Comparative Analysis of Non-Rigid Registration Techniques for Liver Surface Registration

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ABSTRACT

Non-rigid surface-based soft tissue registration is crucial for surgical navigation systems, but its adoption still faces several challenges due to the large number of degrees of freedom and the continuously varying and complex surface structures present in the intra-operative data. By employing non-rigid registration, surgeons can integrate the pre-operative images into the intra-operative guidance environment, providing real-time visualization of the patient's complex pre- and intra-operative anatomy in a common coordinate system to improve navigation accuracy. However, many of the existing registration methods, including those for liver applications, are inaccessible to the broader community. To address this limitation, we present a comparative analysis of several open-source, non-rigid surface-based liver registration algorithms, with the overall goal of contrasting their strength and weaknesses and identifying an optimal solution. We compared the robustness of three optimization-based and one data-driven nonrigid registration algorithms in response to a reduced visibility ratio (reduced partial views of the surface) and to an increasing deformation level (mean displacement), reported as the root mean square error (RMSE) between the pre-and intra-operative liver surface meshed following registration. Our results indicate that the Gaussian Mixture Model - Finite Element Model (GMM-FEM) method consistently yields a lower post-registration error than the other three tested methods in the presence of both reduced visibility ratio and increased intra-operative surface displacement, therefore offering a potentially promising solution for pre- to intra-operative nonrigid liver surface registration.

Keywords: Comparison, liver registration, non-rigid, soft tissue, image-guided surgery, robustness.

1. DESCRIPTION OF PURPOSE

Background: In surgical navigation systems, image-to-physical registration is essential because it helps surgeons observe critical organ structures, thereby reducing the risk of complications. As such, patient-specific information captured using pre-operative imaging is mapped to the intra-operative coordinate and aligned or fused with intra-procedural information, leading to improved navigation accuracy and precision.[1]

The intra-operative soft tissue (organ) surface undergoes shape deformation during surgical navigation; hence, nonrigid registration is a vital component of navigation systems designed for deforming soft tissue applications.[2] The registration is challenged by continuously varying surface features of the deformable soft tissue organs and noisy data from different imaging modalities, among other limitations that often arise during image-guided intervention applications where substantial deformations are expected. In addition, nonrigid registration techniques offer further advantages, namely allowing the handling of complex organ movements, dealing with the partial field of view, and deformations during surgery, all of which have the potential to improve the alignment of pre and intra-operative images with intraoperative imaging data.[1]

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Challenges: The pre-operative image to intra-operative physical liver registration specifically faces several challenges that need to be overcome to ensure sufficiently accurate pre and intra-operative alignment for subsequent surgical navigation. These challenges include the limited structure/texture of the liver surface anatomy, the presence of large deformations between the pre-and intra-operative settings, as well as noise associated with the inherent imaging modalities used to image the liver, both pre-and intra-operatively.[3]

Goal: While a substantial body of research exists in this domain,[4,5] liver registration methods are not readily available to the community due to their proprietary nature. In light of this limitation, this study aims to examine the performance of several open-source non-rigid registration techniques for liver surface alignment, especially the robustness of these methods in the face of varying noise, deformation, and visibility. By assessing the capabilities of several of these accessible methods, this research seeks to provide valuable insights and assistance to fellow researchers in the field, eventually contributing to advancing the field and the access to tools for the broader scientific community.

2. METHODOLOGY

The registration of pre-procedural images and models to the intra-operative data is key to the success of computer-assisted interventions. In the context of the liver application described here, the key is to identify an optimal method that allows us to accurately and robustly register a pre-operative liver surface extracted from a pre-operative CT image to intra-operative liver surface patches reconstructed using video imaging. As such, we evaluate the use of a full pre-operative liver surface mesh together with partial liver surface views as input into three optimization-based non-rigid registration methods: Non-rigid Iterative Closest Point (Non-ICP), Coherent Point Drift (CPD), and Gaussian Mixture Model (GMM)- Finite Element Model (FEM) as well as a data-driven model, Volume to Surface CNN (V2S-Net), and assess the accuracy and robustness achieved using each registration methods.

2.1 Pre-operative Data and Synthetically generated Intra-operative Data

For this work, we utilize a pre-operative liver mesh generated by segmenting a patient-specific pre-operative CT image. Ground truth intra-operative meshes are then generated by assigning prescribed deformation patterns to the pre-operative mesh. As such, the pre-operative mesh is deformed using a finite element solver by applying up to three forces and imposing zero-displacement boundary conditions to random regions of the pre-operative surface mesh, as described in our previous study.[6] The intra-operative sparse liver surface data are generated synthetically by randomly cropping random surface patches from the deformed pre-operative meshes using different visibility ratios.

