Dynamic Tracking of a Deformable Tissue Based on 3D-2D MR-US Image Registration

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ABSTRACT

Real-time registration of pre-operative magnetic resonance (MR) or computed tomography (CT) images with intra-operative Ultrasound (US) images can be a valuable tool in image-guided therapies and interventions. This paper presents an automatic method for dynamically tracking the deformation of a soft tissue based on registering pre-operative three-dimensional (3D) MR images to intra-operative two-dimensional (2D) US images. The registration algorithm is based on concepts in state estimation where a dynamic finite element (FE)-based linear elastic deformation model correlates the imaging data in the spatial and temporal domains. A Kalman-like filtering process estimates the unknown deformation states of the soft tissue using the deformation model and a measure of error between the predicted and the observed intra-operative imaging data. The error is computed based on an intensity-based distance metric, namely, modality independent neighborhood descriptor (MIND), and no segmentation or feature extraction from images is required. The performance of the proposed method is evaluated by dynamically deforming 3D pre-operative MR images of a breast phantom tissue based on real-time 2D images obtained from an US probe. Experimental results on different registration scenarios showed that deformation tracking converges in a few iterations. The average target registration error on the plane of 2D US images for manually selected fiducial points was between 0.3 and 1.5 mm depending on the size of deformation.

Keywords: Multimodal image registration, 3D-2D MR-US registration, image-guided intervention, dynamic finite element modeling, state estimation

1. INTRODUCTION

Recent developments in medical imaging and interventional tools have made image-guided minimally invasive therapy a reliable alternative to open surgery in medical practice. Modern CT and magnetic resonance imaging (MRI) systems can provide informative details of the human anatomical structures. However, high operational cost and incompatibility with other equipment in the operating room render these imaging modalities less suitable for real-time applications and interventional procedures. Ultrasound (US) imaging is widely used in procedures such as image-guided needle biopsy and ablation therapy due to its low cost, compatibility with other equipment, and fast acquisition time. Unfortunately, US imaging is handicapped by a confined field of view, poor image quality and low sensitivity and specificity in detecting relatively small regions (e.g., lesions or tumors). Co-registration of pre-operative MR/CT images with intra-operative US images can take advantage of the strengths of each of these imaging modalities and provide a more comprehensive picture of the tissue than what would be available using only one imager. Pre-operative surgical plans can also be updated accordingly using real-time information from US images.

The fusion of pre-operative MR/CT images with real-time US images has gained significant attention in recent years and several systems have been developed to provide such functionality, e.g., see.1,2 These systems are based on tracking the US probe using an exterior localizer. The US image in a global coordinate frame is registered to the MR image coordinates using fiducial markers, which are attached to the fixed positions with respect to the objects. Therefore, the corresponding image slice of the real-time US in the MR image volume can be interpolated and overlaid on the 2D US image. Such approach would be acceptable when the object is...
rigid and static with respect to the fiducial markers; however, human organs are mostly non-rigid and can move and deform due to the external and internal forces. A closed-loop control system based on rigid transformations is proposed in\textsuperscript{3} to compensate for the prostate motion in transrectal ultrasound (TRUS) guided needle biopsy. Furthermore, a combined statistical-biomechanical model-based approach is proposed in\textsuperscript{4} to non-rigidly register 3D pre-operative MR images with 3D TRUS images of the prostate.

An elastic registration method applicable to multi-modality image registration was previously reported in\textsuperscript{5}. The algorithm was examined by automatically registering 3D MR volume of a breast phantom before compression to 3D low-resolution and 2D image sequence acquired from different orientations after compression. In this paper, we further develop the algorithm to register 3D MR volume of a realistic breast phantom to its 2D US images over time to dynamically track the deformation caused by pushing a linear US probe against the phantom. The method employs an estimation and filtering process based on a linear elastic model of tissue deformation to automatically register the pre-operative 3D MR data to the real-time intra-operative 2D US images.

2. METHODS

Registration of two set of images is usually ill-posed by itself. Physical models associating the mechanical deformation of an object to its geometry and material properties are vastly used in order to find a feasible solution for the registration problem. In our proposed method, we employ a dynamic linear elastic model of tissue deformation discretized by the finite element method (FEM) in a state estimation framework to register pre-operative and intra-operative images.

