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3D Interactive Ultrasound Image Deformation for Realistic Prostate Biopsy Simulation

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Abstract. Realistic medical procedure simulators improve the learning curve of the clinicians if they can reproduce real conditions and use. This paper describes the improvement of a transrectal ultrasound guided prostate biopsy simulator by adding the simulation of real-time prostate movements and deformations. A discrete bio-mechanical model is used to modify a 3D texture of an ultrasound image volume in order to quickly simulate the actual displacements and deformations. This paper describes this model and presents how the mesh deformation is used to induce the UltraSound volume deformation. The validation of the method is based on both a quantitative and a qualitative assessment. Experimental images acquired on a phantom are compared using mutual information metrics to the resulting generated images. This comparison shows that the proposed method offers realistic deformed 3D ultrasound images at interactive time. The method was successfully integrated to improve the transrectal ultrasound simulator.

1 Introduction

Prostate cancer is the second most common cancer worldwide in men [1]. To confirm diagnosis, prostate biopsy procedures are performed to obtain and analyze tissue samples of the gland. Conventional biopsies are performed under TransRectal Ultrasound (TRUS) guidance. In clinical practice, a 12-core biopsy protocol is usually performed, using an end-fire imaging probe. To obtain a complete and accurate cancer diagnosis, these 12 samples have to be well-distributed and located in 12 different 3D anatomical zones of the prostate. The procedure is challenging because it requires a good understanding of ultrasound and an accurate spatial awareness of the prostate which is a small almost spherical organ (about 4 cm in diameter). The clinician has to perform a biopsy by positioning the samples only using information from the visualized UltraSound (US) images. They have to understand the displayed US images in order to evaluate the actual position of the probe and perform the recommended biopsy.

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We first designed a virtual reality simulator combining a learning environment (including a scoring system) and a clinical case database for image-guided prostate biopsy [2]. Its main purpose was to provide a real-time ultrasound simulator dedicated to prostate biopsy giving a score which evaluates how well a biopsy is distributed and accelerates the training phase. In this simulator, a laptop computer is connected to a haptic interface Phantom Omni (Sensable Devices Inc., MA, USA), used as a motion tracker. It is enhanced by a probe mock-up and a silicon-based structure representing the rectum, see Fig. 1a. The probe mock-up position and orientation is used to reslice a 3D recorded US volume. The simulator has a database of anonymized patient volumes and clinical data collected from a UroStation system (Koelis, France). A biopsy feedback is given by visualizing sample positions relative to the 3D image of the prostate and by computing a corresponding score. Initial validation proved its reliability, validated its face and content but it also showed that realism matters, especially for experts [3]. One of the main limitations highlighted by the experts was the absence of image deformation induced by the probe displacement. Because the prostate is a soft and highly-mobile organ, understanding deformation induced by the ultrasound probe manipulation is an important part of the learning process as the deformation will directly influence the sample positioning. The aim of the new simulator version is to include real-time realistic image deformation in order to have a complete prostate biopsy commercial simulator.

This paper presents a new version of the simulator that integrates interactive simulation of the tissue deformation.

2 Context

Ultrasound simulation is a commonly studied theme because on one hand, ultrasound imaging is a widely used image modality during surgical procedure and on the other hand, ultrasound image understanding is quite challenging, which justifies the need to develop simulators. Additionally, ultrasound manipulation strongly depends on the operator’s experience. Ultrasound imaging is well adapted to soft tissue examination. Modeling ultrasound image deformation combines two challenges: to produce a realistic US image and to obtain realistic deformation of organs due to probe manipulation. Two main approaches try to address the first challenge: *a)* the generative approach, which consists in modeling the wave propagation, and *b)* the interpolation approach, which consists in acquiring dense 3D ultrasound volume from which arbitrary images can be generated. Two main approaches try to address the second challenge: the biomechanical continuous approach and the computational discrete one.

To our knowledge, few devices were designed for the simulation of prostate biopsy procedures. Chalasani et al. [4] reported the development and validation of a Virtual Reality TRUS guided prostate biopsy simulator, although without computing any deformation. While a lot of work focuses on only one of the two challenges [5] [6], combining US image generation with a biomechanical model is another challenge on its own. Goksel et al. [7] presents a brachytherapy training simulator with 2D simulated ultrasound and tissue deformation using the interpolating FEM method. D’Aulignac et al. [8] presents on a physical

model for thrombosis diagnosis based on a mass-spring model and on 2D US image simulation using an interpolation approach. Vidal et al. [9] present a simulator of ultrasound guided needle puncture using virtual 2D multiplanar image reconstructed from input CT data.

