comprehensively capture shape variations in the shape space. Thus we don't want to limit the number of training shapes. However, we want to include the patient's most recent images to the dictionary to gain patient-specific knowledge. Training the shape dictionary from scratch is very time consuming. To improve the computational efficiency, dictionary learning techniques have also been employed to train a compact dictionary instead of using all training shapes. We use an online learning method [12] to adaptively and efficiently incorporate new shapes. When new training shapes come, instead of re-constructing the dictionary from scratch, we update the existing one using a block-coordinates descent approach. Using the dynamically updated dictionary, the sparse shape dictionary can be gracefully scaled up to model shape prior from a large number of training shapes without sacrificing run-time efficiency.

3 Experiments

The population-based boundary classifier and sparse shape dictionary are trained from 21 3D CT images of 21 patients across 5 hospitals. Each contour is represented by a 3D mesh with 4096 points. We evaluated the trained boundary classifier and sparse shape model on 44 3D CT images from 11 patients, and each patient has at least 3 treatment images. Figure 4 shows auto-contouring results for 3 patients from top to bottom. Each patient has three snapshots of its axial, sagittal and coronal planes. We compared the auto-contouring results (in red) with the experts' manual contours (in yellow). Despite the two bright seeds inside the prostate producing significant artifacts on the images, the auto-contouring results are very close to the ground-truth contours.

To get a quantitative overview of the performance compared with other methods on the whole testing dataset, Figure 5 shows the Dice values of three different methods. We started by using the Demons method [2] with only one atlas. For each patient's first 3D CT image, we randomly pick one atlas from the population and use the Demons deformable registration method for auto-contouring. Then for the same patient's subsequent images, we use their previous segmented image as the atlas. As shown in Figure 5 (a), the Dice values have large variation mainly due to the bad performance of the first segmented image. With randomly picked single atlas, it can hardly fit the target patient's anatomical structures well. Thus we increased the number of atlases and applied the STAPLE [3] strategy to fuse the deformable registration results from all the atlases. Similarly, for the patient's first planning image, we randomly picked 5 atlases from the population. For the same patient's subsequent images, we included all his/her latest segmented images as atlases. As shown in Figure 5 (b), the boxplot has less outliers and the average performance got improved. But without a patient-specific boundary detector, the algorithm can hardly precisely drive the detected contours to the desired borders. Additionally, the computational cost of using 5 atlases is tremendous. Our method auto-segments the patient's first planning image by the population-based classifier and the population-based sparse

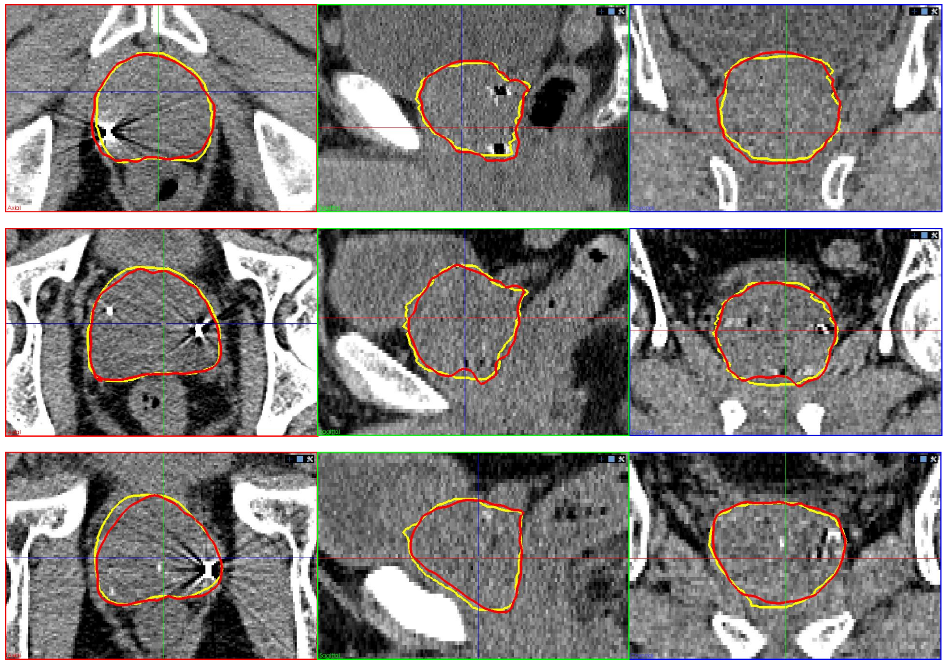

Fig. 4. Auto-segmentation results of three patients (from top to bottom) shown as snapshots on the axial, sagittal and coronal planes (from left to right). The results of the proposed method are shown in red, and the experts' manual contours (ground-truth) are shown in yellow.

shape dictionary, and adaptively learn the patient-specific knowledge during subsequent treatments without sacrificing run-time efficiency. The performance gets improved in terms of accuracy and computational cost (Figure 5 (c)).

4 Conclusions

We proposed a learning-based auto-contouring method for online adaptive radiotherapy. Following the nature of the tasks, the learning system is not only able to generate population-based information, but also capable of adaptively gaining patient-specific knowledge throughout the whole treatment course. The training and online updating steps are fully automatic and completely off-line, so that it doesn't reduce runtime efficiency. It achieves higher accuracy for the prostate segmentation when compared with two other state-of-the-art methods, which makes it very promising for online adaptive treatment planning.

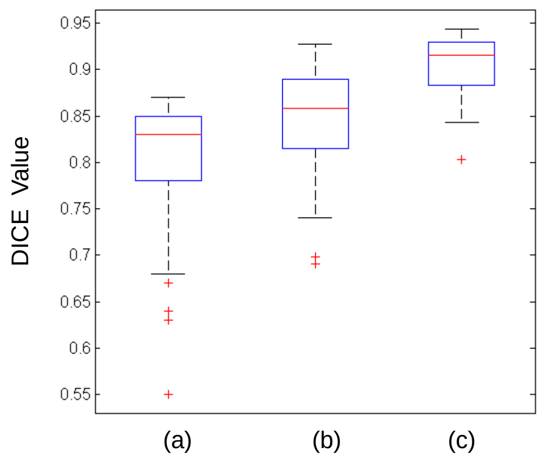

Fig. 5. Dice values of three methods under comparison: (a) the Demons method with only one atlas; (b) the Demons method using 5 atlases with the STAPLE label fusion; (c) Our proposed method.

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