Nonrigid Liver Registration for Image-Guided Surgery using Partial Surface Data: A Novel Iterative Approach

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ABSTRACT

In the context of open abdominal image-guided liver surgery, the efficacy of an image-guidance system relies on its ability to (1) accurately depict tool locations with respect to the anatomy, and (2) maintain the workflow of the surgical team. Laser-range scanned (LRS) partial surface measurements can be taken intraoperatively with relatively little impact on the surgical workflow, as opposed to other intraoperative imaging modalities. Previous research has demonstrated that this kind of partial surface data may be (1) used to drive a rigid registration of the preoperative CT image volume to intraoperative patient space, and (2) extrapolated and combined with a tissue-mechanics-based organ model to drive a non-rigid registration, thus compensating for organ deformations. In this paper we present a novel approach for intraoperative nonrigid liver registration which iteratively reconstructs a displacement field on the posterior side of the organ in order to minimize the error between the deformed model and the intraopreative surface data. Experimental results with a phantom liver undergoing large deformations demonstrate that this method achieves target registration errors (TRE) with a mean of 4.0 mm in the prediction of a set of 58 locations inside the phantom, which represents a 50% improvement over rigid registration alone, and a 44% improvement over the prior non-iterative single-solve method of extrapolating boundary conditions via a surface Laplacian.

Keywords: image guided surgery, liver, registration, deformation

1. PURPOSE

Liver resection surgery in the open abdomen is a challenging setting for the application of image-guided surgical techniques which have been largely limited to procedures involving the cranium in the past. Surgical liver presentation typically begins with mobilization from the surrounding anatomy, followed by stabilization by packing support material underneath and around the organ. Thus large deformations (on the order of several centimeters) often occur between the preoperative (when CT imaging was performed) and intraoperative organ states.

While intraoperative imaging has been used to document the extent of deformation,[1] and guidance solutions using intraoperative imaging have been proposed,[1–5] the workflow requirements and the challenges of integrating preoperative imaging data continue to be a hindrance. As a result, there remains a clinical need to efficiently align preoperative data to the intraoperative patient state, in order to leverage the wealth of preoperative image data that can be collected without incurring the encumbrance of many imaging systems. In prior work, Clements, et al. proposed a robust weighted-patch iterative-closest-point algorithm to perform rigid registration using a surface point cloud obtained from a laser range scan (LRS) combined with salient feature data patches from tooltip swabbing.[6] Subsequently, Dumpuri et al.[7] and Clements et al.[8] investigated methods for an additional nonrigid registration step. Using a linear elastic finite element model generated from the patient's CT data, these methods imposed Dirichlet boundary conditions for normal displacements on most of the organ surface in order to minimize the remaining partial surface misfit from the rigid registration. The boundary conditions were determined from signed closest point distances between the data and the model surface, using various methods for extrapolating these conditions across the entire liver surface, e.g. a surface Laplacian, or a radial filter. This