3 Methods

We propose a method that combines a discrete biomechanical model combined with a 3D elastic texture in order to dynamically re-slice the patient’s 3D prostate volume to obtain ultrasound image deformation, see Fig. 1b. The discrete model is based on shape memory [10]. The displacement of the probe is used as a displacement constraint by the model, which in turn computes the deformation on the physical object. Anonymized 3D US images acquired during actual biopsy of real patients are used as 3D textures. The biomechanical model deformation is used as a 3D texture mapping, which after interpolation and reslicing in the probe direction, generates the deformed US images. For each virtual biopsy sample in the simulator, the corresponding needle position is mapped in the undeformed biomechanical model in order to provide the actual 3D position of the performed biopsy in the undeformed gland. The deformation induced by the needle during the biopsy gun firing procedure is not taken into account in the model and neglected in the simulator.

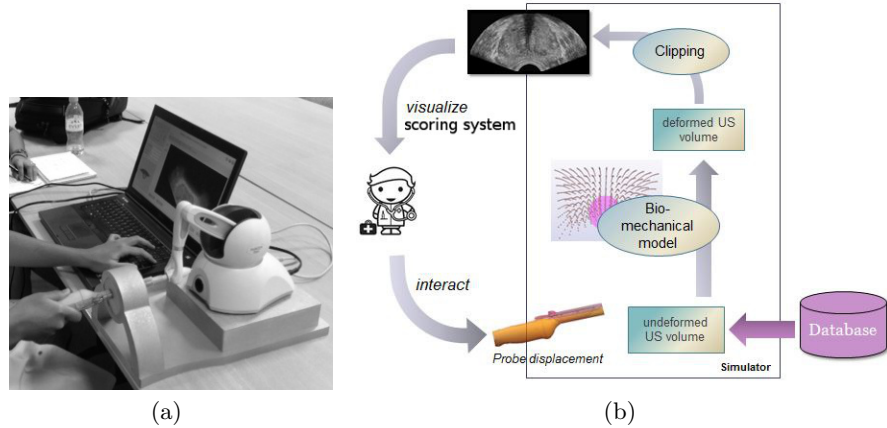


Fig. 1. (a) BiopSym simulator is composed of a laptop and a haptic device, enhanced by a structure simulating the rectum. (b) General architecture of the new simulator

During simulation, we ensure that stability is reached before performing the image generation step by controlling the kinetic energy of the nodes.

Biomechanical Model. Our discrete soft tissue model has been already used in the context of prostate surgical interventions in [10]. It is described by a set of nodes, defined by their positions and their neighbors. In the model, elasticity is computed using shape memory. Each node is located using a shape memory function that depends on its position at rest shape \mathbf{P}^0 (undeformed mesh) and a generalized barycentric coordinates system based on its neighbor positions. During the simulation, the shape memory function directly computes the position

of the node shape attractor \mathbf{P}^* . The shape memory force simulating the local elastic force is defined as $\mathbf{F}_e^t = -k_e \mathbf{P}^t \mathbf{P}^*$, where \mathbf{P}^t is the node current position, and k_e is the elasticity parameter. The shape memory function is defined so that $\mathbf{P}^* = \mathbf{P}^0$ when there is no local deformation of the mesh relative to \mathbf{P} and its neighbors.

In this application, the model geometry directly represents the 3D tissues imaged by the US probe, and therefore can be defined as a regular 3D grid, see Fig. 2 top left. The use of a regular grid yields to a limited number of shape memory configurations: a node is either a corner of the grid, on an edge, on the face or inside the grid. This limited number of configurations is one of the key points for obtaining an optimized elasticity computation time as the shape memory function has only four configurations. For instance, for a node inside the grid, the attractor \mathbf{P}^* is always defined as the isobarycenter of the neighbors.

The displacement of all the nodes on the face opposite to the probe position is fixed. The US probe is simulated by a sphere half inserted in the grid of the same size as the actual end-fire US probe ($\varnothing = 13mm$), see Fig. 2 top left. During the simulation, the nodes that are initially enclosed in the sphere are moved with the probe displacement recorded by the Phantom Omni. Detected collisions with other nodes are processed using a radial projection constraint.

The following algorithm details the main step of the simulation and provides the nodal displacements at each iteration from the probe displacement:

```

for each iteration do
  get probe position and apply radial projection constraint
  for all nodes do
    compute attractor positions (4 possible configuration)
    compute forces
    compute internal forces
  end for
  for all nodes do
    integrate forces (e.g., using a explicit Verlet integrator)
  end for
end for

```

Image Deformation. The next step consists in applying the deformation to the 3D ultrasound volume using the nodal displacements, see Fig. 2. To deform the input volume, a non-linear warp transformation is defined on a 3D uniform grid and computed from the nodal displacements. In order to optimize the execution time, the warping grid is a subsample of the biomechanical grid. The deformed volume is then resliced along the image plane defined by the virtual probe position and orientation.