2.1 Image Registration as a State Estimation Problem

We approach the problem of deformable image registration as a classical state estimation problem. Assume that the tissue deformation dynamics are governed by the following nonlinear state-space equations

\[
x_k = a(x_{k-1}, \tilde{f}_{k-1}) + w_{k-1} \\
z_k = h(x_k) + v_k
\]

(1a)

(1b)

Here, \(x_k\) is a vector of deformation states at time step \(k\), which is comprised of the displacements and velocities of the nodal points of a 3D FE mesh constructed to represent the geometry of the deformable tissue. External forces on the tissue are summed into the vector of nodal forces \(\tilde{f}\). The measurement vector \(z_k\) could be raw grayscale pixel/voxel values over the intra-operative image grid, displacements of the image grid points, or any other form of information/feature derived from post-processing of the raw image data. Nonlinear vector mappings \(a(\cdot)\) and \(h(\cdot)\) can be obtained from the physics of tissue deformation and pre-operative/intra-operative image formation, respectively. The vectors \(w_k\) and \(v_k\) are process and measurement noises that represent uncertainty/error in the deformation dynamics and imaging model. The unknown states of deformation in Equation (1a), \(x_k\), can be estimated using nonlinear state estimation techniques based on intra-operative image data. Although deformation behaviour of biological tissues can be described by complex nonlinear models, we employ a rather simple linear elastic deformation model in this paper. It is difficult to develop an accurate nonlinear model with 3D geometry and inhomogeneous tissue structures. Since a state estimation framework allows for disturbance terms in the system model representing uncertainty and modeling errors, a linear elastic deformation model should suffice for our intended purpose.

The general flow of the registration algorithm depicted in Figure 1. The current state of tissue deformation is estimated based on distance (similarity) between real-time US and pre-operative 3D MR images using the localizer information. The state estimation framework presents a rather straightforward mechanism for tuning the registration algorithm based on the user’s relative confidence in the deformation model versus the image observation, reflected in the choice of statistical properties for the process and measurement noises. In this paper, we use a simple linear elastic model of deformation constructed over a volumetric cubic mesh and the aggregate error due to inaccurate geometry, unknown boundary conditions, unknown external forces, and model and parameter mismatches is represented by the process noise vector \(w_k\). As is shown in Figure 1, the registration algorithm iteratively computes the deformation of the template (pre-operative 3D MR) image \(T\) to match it as closely as possible with the reference (intra-operative 2D US) image \(R\). The measurement vector \(du_c\) is the
observation prediction error, which is computed at certain image grid points (control points) based on a distance (similarity) metric between real-time US image and the corresponding 2D MR slice interpolated from the template image $T$ at current state of deformation using the localizer information and elements' shape function.

### 2.2 Deformation Model

The dynamic of a linear elastic body discretized with tetrahedral finite elements can be represented by a set of second-order differential equations as

$$\mathbf{M} \ddot{\mathbf{u}} + \mathbf{C} \dot{\mathbf{u}} + \mathbf{K} \mathbf{u} = \mathbf{f}$$

where $\mathbf{K}$ is the global stiffness matrix associate with the 3D mesh, $\mathbf{M}$ is the mass matrix of the elements, and $\mathbf{C} = \alpha \mathbf{M} + \beta \mathbf{K}$ is the damping matrix for constant values of $\alpha$ and $\beta$. Furthermore, $\mathbf{u}$ is the vector of nodal displacements and $\mathbf{f}$ is the vector of nodal forces applied to the elastic body. Bathe\textsuperscript{6} transforms the dynamics Equations (2) using a new variable $\mathbf{u} \triangleq \phi \mathbf{x}$ as

$$\tilde{\mathbf{M}} \ddot{\mathbf{x}} + \tilde{\mathbf{C}} \dot{\mathbf{x}} + \tilde{\mathbf{K}} \mathbf{x} = \tilde{\mathbf{f}}$$

where columns of $\phi$ are eigenvectors of $\mathbf{M}^{-1} \mathbf{K}$. Furthermore, $\tilde{\mathbf{M}}$, $\tilde{\mathbf{C}}$, $\tilde{\mathbf{K}}$ are diagonal matrices, and $\tilde{\mathbf{f}} \triangleq \phi \mathbf{f}$. Now, the dynamic finite element equations are decoupled in (3) and each equation describes a vibrational mode of the deformable body. Modes that are very fast compared to the time step used for registration and the rate of changes in external forces can be simply eliminated from the system dynamics without affecting the response at a particular time scale. This modal reduction projects a full model behaviour onto a subspace of lower dimensionality which results in significant reduction of the computations and improves the efficiency and robustness of the state estimation process.

