Purpose/Objective

Accurately segmenting the prostate and surrounding radiation-sensitive organs from a CT planning scan is critical for achieving high-quality IMRT plans. Robust automatic segmentation would both reduce the time spent contouring by the physician, and potentially reduce the variability that arises due to manual segmentation. However, edge-based segmentation algorithms without a shape-model component fail due to the lack of CT contrast between the prostate and adjacent prostate and rectal wall. The inhomogeneous, unpredictable CT number distribution due to gas and filling compound the difficulties of segmenting the rectum. Here, we evaluate the performance of a new segmentation model that uses anatomical constraints to improve rejection of unrealistic configurations of the prostate and rectum.

Materials/Methods

Pelvis anatomy structure

The prostate and rectum are surrounded by the pelvic bones and Levator ani muscle (Fig. 1). We will use these to constrain our automatic segmentation.

Incorporating anatomy information

We use simple image processing algorithms (Fig. 2) to automatically detect the bones and the Levator ani muscle (Fig. 3).

Segmentation framework

Based on our previous work, we train a prostate-rectum joint shape model based on training data contoured by a physician from MSKCC. The shape model can be described by:

\[ S^0 = \tilde{S} + P\beta \]

Where \( \tilde{S} \) is the mean shape and \( P \) are the orthogonal eigenvectors resulting from Principal Component Analysis on the training shapes. Once the model is built, the segmentation problem turns into searching for the best \( \beta \).

Our segmentation is based on the intensity histogram inside \( (h_{ix}, \text{red region in Fig. 4}) \) and outside \( (h_{iu}, \text{green region in Fig. 4}) \) the organs as well as the ratio of volumes: \( \alpha = V_i / (V_r + V_o) \). We also incorporate anatomy constraints using the minimum distances from the prostate to 4 muscle planes and the rectum to the coccyx plane, \( r = \{d_1, ..., d_9\} \).

We find the best \( \beta \) by maximizing:

\[ p(\beta) \propto p(\text{image} | \beta) p(\beta | \text{training}) p(\beta | \text{training}) \]

Here, \( p(\text{image} | \beta) \) is the likelihood of the observed image information, such as intensity, volume ratio or anatomy constraints.

\[ p(\beta | \text{training}) \]

The cost function (1) can be further decomposed as:

\[ \alpha = p(h_{ix} | h_{iu}) p(h_{iu} | h_{ic}) p(\alpha | \gamma) p(\gamma) p(\beta | \hat{\beta}) \]

Where the red, green and blue terms denoted the intensity cost, anatomy cost and shape cost respectively.

Results

Fig. 5 shows segmentation results, and Table 1 reports quantitative results, with \( \text{dim}(\beta) = 4 \).

We can use standard kernel density estimation to estimate each term in the above equation using training data. The distribution over histograms can be defined as:

\[ p(h_i | \hat{h}_i) \propto \frac{1}{\text{N} \cdot \sigma^2} \exp \left( -rac{1}{2} \frac{D(h_i, \hat{h}_i)}{\sigma^2} \right) \]

Where \( D(h_i, \hat{h}_i) \) is a distance measure on histograms; we use the cumulative distribution function distance here.

Conclusion

The quality of the automatic segmentation declines when we remove the two innovations described above, indicating that the anatomical constraints are important cues for accurate segmentation. One goal for future research is to incorporate the bladder into the joint model, to improve the accuracy and the clinical usefulness of the algorithm.

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