Biopsy. In order to provide the 3D mapping of the complete biopsy and the associated score, the sample positions are computed from the positions taken in the deformed US volume and mapped to the undeformed volume. We used the mean value coordinates method [11] in order to map the sample position from the deformed volume to the undeformed biomechanical mesh.

Validation Process. Our objective is to obtain realistic deformed images. The validation process is both qualitative and quantitative. Qualitative assessment is

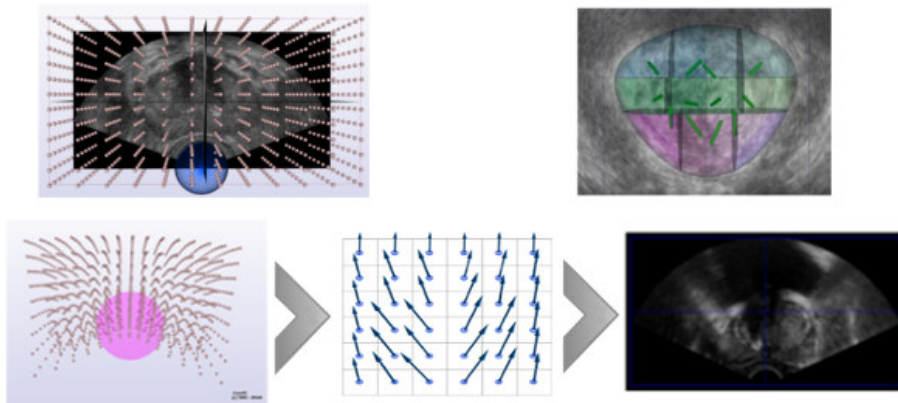


Fig. 2. Top left: US volume and nodes grid at initial step. Top right: Biopsy samples represented in the 3D prostate volume. Bottom: The algorithm starts by using a grid of physical nodes, from the displacements of those physical nodes a grid containing control points is created. This grid is then used to compute image voxels displacements.

achieved by comparing real procedure prostate deformation with the images generated by the simulator, based on real patient data. Fig. 3 compares the images obtained with and without the image deformation. The absence of quantified data related to US probe position during US volume acquisition on real patients led us to perform experiments on prostate phantom. From a quantitative point of view, the validation is based on image similarity comparisons between original and deformed images. This quantitative validation requires original and deformed images as well as each associated probe position. We used a set of 4 volumes obtained from a prostate tissue-mimicking deformable PVC phantom [12] with a size of $87 \times 100 \times 145mm$. Polaris localizer (NDI, Waterloo, Canada) markers are attached to the TRUS probe to track its position. The initial undeformed volumes and final deformed volumes resulting from each probe displacements within the phantom are recorded alongside the corresponding probe final positions. The same probe positions are then simulated by interpolating them by steps of $1mm$ and the resulting simulated deformed images are saved. A region of interest centered on the prostate is defined in order to compare the simulated with the real deformed volume using mutual information [13]. The expected result is an increase of mutual information between the simulated volumes and the real deformed volume as the simulated probe position is nearing the final position step-by-step.

Implementation. The simulator, the image deformation methods and the validation process are implemented in C++ using the framework CamiTK¹ [14], ITK, VTK and OpenHaptics libraries. Mutual information is computed as explained in [15]. The size of the regular mesh for the biomechanical model is $20 \times 20 \times 20$ (8,000 nodes). The simulation time step and elasticity stiffness k_e were

¹ See <http://camitk.imag.fr>

chosen to optimize stability. The size of the warping grid is $10 \times 10 \times 10$ (1,000 control points). The size of the images of the phantom are $105.6 \times 105.6 \times 79.1$ mm with a resolution of $199 \times 199 \times 199$ voxels and the probe displacements are in a range of $[20.9 - 27.3]$ mm.

4 Results and Discussion

Without any deformation (only reslicing), the computing time is 70 ms on a Intel Core i7.3740QM 2.70 Ghz Pentium computer. Our method can generate slices in 178 ms on average. For each step, the relative computation time is 15% for the biomechanical computation, 45% for image deformation and 40% for the reslicing. One iteration of the verlet integrator on our discrete biomechanical model takes 0.6 ms. Thanks to the discrete model and the dynamic integrator, the computation time of one iteration is very low. Therefore the kinetic energy threshold is quickly reached when the probe movement is small (about 40 iterations), which provides a smooth user interaction.