The continuous-time dynamics of the deformation in (3) are transformed into discrete time with a sampling time of $T_s$ using the central difference method.\textsuperscript{6} The discrete-time reduced dynamics can be represented in state-space form as

$$\mathbf{x}_k = \mathbf{A} \mathbf{x}_{k-1} + \mathbf{B} \tilde{\mathbf{f}}_{k-1} + \mathbf{w}_{k-1}$$

where $\mathbf{x}_k$ is the vector of unknown states and $\mathbf{w}_k$ is the process noise. States transition matrix $\mathbf{A}$ and input matrix $\mathbf{B}$ can be derived based on reduced matrices of $\tilde{\mathbf{M}}$, $\tilde{\mathbf{C}}$, $\tilde{\mathbf{K}}$, $T_s$. It should be noted that the above state dynamics model is a linear version of the one in (1a).
2.3 Observation Model and Estimation

The observation model relates the deformation states to the real-time 2D US images. In this paper, we assume that our measurements are the displacement of certain points on the US image grid called control points. The deformation states $x$ are mapped to the nodal displacements of the FE mesh using the relation $u = \phi x$. Therefore, the displacements of the measurement grid points $u_c$ can be computed using $u_c = \Lambda u = \Lambda \phi x$, where $\Lambda$ is assembled from the elements shape function for individual points. With this representation, the observation model can be expressed as

$$
\mathbf{z}_k \triangleq \mathbf{u}_c = \mathbf{H}\mathbf{x}_k + \mathbf{v}_k ; \quad \mathbf{H} \triangleq \Lambda \phi
$$

where $\mathbf{v}_k$ is the measurement noise vector. This model is linear and the length of $\mathbf{z}_k$ can be chosen by the user depending on the registration application requirements.

The state (4) and observation (5) models are in standard form for application of a linear state estimator such as the Kalman filter. The equations for the time and measurement updates of the filter are given in. In Equation (4), the vector of unknown forces $f_k$ is modeled together with the process noise $w_k$ as white Gaussian noise with a normal probability distribution of $p(f_k) = N(0, \Sigma)$. The power of the process noise reflects the user confidence in the accuracy of the model, i.e., the stronger the noise the less accurate the model is. As is given in, in the Kalman filter framework, the state estimates are updated using

$$
\dot{\mathbf{x}}_k = \dot{\mathbf{x}}_k^- + \Gamma_k (\mathbf{z}_k - \mathbf{H}\dot{\mathbf{x}}_k^-) = \dot{\mathbf{x}}_k^- + \Gamma_k \mathbf{d}_u_c
$$

where $\mathbf{d}_u_c = \mathbf{z}_k - \mathbf{H}\dot{\mathbf{x}}_k^-$ is called the observation prediction error and $\Gamma_k$ is the filter gain. It should be noted that, based on algorithm flowchart in Figure 1, the measurement vector contains the displacements computed at control points given the real-time US image and the deformed template image, i.e., $\mathbf{d}_u_c$, whereas $\mathbf{u}_c$ is the vector of total displacements from the initial state at control points. Therefore, the observation prediction error needs to be computed accordingly.

We employ an intensity-based distance (similarity) metric called modality independent neighbourhood descriptor (MIND) in the registration. MIND is based on the similarity of small image patches within the image and extracts distinctive structures in a local neighborhood, which are independent from imaging modalities. Then, the distance metric at any point is the sum of absolute differences (SAD) between locally extracted descriptors in two images. We compute the observation prediction error $\mathbf{d}_u_c$ at control points based on the numeric gradient of the distance metric. $\mathbf{d}_u_c$ is on the plane of US image which represents a three-dimensional displacement vector when projected to the MR volume coordinate. Although the measured displacement is on the plane of US image at each iteration, the final computed deformation is not limited to this plane because the whole volume is deformed at every iteration based on the 3D deformation model.

3. EXPERIMENTS AND RESULTS

The proposed registration algorithm was evaluated in dynamically tracking the deformation of a triple modality biopsy training breast phantom (CIRS model 051). It was mounted on an apparatus made of plexiglass shown in Figure 2a. Eight fiducial markers, which are visible in the MRI scan, were employed for the registration of the MRI and optical tracker coordinate frames. A 3D image volume of $512 \times 512 \times 108$ with voxel size of 0.47×0.47×1 mm was acquired from the phantom tissue using a GE Discovery MR750 3 T scanner. The MRI volume was rigidly registered to the real-time 2D US images using a system by Hologic Inc., which integrates SonixTOUCH ultrasound with Aegis Navigation (see Figure 2b). In this system the US transducer is tracked by an optical tracker system allowing for investigation of the same anatomical features under both US and MRI modalities. The accuracy of this registration quickly degrades when the tissue is deformed due to the force of the ultrasound probe. This is evident, for instance in Figure 2b, where the green line on the MR image, that represents the transducer surface, is well inside the phantom tissue boundary.

