Automatic segmentation of the prostate and surrounding structures for image-guided radiotherapy

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Abstract

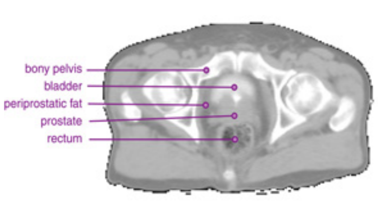
The objective of this research is to build a computer algorithm that can automatically segment the prostate and surrounding structures to aid cancer treatment. To fully utilize the usefulness of Intensity Modulated Radiotherapy (IMRT), which can treat a region of interest with high accuracy, the daily position information about the objects of interest is necessary. Manual segmentation of a series of CT scan images by an oncologist before treatment is a time-consuming task. Therefore, a fast automatic segmentation algorithm would be of tremendous help in the process. The goal is to develop a fast algorithm that matches the segmentation accuracy of a human expert.

State of the art

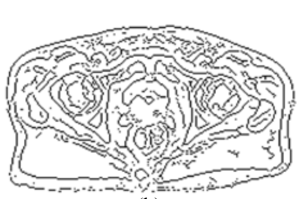
- IMRT: Achieves almost arbitrary 3-D dose distribution.
- Linear Accelerators (linacs): Deliver intensity modulated radiotherapy.
- Statistical model based computer vision algorithms for biomedical image segmentation
- Segmentation using parametrically deformable elastic models for 3-D objects.
- Medial representation for image analysis.

Challenges and significance

- Objects of interest inside the human body are non-rigid structures that deform continuously day-to-day.
- CT scan images are low-contrast, so simple intensity-based methods are inadequate.
- Computer vision algorithms for 3-D object studied so far works on surface only – not the entire volume as needed for dose painting.



(a)



(b)

Figure 1. (a) A CT scan image of the prostate and surrounding structures. (b) Result of edge detection on image (a). Due to the low-contrast of the image, the edge information is not useful in segmenting the objects of interest.

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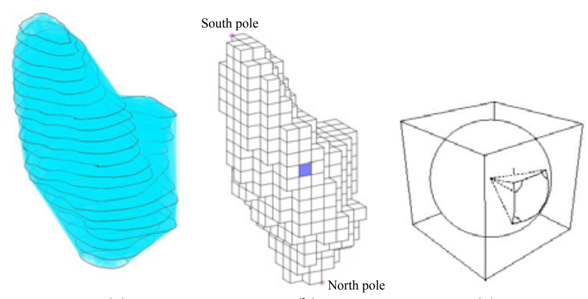
Technical Approach

Parameterization of a solid 3-D object (off-line)

Idea

1) Map the entire volume of a 3-D object $\mathbf{p}(x,y,z)$ to a unit ball in spherical coordinate $\mathbf{p}(r,\phi,\theta)$.
2) Express $\mathbf{p}(r,\phi,\theta)$ as a weighted sum of basis functions.
3) Build Shape and Appearance Model based on the basis functions.



(a) (b) (c)

Figure 2. (a) Original object (bladder) with segmentation information (b) voxelized object (c) corresponding unit ball in spherical coordinate.

a) Initial parameterization

Latitude: Laplace equation with Dirichlet condition

$$\nabla^2\phi = 0, \quad \phi_{north} = 0, \phi_{south} = \pi$$

Longitude: Cyclic Laplace equation

$$\nabla^2\theta = 0 \quad \text{with } 2\pi \text{ discontinuity when crossing meridian}$$

Radius: Laplace equation with Dirichlet condition

$$\nabla^2 r = 0, \quad r_{center} = 0, r_{surface} = 1$$

(We are investigating more appropriate line/surface with $r = 0$, e.g., medial axis because this is not always possible.)

