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Seminar Presentation Summary

Large Deformation Three-Dimensional Image Registration in Image-Guided Radiation Therapy

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Abstract:

The paper presents and validates a novel deformable image registration algorithm for processing CT images. Unlike many other algorithms, the algorithm proposed does not assume a one-to-one point correspondence between to the two scans. The algorithm presented in the paper extends previous algorithms by accounting for the fact that regions exist with no correspondences. The registration technique can also be extended for the use with organ segmentation. The algorithm was validated in comparison with human raters.

This paper appears to relate to our research in that we need to implement a deformable registration algorithm which can account for the large loss of mass resulting from surgery. In our trials, a mass is removed from a pig tongue. The tongue is then sewed shut. A deformable registration algorithm is need to register the open wound CT scan to the pre-operative CT scan and from the pre-operative CT scan to the closed surgical wound CT scan. With the large mass of tongue being removed, surely, a perfect point correspondence between the scans will not exist.

Introduction

With modern advances in radiation therapy, it has become possible to radiate a specific are with high intensity and high accuracy with minimal effect on surrounding tissue. This issue in this lies in the ability to accurately detect the location of the tumor to be irradiated. This paper looks at registration of CT scans of the prostate. Internal organs are subject to changes in location due to such actions as the bladder filling. The traditional approach to dealing with this fact has been to treat with a large amount of radiation at the center of the target volume with decreasing strength towards the edges. To account for movement of organs, it had been assumed that organ motion was uniform.

There is much need to account for the fact that tissues deform with movement inside the body. To deal with this, a deformable registration method is needed.

The paper looks at the need for deformable registration as a result of tissue movement, deformation and loss of mass. Bowel gas can be present in one CT image, but not in another. Consequently, tissue can move fairly rapidly and significantly. Likewise, the tongue is not a rigid body. It can move in relation to the mouth and can be compressed. Similar to when bowel gas can be present or not present in any image, the result of the removal a tumor from the tongue will result in an obvious loss of mass. The fact that a volume may only exist in one CT scan must be accounted for in both the authors' algorithm and in an algorithm for our work.

Deformable Image Registration

The necessity of a deformable image registration algorithm comes from the authors' need to measure organ motion. Organ motion is the result of both set-up error and internal tissue changes. The motion can be characterized by the difference between two separate CT scans.

The goal with the registration algorithm is to deform the treatment image to the planning image. This accomplished by minimizing the energy term:

$$E(h) = \int_V \left(I_p(x) - I_T\big(h(x)\big)\right)^2 dx$$

Where

$$I_p \text{ is the intensity of a voxel in the planning image}$$
$$I_T \text{ is the intensity of a voxel in teh treatment image}$$
$$h: V \rightarrow V \text{ maps a voxel in the planning image to the treatment image}$$

This equation simply looks to minimize the square of the error between the two scans. This is accomplished by deforming one image into another.

Rigid Motion

For rigid motion, the image correspondence can be viewed as the result of a translation vector, τ. That is:

$$h(x) = x + \tau$$

From this the energy function to minimize becomes

$$E(\tau) = \int_V \left(I_p(x) - I_T(x + \tau)\right)^2 dx$$

To minimize $E(\tau)$, a method developed in Joshi, Lorenzen, Gerig and Bullitt, *Structural and radiometric asymmetry in brain images (2003)*. It constructs a sequence $\{\tau_k\}$ such that $E(\tau_k)$ converges to a local minimum.

$$Let\ \tau_{k+1} = \tau_k + \Delta\tau_k \ and\ x' = x + \tau_k$$

Then

$$I_T(x + \tau_{k+1}) = I_T(x' + \Delta\tau_k)$$

Expansion in a first order Taylor series about x'

$$E(\tau_{k+1}) \approx \int_V \left(I_P(x) - I_T(x') + \nabla I_T(x') \cdot \Delta\tau_k\right)^2 dx$$

The $\Delta\tau_k$that minimizes $E(\tau_{k+1})$

$$\Delta\tau_k = \left(\int_V \nabla I_T(x')\nabla I_T(x')^T dx\right)^{-1} \int_V \left(I_p(x) - I_T(x')\right) \nabla I_T(x')\big) dx$$