For the experiments, we pushed and moved a linear US transducer against the phantom in different scenarios to capture different features inside the phantom. In each experiment, we recorded the US images at the rate of 13 frames-per-second (fps) as well as synchronized navigation system information. Therefore, for a given
Figure 2: Experimental setup: (a) a breast phantom and the tracking system, (b) real-time US and corresponding MR images out of the Aegis navigation system.

2D US image at any time, the corresponding slice can be interpolated from the volume of MR images using the transformation given by the navigation system. A cubic mesh with 16,732 tetrahedral elements, which encompassed the entire volume of the breast phantom, was generated using the COMSOL Multiphysics and Simulation software (Figure 4a). Using this mesh, an isotropic linear elastic model of deformation was created with the Young’s elasticity modulus $E = 3$ kPa, the Poisson’s ratio $\nu = 0.49$ and a mass density of $\rho = 0.95 \text{ g/cm}^3$. Only 500 modal pairs of the original model were considered in the deformation model.

The US image grid was extended with 0 (black) grayscale values in the direction normal to the transducer face. This extension allows the edges of the phantom to be considered in the MR images, providing extra features and facilitating the registration process. The extended US image grid (reference image) was 92×76 from which 23×19 points were used as control points for computing the vector of observation prediction error. Before starting the iterative deformable registration, the first US frame was rigidly registered to the volume of MR images using the MIND-based distance metric. This reduces the number of iterations in the deformable registration algorithm for convergence to a solution. Both MRI and US images were filtered before registration using a Wiener filter to decrease image noise.

As is shown in Figure 3, the deformable registration aligns the pre-operative MR and real-time US images and compensates the deformation and movement caused by the force of the US probe. The top row of this figure shows the first recorded slice, where the probe is slightly pushed against the phantom, whereas in the second and third rows the deformation increases. Although the US frame rate was 13 fps, only one from every five frames was recorded and employed for the registration, yielding an effective frame rate of 13/5 fps. Images shown in the second and third rows were after using 11 and 21 frames respectively, for updating the estimates of the deformation states. The average target registration error on the plane of 2D image for selected points on the edge (three points) and lesions inside the phantom (two points) depends on the size of deformation and was between 0.3 and 1.5 mm. As can be seen in Figure 2, both US and MR images are noisy with shadows and inhomogeneities. Furthermore, the internal structures of the phantom have different intensity levels for US (dark) and MR (bright), but the algorithm using the MIND-based distance metric could easily register these.
Figure 3: 3D-2D MR-UD registration results for three sample times: (a) MR image out of Aegis (registration based on the localizer) (b) US image, (c) US image laid over the MR image out of Aegis, (d) registered MR image, and (e) US image laid over registered MR image. Images are 45×38 mm. Top, middle and bottom rows are images for the results of the first, 11th and 21st slice registration, respectively.

The undeformed and deformed FE mesh employed in the registration are shown in Figure 4. The whole area of the US image plane, i.e., the tissue and extended black area, was laid inside the FE mesh. The deformation happens in the phantom tissue, not in the extended black area. Therefore, most of the captured deformation in the FE mesh occurs actually inside the mesh and is not visible from the surface of the mesh in Figure 4b.

4. CONCLUSIONS

An automatic model-based registration method was proposed in this paper to non-rigidly register pre-operative volumetric MR data to real-time 2D US images. The method employs a dynamic linear elastic deformation model with a distance (similarity) metric between images to estimate the states of the deformation using a filtering approach. The dynamic model correlates US image information acquired from different orientations over time to dynamically track the deformation of the tissue and update the pre-operative image volume accordingly. Experiments with breast phantom tissue demonstrated the effectiveness of the proposed registration algorithm.

The parameters of the registration algorithm as well as the interval for using new US image slice must be adjusted based on the real-time US frame rate, deformation speed, and the computation time needed for the registration of each slice. The registration algorithm includes tasks such as matrix computations, image
interpolation, and identifying the element in which a point falls. All of these computations are highly amendable to parallelization using graphics processing units (GPUs).

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