Improved Non-rigid Registration of Prostate MRI

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Abstract. This paper introduces a fast non-rigid registration method for aligning pre-operative 1.5 T MR images to intra-operative 0.5 T MR images for guidance in prostate biopsy.

After the acquisition of both pre-operative 1.5 T and intra-operative 0.5 T, an intensity correction method is applied to the pre-operative images to reduce the significant artifacts in the signal intensities due to the presence of an endo-rectal coil. A fast manual segmentation of prostate in both modalities is carried out to enable conformal mapping of the surface of the pre-operative data to the intra-operative data. A displacement field is estimated with a linear elastic inhomogeneous material model using the surface displacements established by the conformal mapping. We then use this as an initialization for a mutual information based non-rigid registration algorithm to match the internal structures of the prostate. This non-rigid registration is based on a finite element method discretization using the mutual information metric with a linear elastic regularization constraint. The registration is accelerated while preserving accuracy by using an adaptive mesh based on the body-centered cubic lattice and a significantly improved registration is achieved.

1 Introduction

Prostate cancer is a leading cause of morbidity and mortality. This cancer is currently diagnosed by transrectal guided needle biopsy. In our institution, Magnetic Resonance Imaging (MRI) is used for intra-operative surgical navigation. MRI can clearly depict not only the prostate itself but also its substructure including the peripheral zone. However, the tumor foci can be better localized and identified on the pre-operative 1.5-T MRI than on the 0.5-T used for surgical navigation. Prostate shape changes appear between images caused by different patient positions before and during surgery. For this reason, the development of fast and accurate registration algorithms to fuse pre-operative and intra-operative data in the operating room is a challenging problem.

Although rigid registration methods for the prostate have been presented [2,5], few non-rigid registration methods for this application are present in the literature. At our institution, we have used alternative methods in the past [3,8,7]. Bharatha et al.[3] presented an alignment strategy utilizing surface matching with an inhomogeneous material model. The surfaces of both segmented pre-operative and intra-operative MR images were registered using an active surface algorithm. Then the volumetric deformations were inferred from the surface deformations using a finite element model and applied to the pre-operative image. Later, the active surface step was replaced by a conformal mapping strategy [1]. More recently, we proposed a mutual information based deformation strategy to register multi-modality data [7].

Furthermore, the quality of tetrahedral meshes became an important issue to ensure a good convergence of FEM registration methods. Indeed, avoiding flat tetrahedrons so-called slivers can lead to better accuracy and stability of the numerical solutions. A broad range of strategies permits to refine adaptive tetrahedral meshes and to keep better shaped elements. The Laplacian smoothing technique is one of the most frequently applied. This method changes the positions of nodes by solving the Laplacian equation to move interior nodes with given positions of the boundary nodes. The smoothing is iteratively repeated until the movement of the nodes goes lower than a specified threshold. If the Laplacian smoothing technique increases the quality of the mesh in average, some elements may be more distorted. Other optimization methods have been proposed to optimize the element with respect to a specific cost function [4,9]. Recently, a body-centered cubic (BCC) based lattice offering a nice compromise between the density of the lattice and the number of nodes has been developed [14]. The elements composing this mesh may be divided into finer elements of same shape to adapt the object to mesh without moving nodes.

The new registration algorithm improves upon the surface to surface matching previously proposed by using an accelerated robust mutual information based volumetric registration. High speed and fidelity is achieved through an adaptive body-centered cubic lattice based meshing. Together, these methods enable a fast and accurate alignment of pre-operative and intra-operative MRI.

2 Registration Strategy

The mapping from the space of one image to another image is defined by a transformation model. We used a volumetric tetrahedral mesh to approximate the transformation which is parameterized by the displacements at each vertex of the mesh. The vertices displacements, derived from image based forces, are propagated to any point of the fixed image volume using the shape (basis) functions of the element containing this point. The finite element framework provides a broad family of elements and associated shape functions.