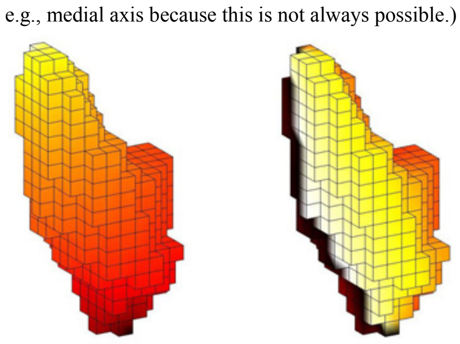
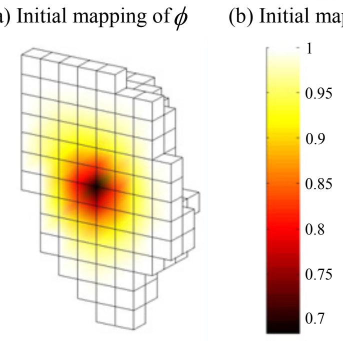


Figure 3. (a) Initial mapping of ϕ (b) Initial mapping of θ



(c) Initial mapping of r

b) Optimization of the parameters

Variables: r, ϕ, θ

Cost function and constraint should be defined in such a way that the parallels and meridians are evenly spaced and orthogonal and the radius parameters are well distributed.

c) Parameterization of the object mapped into unit ball

Decompose the object in unit ball into basis functions.
One candidate: spherical harmonic basis functions (SPHARM)
(But, radius parameter is not directly embedded.)

$$p(\phi,\theta) = \sum_{l=0}^{\infty}\sum_{m=-l}^{l} c_l^m Y_l^m(\phi,\theta), \quad c_l^m = \begin{pmatrix} c_{xl}^m \\ c_{yl}^m \\ c_{zl}^m \end{pmatrix} : \text{Fourier Descriptor coefficients}$$

$$c_l^m = \left\langle p(\phi,\theta), Y_l^m(\phi,\theta) \right\rangle = \int_0^{\pi}\int_0^{2\pi} p(\phi,\theta) Y_l^m(\phi,\theta)\, d\theta \sin\phi\, d\phi$$

$$\text{where } Y_l^m(\phi,\theta) = \sqrt{\frac{2l+1}{4}\frac{(l-m)!}{(l+m)!}} P_l^m(\cos\phi) e^{im\theta}$$

$$P_l^m(x) = \frac{(-1)}{2^l l!}(1-x^2)^{m/2}\frac{d^{m+l}}{dx^{m+l}}(x^2-1)^l$$

d) Building of shape and appearance model

In parameter space, conduct Principle Component Analysis (PCA) on the coefficients of basis functions to get shape and appearance model. Only small set of parameters will be sustained to model the rich variability of the training data.

Segmentation (real-time)

Using the shape and appearance model built from training data, a new image is segmented to find the location of the objects of interest.

Accomplishment through current year

- From real data segmented by an expert, the representation in voxel was obtained.
- Initial mapping of parameters was achieved.
- 3-D volume visualization of a series of CT scan slices.

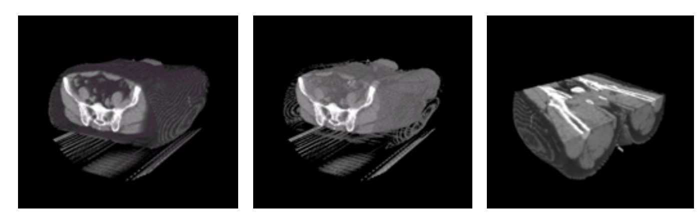


Figure 4. 3-D view of a series of CT scan images using CenSSIS medical volume visualizer.

Plans

- After initial parameterization of $\mathbf{p}(r,\phi,\theta)$, the parameters are optimized.
- Using the optimized parameters $\mathbf{p}(r,\phi,\theta)$, decompose the object as a weighted sum of basis functions.
- Each training data is expressed in terms of basis functions. And shape and appearance model that accounts for most of the training data is built.
- Given a new image, the shape and appearance model automatically segments the objects of interest in the image.

Value added to CenSSIS

- This project is essential to the success of the S2 engineered system.
- It uses R1 modeling of physical deformation, R2 advances in segmentation and shape modeling, and R3 organization of a large multidimensional database.

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