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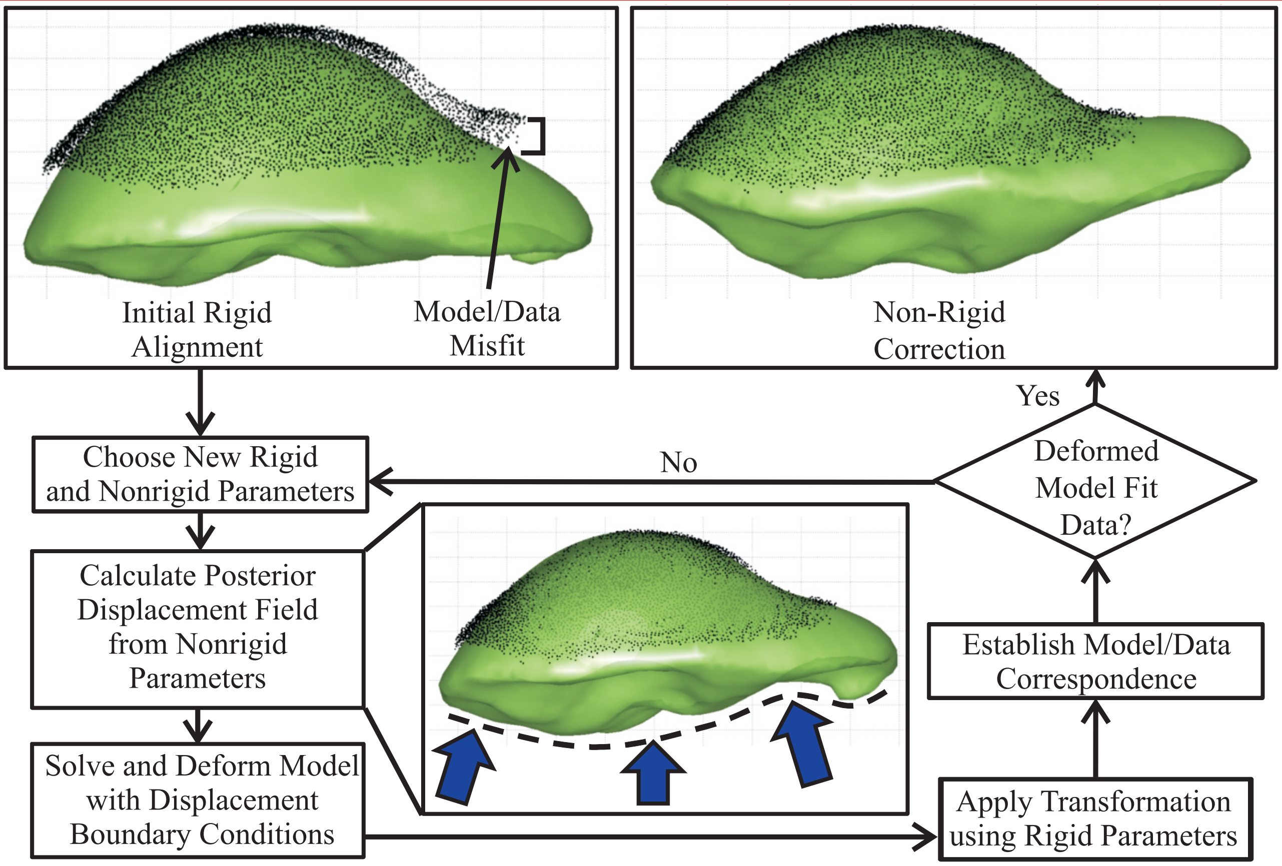

Figure 1. Our proposed iterative non-rigid registration method depicted is based on a nonlinear optimization framework. Parameters defining a smooth displacement field on the posterior surface (where support contact is likely during surgery) are iteratively selected to minimize the model/data misfit on the anterior surface of the organ.

concept has recently been incorporated into a complete surgical guidance system and commercialized through our industrial collaborator, Pathfinder Therapeutics Inc. (PTI) (Nashville, TN, USA).

Our aim in this paper is to introduce a novel way to approach the nonrigid registration problem in the context of aligning a solid liver model to partial intraoperative surface data. We detail the results of an experiment with a phantom liver undergoing large deformations consistent with a typical surgical presentation, and demonstrate that our proposed iterative approach yields more accurate predictions than the previous non-iterative single-solve method of boundary condition extrapolation.

2. METHODS

In this section we briefly describe the steps taken in our data pipeline from preoperative data collection to deformation correction based on intraoperative data. We then detail the procedures of a feasibility experiment involving a liver phantom undergoing realistic surgical deformations.

2.1 Biomechanical Model Generation

Beginning with a CT image volume acquired preoperatively, we segment the organ surface either manually or using a semiautomatic method developed by Dawant et al.,[9] Pan and Dawant.[10] Isosurfaces are then generated from the liver segmentation via the Marching Cubes Algorithm[11] and smoothed via radial basis functions (FastRBF toolkit, FarField Technology, Christchurch, NZ). From this surface we generate a tetrahedral mesh for building a finite element system using the customized mesh-generation software SPMESH.[12]

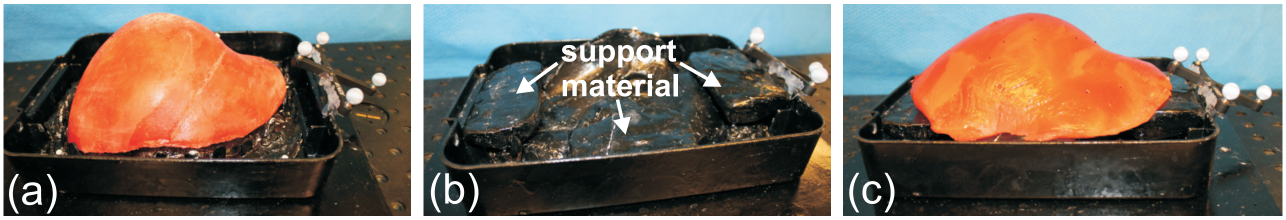

Figure 2. (a) The phantom liver tissue in its "preoperative" undeformed state, resting in the mold from which it was made. (b) Thick support material was placed on three sides of the mold. (c) The phantom liver in its deformed "intraoperative" state, due to the presence of the extra material underneath.