The registration strategy is divided into five steps. After the acquisition of both pre-operative and intra-operative images, an intensity correction has to be applied. After a manual segmentation of both images, the surface of the

pre-operative prostate image is deformed to map onto the surface of the intra-operative data. The deformation field is then inferred into the whole volume. Finally, a mutual information based deformation method is applied to map the internal structures of the prostate.

2.1 Acquisition

Although 0.5 T T2-weighted images provide good visualization of the gland, 1.5 T imaging with endorectal coil provides better spatial resolutions and contrast. More precisely, the ability to visualize the substructure of the prostate is improved. Pre-treatment 1.5 T images provide detail, allowing accurate definition of the gland, its margins, and in most cases, the tumor, all of which are useful for complete treatment planning. It should be noted that of all modalities, MR imaging of the prostate provides the most optimal imaging not only of the gland and its adjacent structures, but importantly, of its substructure [3].

The 1.5 T fast spin echo MR-images were acquired using an endorectal coil with integrated pelvic phased multi-coil array. The intra-operative imaging was performed in the open-configuration 0.5 T MR Interventionnal Magnetic Resonance Therapy scanner. The typical acquisition times were 6 minutes.

2.2 Intensity Correction

Acquisition of pre-operative images using an endorectal coil resulted in significant intensity non-uniformity throughout the images acquired. Our experience has been that such an artifact can have a negative impact on the registration process [7]. In order to solve this problem, a retrospective correction method based on entropy minimization was employed. From the method described in [12] we developed an adaptive algorithm using a multi-resolution framework for speed and stability, to help accomodate the significant magnitude of the artifact in the images under study.

2.3 Transformation Model

We implemented the crystalline adaptive mesh based on the body-centered cubic lattice. The method was first proposed by [14]. The basic resolution of tetrahedrons is created by splitting two interlaced regular grids of hexahedrons. The mesh is then refined in specific regions of interest, as surfaces or specific organs, without loss of quality for the elements. The finer resolutions are obtained by dividing the principal tetrahedrons in eight children of same shape and quality. Specific patterns are then used to bind different resolutions. Our algorithm obeys the five following steps:

To obtain a new resolution, do at the current resolution:

Step-1. Find the neighbors of each tetrahedron by a search in the children of the neighbors of the father element at the previous resolution.

Fig. 1. The first resolution is based on a body-centered cubic lattice. The basic resolution of tetrahedrons is created by splitting two interlaced regular grids of hexahedrons.

Step-2. Search and mark which tetrahedrons have to be refined into 8 children (Figure 2-2) following a given criterion (curvature, edge, variance or other criterions).

Step-3. Complete the topology. Indeed if the neighboring tetrahedrons of the current one have to be split, mark that this current tetrahedron must be refined to avoid floating nodes.

Step-4. Bind the resolutions by labeling the tetrahedrons following patterns 3 to 5 (Figure 2) to avoid floating nodes. The father of these tetrahedrons should obey pattern 2 to keep a good quality ratio and avoid flat elements. Otherwise we return to the coarser resolutions to transform the ancestors of the current tetrahedrons into a pattern 2 and apply steps 2 to 4 again.

Step-5. Create the nodes and elements of the new resolution following the labels given during steps 2 to 4.

This mesh generation allows to fit the region of interest without loss of quality of the tetrahedrons. Furthermore, the choice of refinement criterion is free. Finally, we implemented the mesh generator within the ITK framework [11].

Fig. 2. The five possible patterns. A tetrahedron a one resolution (1) may be split into a pattern (2). The other patterns (3-5) bind the new resolution to the previous one.

Fig. 3. Intensity correction results. The pre-operative image (a) was acquired using an endorectal coil resulting in significant intensity non-uniformity throughout the image. This image underwent an intensity correction based on entropy minimization (b).

Fig. 4. Results of the surface based registration matching. The pre-operative image (a) has been manually segmented before the surgery and registered to the segmented intra-operative image (b). The result has been overlaid onto the intra-operative image for better visualization (c).