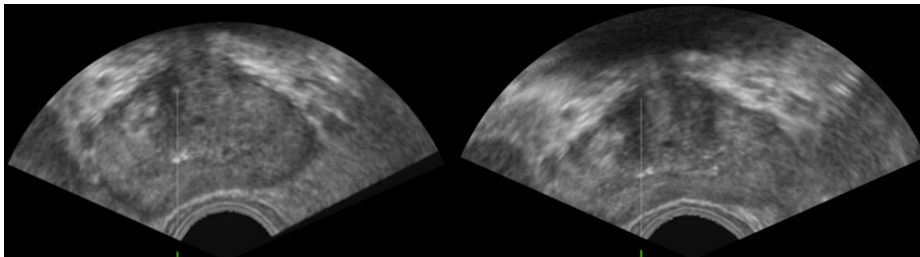
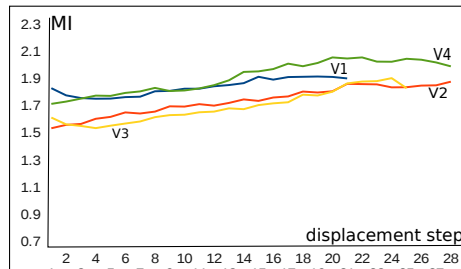


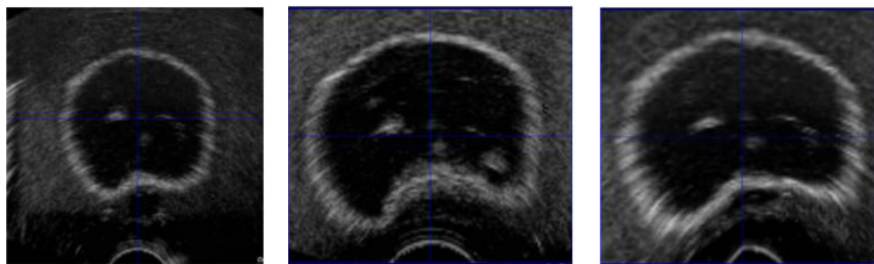
Fig. 3. The figure presents the 2D image of the undeformed volume (with no probe inducement) and the 2D image of the deformed volume (with a horizontal probe inducement of 13 mm). The white line represents the needle position during the biopsy fire.

Some of the acquired and simulated images are presented in Fig. 4a and b. The results can be visualized at <http://youtu.be/wzjCk2fPwYE>.

The purpose of this work and its first validation was to evaluate the feasibility of the method in terms of calculation time and increase the realistic visual quality. The discrete biomechanical model was not build to reproduce very accurate behaviour: k_e is not directly linked to physical properties and the model does not simulate the heterogeneous tissues nor their interaction. Despite this lack of physical realism, and as all constraints are based on displacements, we found that the equilibrium positions of each frame were not dependent of the elasticity parameter k_e . The main direction of improvement, especially in terms of predictive abilities on the biopsy score would be to model different organ structures, model the needle interaction with the tissue and to improve the probe interaction. Moreover, some boundary conditions can be easily added by applying a constraint of null displacement to any node, in order to simulate for instance the pelvic bone. The resulting generated images seem qualitatively satisfactory; the prostate has the characteristic bean-shape as seen during TRUS prostate examination, see Fig. 4. The main limitations of the qualitative experiments are



(a)



(b)

(c)

(d)

Fig. 4. (a) Computed mutual information on voxel values at each step for the 4 volumes (b) The initial input is an acquisition of the phantom without probe inducement (c) Slice of deformed volume acquired (d) Generated image

a) the unknown intermediary images and probe displacements and *b)* the rather large probe displacements compared to a real procedure, where experts estimate a normal probe displacements to be around 10 mm. We plan to do new experiments on the phantom in order to record intermediate deformed volumes with smaller and more realistic probe displacements to improve the qualitative validation relevance. Quantitatively, the computed mutual information between each generated image and original final image for the set of 4 volumes shows that the image similarity increases, see Fig. 4b. This is a satisfactory result considering the fact that we did not use a classical finite element biomechanical model. While the biomechanical grid resolution has no strong effect on the time performance, the main bottleneck comes from the dimensions of the input volume and the warping grid resolution. The limitation due to the input volume directly comes from the choice of the interpolative approach. The wrapping grid resolution could be optimized based on more experimental evaluation. Finally, it could be useful to integrate haptic force generation to take into account the model data in order to add realism.

5 Conclusion

In this paper, a fast ultrasound image deformation method based on a discrete biomechanical model that deforms real patient 3D volumes was presented. The implementation was successfully integrated into a learning simulator, to improve on classical simulators such as those described in [3,4]. A first validation was performed both qualitatively and quantitatively, showing an increase in the visual

realism. The next step will be to evaluate the impact of our simulator, with and without including the image deformation, compared to traditional training.

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