Preoperative to intraoperative deformed liver volumes registration

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Abstract
3D-3D laparoscopic registration is a crucial task in image-guided surgery. Our approach leverages anatomical structures to constrain the deformation process using the Finite Element Method (FEM), resulting in more realistic liver deformations. We use annotated 3D liver models from the P2ILF dataset as preoperative models and generate deformed liver shapes to represent intraoperative models. A learning-based network is then employed to establish correspondences between the preoperative and intraoperative liver models. To estimate the rigid transformation between the two models, we apply RANSAC-ICP refinement.

Introduction

Deep learning has demonstrated a remarkable ability to learn patterns and correspondences from data. Several studies have explored simulating different liver deformations to train neural networks for correspondence prediction, with Finite Element Method (FEM) being a widely used approach for generating realistic deformations [1]. In this work, we utilize laparoscopic data from the P2ILF dataset [2], which provides preoperative 3D liver models along with 3D/2D anatomical annotations.

We extract annotated ligament vertices from the 3D liver models obtained from CT/MRI and use them as boundary conditions for FEM-based simulation, generating a variety of deformed liver shapes. These deformed models represent intraoperative scenarios and are used to train the network. Since the visible surface of the liver during laparoscopy is limited, the simulated livers are cropped into partial point clouds to mimic the actual view encountered during surgery. For training, we adopt the LiverMatch framework [3], which predicts correspondences between the full preoperative liver model and the partial, deformed intraoperative liver model. This work lays the foundation for future studies. By demonstrating the ability to predict correspondences from the preoperative to the deformed model.

Methodologies

Deformation generation

Prior to simulation, we processed the liver model using MeshLab to clean the model. Unlike the method proposed in [4], which applies random boundary conditions to the FEM solver, we extract anatomically meaningful ligament vertices from the annotations provided for each patient. These anatomical landmarks serve as boundary conditions for FEM, as they form the primary structure of the liver. For the simulation, we adopt the Ogden hyperplastic material model, which is well-suited for representing soft tissues such as the liver [5]. In addition to the fixed ligament vertices, we randomly select a point on the liver surface to act as the center of an applied force. All mesh nodes

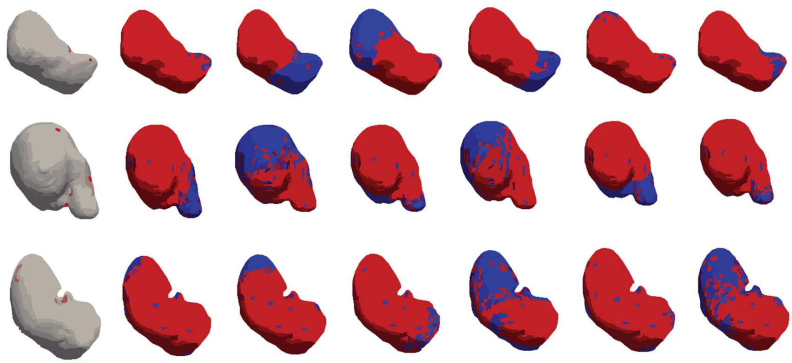

FIGURE 1
Liver deformation simulations: the red 3D point cloud represents the original preoperative model, while the blue 3D point cloud represents the deformed intraoperative liver model.

within 5 mm of this center point are also selected, and a total force of 50 N is evenly distributed across these nodes in the direction of the z axis. The deformation simulations are implemented using the FEBio software [6]. In total, 1000 deformed liver models are generated for each patient. Figure 1 illustrates six deformations for 3 patients compared with the corresponding preoperative model. The first column shows the preoperative liver model with its ligament vertices highlighted. In the remaining six columns, the red surface represents the preoperative model, and the blue surface shows the corresponding deformed liver.