2.4 Registration Using Image Based Forces

First, an affine registration process has been applied to center the 0.5 T and 1.5 T segmented datasets and correct the scaling between images. Then a non-rigid registration driven by a conformal mapping technique [1] is applied to match the surface of the prostate from the pre-procedural image to the intra-procedural image. The volumetric displacement field is then inferred from the surface deformation field using the finite element method. The data scans are segmented using the 3D Slicer, a surgical simulation and navigation tool [10]. Finally, to refine the mapping between the internal structures of the prostate, we used a mutual information based [16,13] non-rigid registration method [6]. The finite element approximation of the transformation is regularized by the linear elastic energy

$$C(I_1, I_2) = MI(I_1, I_2) + \frac{\alpha}{2} \cdot u^t K u \quad (1)$$

Fig. 5. Results of the mutual information based registration. The pre-operative image after surface registration (a) has then been registered to the intra-operative image (b) using our mutual information based registration method. We can observe in the resulting image (c) that the internal substructure aligns well with the intra-operative image.

where K is the stiffness matrix associated with the volumetric mesh [17], u the vector of vertex displacements and α is a weighting factor to balance the action of the mutual information term.

The optimization technique used is the Simultaneous Perturbation Stochastic Approximation (SPSA) firstly introduced by Spall [15]. SPSA has attracted considerable attention for solving optimization problems for which it is impossible or time consuming to directly obtain a gradient of the objective function with respect to the parameters being optimized. SPSA is based on a highly efficient gradient approximation that relies only on two evaluations of the objective function to be optimized regardless of the number of parameters being optimized and without requiring an explicit knowledge of the gradient of the objective function.

3 Results

Pre-operative 1.5 T endorectal coil images were acquired for the supine patient and intra-operative 0.5 T were acquired in the lithotomy position. The difference between positions let deformations appear. The images used were acquired in the Open Magnet System (Signa SP, GE Medical Systems, Milwaukee, WI). The pre-operative prostate images were corrected in the gray-level domain. Figure 3 shows the prostate image before and after correction based on entropy minimization. The brightness artifact has been removed. The processing time is dependent of the machine and the size of the data. For a $256 \times 256 \times 60$ image, this process needs about 10 minutes but is made before surgery.

The following step is the segmentation and the surface registration of prostates in both modalities. The figure 4 presents a result for this step. The pre-operative prostate image (Figure 4-a) has been segmented to fit the segmented prostate of the intra-operative image (Figure 4-b). The result has been fused in the intra-operative image (Figure 4-c) for better visualization. This surface registration

needs less than 90 seconds. While the pre-operative data can be segmented before the surgery, we need some more minutes to segment the prostate in the intra-operative images.

The last step is the mutual information based registration. Since we are mainly interested in capturing the deformations of the substructure inside the prostate, we use the segmentation of the intra-operative prostate as a mask to measure mutual information. Figure 5-a presents the pre-operative prostate after surface based registration, Figure 5-b the intra-operative image of the prostate and Figure 5-c the result after registration. This last step needs less than 2 minutes.

We placed a set of landmarks inside prostates. The minimum distance between landmarks after surface and after mutual information based registration is about 0.3 mm. The largest distance goes from 3.8 mm after surface registration to 2.5 after MI registration and the mean distance from 2.3 mm to 1.3mm for a voxel size of $0.9 \times 0.9 \times 2.5$ mm.

4 Conclusions and Future Work

In the former section, our algorithm has been proven to estimate the deformation induced by different positions of the patient before and during prostate surgery. Prior information can be included in this registration strategy by using the adaptive mesh. This adaptation of the basis functions used to represent the dense deformation field is the main advantage of finite element meshes compared to radial basis functions. Pre-operative segmentations also enable to employ different material characteristics. Volumetric FEM meshes following the surfaces of the anatomical objects make possible the inclusion of statistical shape information in determined deformation patterns. Furthermore, other refinement strategies could be investigated. Refining only the mesh in elements with a high gradient of the mutual information would allow to improve the computation time.

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