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To cite this version:

Lucas Royer, Maud Marchal, Anthony Le Bras, Guillaume Dardenne, Alexandre Krupa. Interactive Tracking of Soft Tissues in 2D Ultrasound Images. 2014. hal-01080676

HAL Id: hal-01080676

https://hal.science/hal-01080676v1

Submitted on 5 Nov 2014

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Interactive Tracking of Soft Tissues in 2D Ultrasound Images

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June 12, 2014

1 Introduction

In several medical applications such as liver or kidney biopsies, an anatomical region needs to be continuously tracked during the intervention. When using ultrasound (US) image modality, tracking soft tissues remains challenging due to the deformations caused by physiological motions or medical instruments, combined with the generally weak quality of the images. In order to overcome the previous limitation, different techniques based on physical model have been proposed in the literature. [SMSM06] proposed a registration method based on the mass-spring system in order to constrain the deformation, and Zhang *et al* [ZW13] introduced an other registration technique based on finite element model where the extraction of the scale invariant features is needed. However, their model are built from features which are difficult to extract in US images due to the speckle noise. Finally, Marami *et al* [MSFC14] presented very recently an elastic registration method applicable to multi-modality image registration where the deformation is computed from modality independent neighborhood descriptor. In this paper, we propose an approach for tracking deformable target within 2D US images based on a physical model driven by smooth displacement field obtained from dense information. This allows to take into account highly localized deformation in the US images. Section 2 presents our method based on a combination of an intensity-based approach and a physically-based model. Section 3 describes the performances of our approach and comparisons on real data. Section 4 concludes the paper.

2 Method

2.1 Definition of the Tracking Region

The target is defined by a region of interest composed of N_p pixels. A grid of N_c control points is superimposed on it such that $N_c << N_p$. The grid is composed of a set of blocks where each corner represents a control point. Each block includes a constant number of pixels N_b and four controls points. A pixel position P is related to the associated control points by using a bi-linear interpolation. Thus, for the vector $\mathbf{P}$ containing all the pixel positions, and the vector $\mathbf{P_c}$ containing the control points positions, we have the following relation:

$$\mathbf{P} = \mathbf{C}.\mathbf{P_c} \tag{1}$$

where $\mathbf{C}$ is a matrix $N_p \times N_c$ which contains all the bi-linear coefficient of each pixel position in function of its control points. The equation 1 allows to estimate the N_p pixels positions from the control points coordinates. In this paper, our objective is to interactively find the positions of the control points such that the region of interest keeps being tracked at any time thanks to the intensity variation of each pixel.

2.2 Intensity-based Approach

Let us define $\mathbf{I}$ the vector composed of the intensity values of the N_p pixels. The objective is to define the optimal displacement of the control points such that the error difference on the pixel intensities between the initial image

and the current image is minimized. We propose to use an approach which relates the intensity time variation to the displacements of the control points by using a Jacobian $\mathbf{J}$:

$$\dot{\mathbf{I}} = \mathbf{J}.\dot{\mathbf{P_c}} \tag{2}$$

where $\dot{\mathbf{I}}$ is the time variation of the pixel intensities and $\dot{\mathbf{P_c}}$ the displacements of the control points. Combining equations 1 and 2, the Jacobian can be expressed as:

$$\mathbf{J} = \nabla\mathbf{I}.\mathbf{C} \tag{3}$$

where $\nabla\mathbf{I}$ represents the gradient of the pixel intensities regarding the x and y. As it was shown in [NK13], if we want to ensure an exponential decrease of the error between the reference and current template, we can express the variation of the control points $\widehat{\dot{\mathbf{P_c}}}$ between the initial and current states as :

$$\widehat{\dot{\mathbf{P_c}}} = -\lambda.\mathbf{J}^{+}.(\mathbf{I_{current}} - \mathbf{I_{ref}}) \tag{4}$$

where $\lambda > 0$ is the proportional coefficient involved in the exponential convergence decrease of the difference between the current intensities $\mathbf{I_{current}}$ and the initial ones $\mathbf{I_{ref}}$. $\mathbf{J}^{+}$ represents the pseudo-inverse matrix of the Jacobian $\mathbf{J}$. In this work, we chose to constrain the deformation by integrating a physically-based model of the expected deformation.