Learning based Matching
3D-3D rigid registration typically involves finding correspondences between the models to be aligned [7]. However, when the models undergo deformation, this task becomes more challenging. In this work, we utilize a deep learning framework called LiverMatch to estimate these correspondences. The LiverMatch framework consists of a Kernel Point Convolution (KPConv) module [8] for initial point cloud feature extraction.

This is followed by a cross-attention transformer that allows communication between the preoperative and intraoperative liver models. Decoder layers are then used to regress the point-wise correspondences, and a visibility score is computed via a 1D convolutional layer to identify the most reliable matches. We train the model from scratch using our simulated dataset, where data from patient 1 to patient 7 are used for training and validation, and data from patient 8 and 9 are used for testing. The maximum 45-degree rotation and 20 mm translation is randomly applied to the point cloud for data augmentation.

Results and Conclusions

The Registration Error (RE) is used to evaluate the performance, calculated as root mean square error between predicted displacement vectors and ground truth displacement vectors. This can be written as equation: $\mathrm{RE} = \sqrt{\frac{\sum_{i=1}^{n} ||D_{gt}(i) - D_{pred}(i)||^2}{n}}$, where n is the number of source points, $\mathbf{D}_{\mathbf{pred}}$ is predicted displacement vector, and $\mathbf{D}_{\mathbf{gt}}$ is the ground truth displacement vector, which includes both deformation and rigid transformation. Also, we calculate the **inlier ratio** (IR), the ratio of number of inliers n_{inlier} to the number of matches by model prediction n_p. This can be written as $IR = \frac{n_{\text{inlier}}}{n_p}$. Additionally, Matching Score (MS) is reported, which is the ratio between number of inlier and the number of points of target point cloud m, $MS = \frac{n_{\text{inlier}}}{m}$. In table 1, quantitative comparisons based on the above metrics are evaluated. The model achieves 8.91 *mm* RE error for patient 8 and 7.53 *mm* for patient 9. The model scores the same IR of 98.2% for both patient 8 and 9 data. The model shows a higher MS for patient 9 (84.1%) compared with 83.8% for patient 8.

TABLE 1: Quantitative evaluation for data from patient 8 and patient 9

Metric	RE (mm)	IR (%)	MS (%)
Patient 8	8.91	98.2	83.8
Patient 9	7.53	98.2	84.1

Figure 2 shows qualitative results of patient 8 (first row) and patient 9 (second row) during testing. The red point clouds refer to the predicted point clouds and blue point clouds being the ground-truth point clouds.

To summarize, we presented a deformation simulation approach using the FEM to model liver deformations during the intra-operative stage. A convolutional neural network was trained on our custom-generated dataset, demonstrating a certain level of effectiveness in performing deformation-aware registration. For future work, we plan to explore registration between point clouds recovered from depth estimators, with the goal of advancing 3D-2D laparoscopic liver registration tasks.

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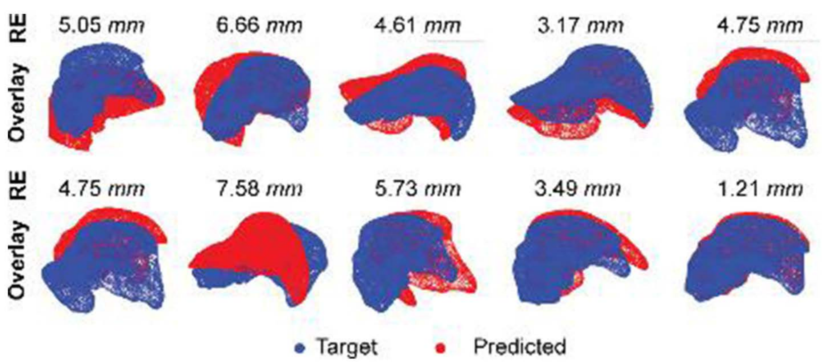

FIGURE 2
Qualitative registration overlays: (in red) with point-cloud with predicted transformation and (in blue) target point-cloud. The first row corresponds to patient 8, and the second row corresponds to patient 9.

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