2.2 Intraoperative Data Collection

In the intraoperative setting we can acquire a textured point cloud representation of a portion of the organ surface using a custom-built commercial laser range scanner (Pathfinder Therapeutics, Inc., Nashville, TN). The scanner sweeps a laser line over the surface of interest and records both shape and color information. The partial organ surface can then be rapidly segmented from the textured cloud, and salient anatomical features can be designated (e.g. falciform ligament, inferior ridges, round ligament). A salient feature ICP method[6] is then used to obtain an initial rigid registration.

2.3 Proposed Algorithm

As depicted in Fig. 1, our proposed iterative nonrigid registration method is based on a nonlinear optimization framework where the objective is to minimize the misfit between the model surface and the intraoperative data. Our approach aligns the model surface to the data via a combination of rigid and nonrigid transformations which are selected iteratively. The nonrigid deformation is generated by solving a linear elastic finite element organ model with displacement boundary conditions applied to a designated portion of the surface. In typical surgical presentation the organ is likely to be supported on the posterior side of the organ (the bottom side in Fig. 1), so we define a displacement field for this surface as follows:

$$\boldsymbol{u}_s = \hat{\boldsymbol{n}}_s \sum_{1 \leq i+j \leq n} c_{ij} t_1^i t_2^j \tag{1}$$

where $\boldsymbol{u}_s$ is the displacement vector for a point on the support surface, $\hat{\boldsymbol{n}}_s$ is the average unit normal vector over the designated support region, and t_1 and t_2 are tangential coordinates of the point on the support surface (measured from the origin perpendicular to $\hat{\boldsymbol{n}}_s$ in two orthogonal directions). Solving the finite element model with these displacement conditions reproduces nonrigid deformation modes consistent with the typical practice of "packing" support material underneath the liver to stabilize its presentation. After solving the finite element model, a rigid-body transformation with six degrees of freedom is applied to the deformed nodal coordinates. Thus, the set of parameters selected at the beginning of each iteration consists of the nonrigid coefficients c_{ij} (we used $n = 3$, which results in nine coefficients) plus the six rigid parameters. This set of parameters defines the final displacement field which provides the model prediction for the current iteration.

At the end of each iteration the deformed model is compared to the intraoperative data. Due to the potentially large displacements involved, correspondences between the model surface and the data are re-established in each iteration via closest point relationships, and the corresponding model/data misfit (sum of squared errors) is evaluated as the objective function to be minimized. The rotational component of the rigid body transformation is inherently nonlinear, and additional nonlinearity is incurred by re-updating the correspondence relationships at each iteration. Thus, our approach involves iteratively updating the parameter set at each iteration via a nonlinear optimization routine (in this work we use a Levenberg-Marquardt procedure with the required gradients computed via finite differences). The algorithm is terminated when the model/data misfit is low, or other termination criteria like a maximum number of iterations are met. After termination, the resulting displacement field (which contains both rigid and nonrigid components) represents an enhanced registration from the peroperative image set to the intrapoerative patient space and can be used within in a surgical guidance system.

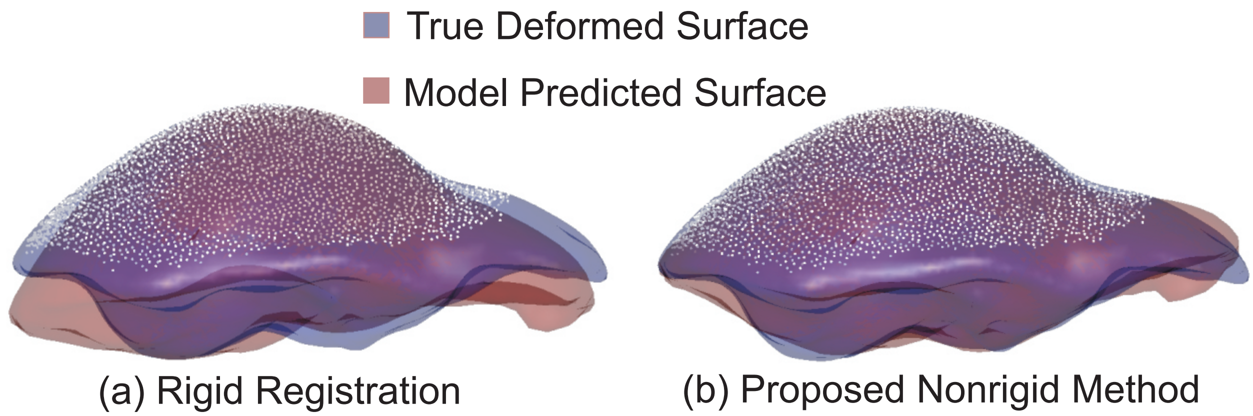

Figure 3. **(a)** The red surface is the model generated from the CT images taken in the phantom's undeformed state and rigidly registered to the deformed partial surface data captured by the scanner. The true deformed surface generated from post deformation CT images is shown in blue. **(b)** The red surface is the deformed model prediction using our proposed nonrigid registration algorithm. The true deformed surface generated from post deformation CT images is again shown in blue.