In the more general setting where the transformation *h* depends on a parameter vector *a* and *x* and not just τ, we can write $h = h_a(x)$ and solve for Δa_k:

$$\Delta a_k = \left(\int_V \nabla_{\mathrm{a}} I_T(h_a(x))\nabla_{\mathrm{a}} I_T(h_a(x))^T dx\right)^{-1} \int_V \left(I_p(x) - I_T(h_a(x))\right) \nabla_{\mathrm{a}} I_T(h_a(x))\big) dx$$

In the case where h is affine transformation of the form

$$h(x) = Ax + \tau$$

Then $\nabla_{\mathrm{a}} I_T(h_a(x))$ can be expressed with

$$a = [A_{11}\ A_{12} \ldots A_{32}\ A_{33}\ \tau_1\ \tau_2\ \tau_3]^T$$

And

$$X = \begin{bmatrix} x_1 & x_2 & x_3 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & x_1 & x_2 & x_3 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & x_1 & x_2 & x_3 & 0 & 0 & 1 \end{bmatrix}$$

So that

$$Ax + \tau = Xa$$

$$\nabla_a I_T\big(h_a(x)\big) = \left(\nabla I_T \Big|_{h_a(x)}\right)^T X$$

Deformation

In the case of a large deformation, then we must not constrain the *h* term to a specific form. This is accomplished by adding a regularity term to the energy function and make *h* dependent on a time varying velocity field.

$$E(h) = \int_V \Big(I_p(x) - I_T\big(h(x,t)\big)\Big)^2 dx + E_{reg}(h)$$

And

$$h(x,t) = x + \int_0^t v(h(x,s),s)ds$$

and

$$E_{reg}(h) = \int_{V,t} \left|\left|L_{reg}v(x,t)\right|\right|^2 dxdt$$

Where L_{reg} is a suitable differential operation

They use

$$Lv = \propto \nabla^2 v + \beta\nabla(\nabla \cdot v) + \gamma v$$

Motivated by Navier-Stokes

Bowel Gas

In the images of the pelvic region, bowel gas will appear in some CT scans causing deformation in the image. To resolve this issue, a variation of the algorithm referred to as deflation was used. Deflation is not meant to simulate true tissue motion, but eliminates the gas. Deflation needs to be applied to both the planning and treatment images because gas pockets can appear in different parts of the images.

To deal with the gas, a threshold is first placed on the image. The contrast between gas and tissue is very high in CT images, so this easily accomplished. The gas is then shrunk to a point. Small pockets of gas are disregarded. The volume of gas shrinks towards the middle.

Composition Transformation

The complete transformation is simply the three transformation combined in a sequence. It starts with the rigid transformation, followed by deflation and ultimately ends with the deformable registration.

Segmentation

The registration technique provides direct expansion to automatic segmentation. If a manual segmentation is made, the registration technique will properly contour the lines from the planning image to the treatment image.

Results

The final results were evaluated compared to human raters. Human raters have definite differences when it comes to segmentation. Therefore, the method that was used was comparing the variation between two human raters and the variation between a human rater and the automatic segmentation. The registration technique appeared to perform comparable to that of human from this analysis.

Analysis

The main questions I have with this method that pertain to our research have to do with how well the algorithm will translate to being used on the tongue.   My assumption is that the removal of a mass from the tongue can be modeled similarly to the movement of gas throughout the pelvic regions.

Criticism

My main piece of criticism for the research has to do with why the optimization problem was not scaled to adjust for intensity differences. The equation,

$$E(h) = \int_V \left(I_p(x) - I_T\big(h(x)\big)\right)^2 dx$$

assumes that the intensities in both images will be approximately the same. I think the problem would be better suite with an equation that resembled

$$E(h) = \int_V \left(I_p(x) - cI_T\big(h(x)\big)\right)^2 dx$$

where c is a constant (or even possibly a function) which adjusts for the fact that intensities can vary between different scans.

Works Cited

Beg M F, Miller M I, Trouve A and Younes L 2005. Computing large deformation metric mappings via geodesic flows of diffeomorphismsInt. J. Comput. Vis. 61 139–57

M. Foskey, B. Davis, and L. Goyal et al., “Large deformation three-dimensional image registration in image-guided radiation therapy,” *Physics in Medicine and Biology*, vol. 50 pp. 5869-5892, 2005.

Joshi S, Lorenzen P, Gerig G and Bullitt E 2003 Structural and radiometric asymmetry in brain images Med. ImageAnal. 7 155–70

Miller M I, Trouve A and Younes L 2002 On the metrics and euler-lagrange equations of computational anatomy Annu. Rev. Biomed. Eng. 4 375–405