2.3 Deformable Component

In order to take into account the deformations of the region of interest, a deformable model is superimposed to it. Our deformable model consists of a mass-spring-damper system where the nodes are the controls points of the grid. Thus, the force F_{ij} exerted on a control point P_c^i from a neighbor point P_c^j is:

$$F_{ij} = (K_{ij}(d_{ij} - d_{ij}^{init}) + D_{ij}(\dot{P_c^i} - \dot{P_c^j}))(P_c^i - P_c^j) \tag{5}$$

where d_{ij} represents the distance between the two control points in their current position. d_{ij}^{init} represents the initial distance value. K_{ij} is the stiffness of the spring while D_{ij} is the damping coefficient. The values of these coefficients can be different, depending on the homogeneities of the tissues. The forces applied on each control point P_c^i of the deformable system could be summarized in F_i:

$$F_i = \sum_{j^{neighbors}} F_{ij} + G_i\dot{P_c^i} + F_{ext} \tag{6}$$

where G_i is the velocity damping coefficient and F_{ext} corresponds to the external forces. We chose to use a semi-implicit Euler integration scheme for simulating our system. The external forces are computed from the control points displacements $\widehat{\dot{\mathbf{P_c}}}$ from equation 4. We integrate at each time step this displacement to obtain the external force representing the intensity variation. Once the external forces have been applied to the mass-spring-damper system, the simulation is performed in order to obtain the resulting displacements of the control points.

3 Results

We evaluated the performances of our method on real sequences of acquired 2D US images. The deformable targets were chosen in human liver US images acquired thanks to a 2D convex US probe of 2-5 MHz frequency bandwidth (C60, Sonosite). The tracking system is built from ViSP C++ library, and its computation time is estimated to 1.4 second per frame with non-optimized code. In order to test the robustness of both method on real data, we performed our test on a real sequence containing 173 images of 640×480 pixels. In this sequence, the target represents an hyper-echogenic area. Moreover, we added an extra rigid motion which translates and rotates the original sequence. We also launched the tracking without mass-spring based only on the intensity image variation. The results are presented in figure 1 from which we can see that the presence of dynamic noise results to the mis-estimation of the deformation which makes the target tracking fails without the mass-spring system. With our approach the deformable target is well tracked (fig. 1).

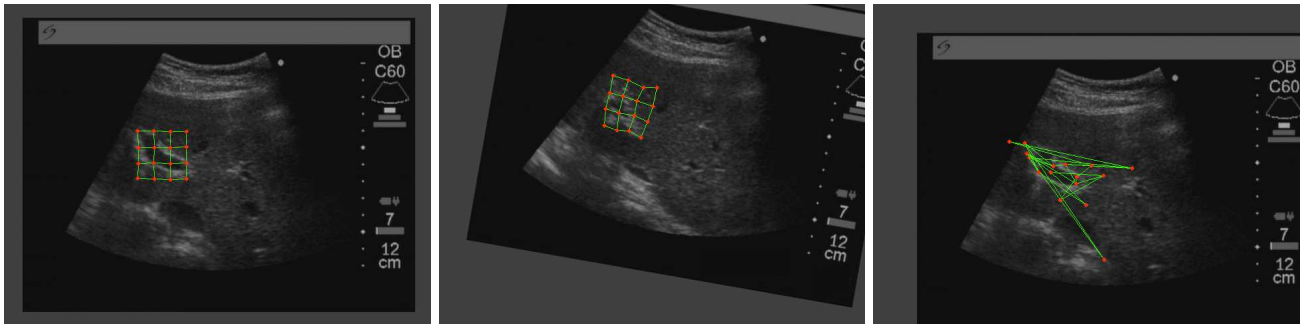

Figure 1: Results estimated on real data. (Left) Template tracking with mass-spring system at initialization (frame 1). The grid (size of each block 8×8 pixels) is with its initial shape due to low amount of deformation. (Middle) Template tracking with mass-spring system after deformation (frame 65). We can observe that the grid is deformed due to low similarity between reference template and current template. (Right) Template tracking without mass-spring system at frame 13. For the last case, we observe tracking failure due to the speckle noise presence.

4 Conclusion

We proposed an interactive approach for tracking deformable target within 2D US images based only on dense information and a physically-based model. In order to estimate both the rigid and the elastic motions of the soft tissues, we included in our approach a physically-based model superimposed to the region of interest. This deformable model is controlled by the intensity variation of the image and allows to take into account highly localized deformations in the US images. It opens novel perspectives in computer-assisted interventions based on US imaging and where deformable organs are involved, such as image-guided needle biopsy.

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