2.4 Feasibility Experimental Procedure

As depicted in Fig. 2(a), a compliant polyvinyl liver phantom was made and placed in a rigid container with markers identifiable by the CT scanner and a camera tracking system. A CT scan of the phantom was taken, and a tetrahedral mesh was generated from the resulting image volume. We define this pose as the undeformed state simulating data that would be acquired prior to surgical resection.

Next, as shown in in Fig. 2(b), the phantom was removed from the container, and blocks of support material were added on three sides. The phantom was then returned to the container as shown in Fig. 2(c), where the extra support material caused significant upward displacement of the supported portions of the phantom, while the unsupported portions sagged down to the bottom of the container. This was intended to simulate the effects of intraoperative mobilization of the liver and subsequent stabilization with sterile towels to better access resection planes. With the phantom in its deformed state, a second CT scan was taken, and a surface LRS was acquired.

After rigid registration, i.e. initialization, via the weighted patch ICP,[6] the algorithm described in Section 2.3 was applied to nonrigidly register the phantom model to the LRS surface scan. 10 surface targets and 48 subsurface targets were evenly dispersed and embedded within the phantom and subsequently identified within the undeformed and deformed CT volumes. The undeformed locations were transformed using the displacement mapping generated by our algorithm and compared to their ground truth locations to assess the accuracy of the method.

3. RESULTS

The results of our feasibility experiments show that the proposed nonrigid registration method improves accuracy with respect to ground truth measurements considerably when compared to rigid registration alone and the previously investigated method of boundary condition extrapolation.

In Fig. 3, we show the deformed model surface resulting from our algorithm in red, with the true deformed surface generated from the second CT scan overlaid in blue. We note that the deformed model visually matches the partial surface data as closely as possible and also displays the same qualitative behavior as the true surface in regions where data is absent. For example, the three supported sides are displaced upward and the middle and back of the posterior model surface have sagged down to the level of the true surface.

To evaluate ground-truth subsurface rigorous error, we examine the target registration error (TRE) between the registration-predicted locations of the embedded targets and their post-deformation CT measured positions.

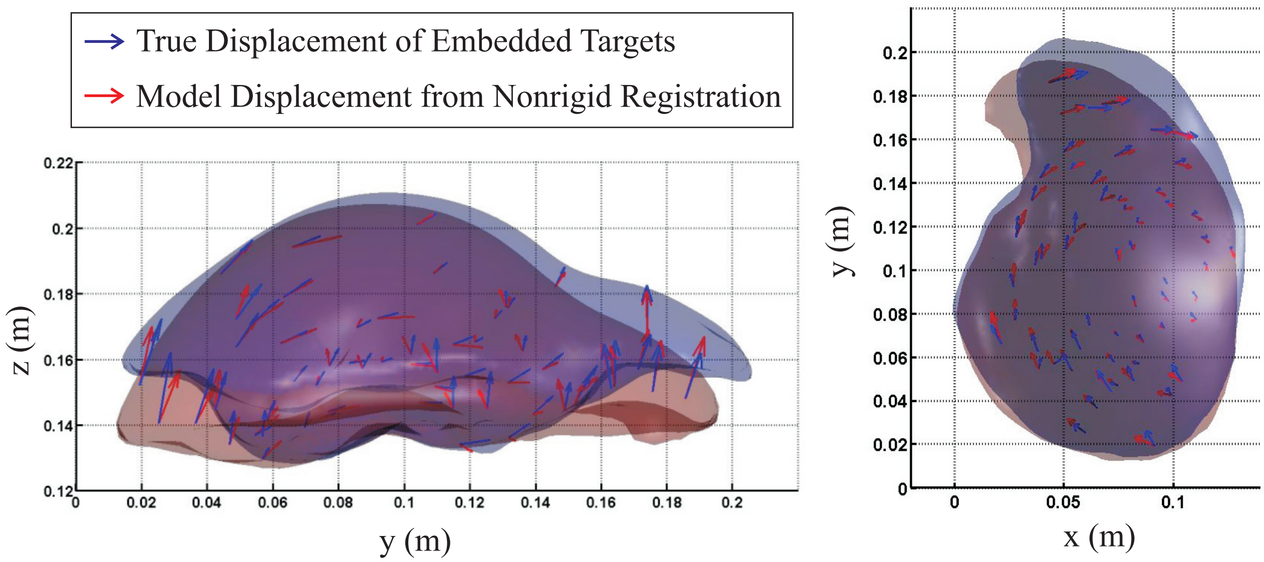

Figure 4. The red surface is the unregistered model surface. The blue surface is the post-deformation CT segmented surface. The displacement arrows originate at the unregistered target locations and terminate at the model-predicted target locations (red arrows) and the true post-deformation target locations acquired from the CT scan (blue arrows). The model prediction arrows shown in this case entail a rigid registration followed by our proposed nonrigid registration algorithm driven by the LRS surface data.

Figure 5 shows a histogram a for all 58 target registration errors across three different registration methods for comparison. In red, the weighted patch ICP rigid registration method of Clements et al.[6] is shown with a mean TRE of 8.0 mm. In green, with a mean TRE of 7.2 mm we show the results of a nonrigid registration method with a boundary conditions constructed from a non-iterative single-solve Laplacian extrapolation method, as detailed in Dumpuri et al.[7] In blue, our proposed iterative method is shown with a mean TRE of 4.0 mm and has significantly less deviation from the median target error.

4. CONCLUSIONS

We have introduced a new method for nonrigid alignment of a preoperative liver image volume to the intra-operative setting where organ deformation has occurred. We conclude that the proposed iterative method for nonrigid registration of the preoperative liver to the intraoperative environment is feasible and can effectively compensate for tissue deformation within an intraoperative navigation and guidance system. In our experiment the proposed method out performed the previous nonrigid method and the rigid registration method used in the existing commercial system by 44%, and 50% respectively in the prediction of locations throughout the phantom. Future work will include further testing on clinical datasets.

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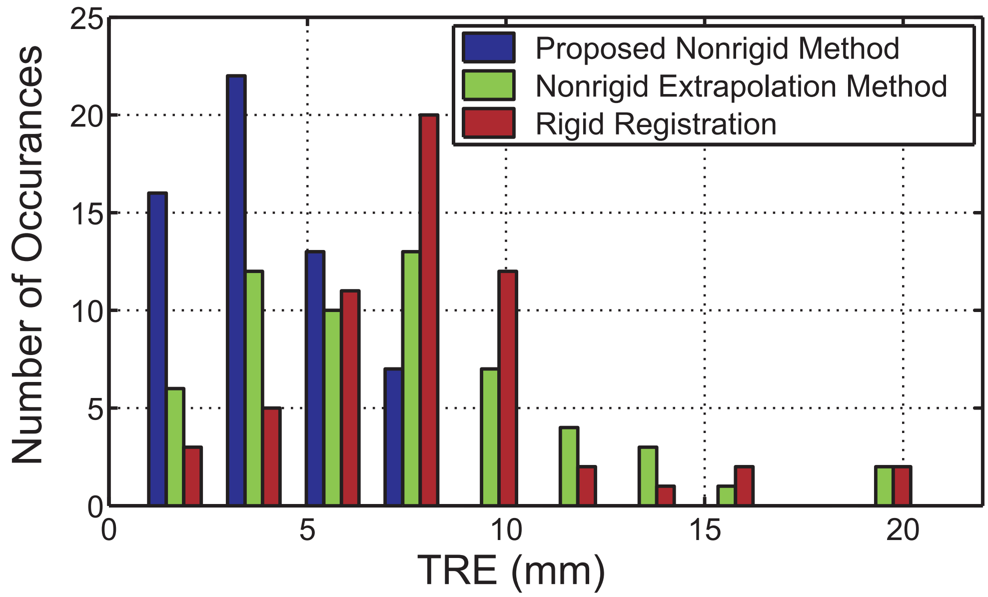

Figure 5. Statistical histogram of the 58 target errors resulting from three different methods of registration applied to our phantom dataset. Red - The results of a rigid registration using the weighted patch ICP method of Clements et al.[6] Green - After the rigid registration, the results of a subsequent nonrigid registration using a surface Laplacian to extrapolate boundary conditions as detailed in Dumpuri et al.[7] Blue - After the rigid registration, the results of a subsequent nonrigid registration using the proposed iterative method.

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