2.2 Non-rigid Iterative Closest Point (Non-ICP) Registration

The Non-rigid ICP[7] is the extended version of the traditional ICP[8] used for point cloud registration. This method, available as an open-source resource on GitHub (`https://github.com/charlienash/nricp`), assigns an affine transformation to each vertex of the point cloud by incorporating a local affine regularization technique to optimize the transformation between two vertices of the mesh. This method aims to align each data point of the liver surface and apply a local transformation to each point to align with the corresponding datasets.

2.3 Coherent Point Drift (CPD) Registration

The Coherent point drift (CPD)[9] is a probabilistic approach for registration. This point-set registration aims to establish correspondence between two sets of point clouds and determine the transformation that maps the pre-operative liver mesh to the intra-operative liver mesh. The method assigns probabilities to coherent transformations by finding mesh node correspondences while adapting for noise, partial overlaps, or irregularities in the point cloud.

2.4 Gaussian Mixture Model - Finite Element Model (GMM-FEM) Nonrigid Registration

The GMM-FEM[10] method uses a probabilistic framework based on a Gaussian mixture model (GMM) to establish the correspondence between the pre- and intra-operative liver surfaces. The algorithm treats one surface of the liver mesh as a potentially partial observation. To extrapolate and constrain the deformation field, biomechanical prior knowledge is incorporated in the form of a finite element model (FEM). The open-source implementation is available in GitHub (https://github.com/siavashk/GMM-FEM) and contains applications to perform rigid, affine, and non-rigid registration.

2.5 Volume to Surface Registration Network (V2S-Net)

The V2S-Net[2] method is a deep learning deformable registration technique that uses a convolutional neural network (CNN) to handle non-rigid registration. When a pre-operative (source) volume mesh and an intra-operative (target) partial target mesh are used as the input, the algorithm finds the displacement field that deforms the source mesh to align with the target mesh. This method is available in GitLab (https://gitlab.com/nct_tso_public/Volume2SurfaceCNN).

2.6 Registration Parameter Optimization

To address the challenges of these non-rigid registration methods, we execute a combination of methodologies and optimizations across the algorithms to improve the accuracy and robustness of our results. For Non-rigid ICP and CPD, we optimized the default parameter configurations provided in the open-source packages. In the case of CPD, we further enhanced the analysis by down-sampling the intra and pre-operative meshes. Additionally, we employed K-nearest neighbor (KNN) interpolation to validate missing points. The GMM-FEM method was executed with the default parameters available in the open-source packages. Concerning V2S-Net, we calculated the displacement field and applied it to the source (pre-operative) mesh. The deformed mesh was generated by iterating over all points in the pre-operative mesh, interpolating into the displacement field at their positions, and adding the estimated displacement field to their coordinates. We utilized this newly generated deformed mesh for subsequent error analyses.

2.7 Evaluation Metrics and Procedures

To assess the accuracy and robustness of the investigated registration methods, we compute the root-mean-square (RMS) error between the full ground truth intra-operative surface (generated by deforming the pre-operative liver using the prescribed deformation patterns as described in 2.1) and the pre-operative liver surface mesh deformed using the registration transformation obtained by each of the four registration methods being evaluated.

3. RESULTS

We present the qualitative results of three optimization-based non-rigid registration methods and one data-driven registration method. Firstly, we assess their performance in response to handling reduced partial views of the liver mesh (100%, 42%, 21%). By cropping the ground truth liver mesh, we simulate the target model by creating partial views of the liver, one with the entire frontal surface and two others portraying only partial surfaces consisting of 42% and 21% of the entire surface. This step was manually executed in MeshLab.

To evaluate the performance of each method, we calculate the Root Mean Square Error (RMSE) between the estimated registration and ground truth results. Fig. 1 illustrates the registration outcomes and RMSE values for different partial view percentages associated with each method. Noticeably, for the case of complete visibility, the ICP and CPD methods report a minimal error, whereas the GMM and V2S-Net reports an error of .2mm and 4.46mm respectively.

However, as the visibility decreases, the GMM-FEM outperforms the other two optimization-based methods. On the other hand, V2S-Net outperforms non-ICP and CPD but yields a relatively higher error than GMM-FEM. This finding highlights the robustness of the GMM-FEM for lower visibility scenarios and reports its improved accuracy when handling limited partial views of the surface.

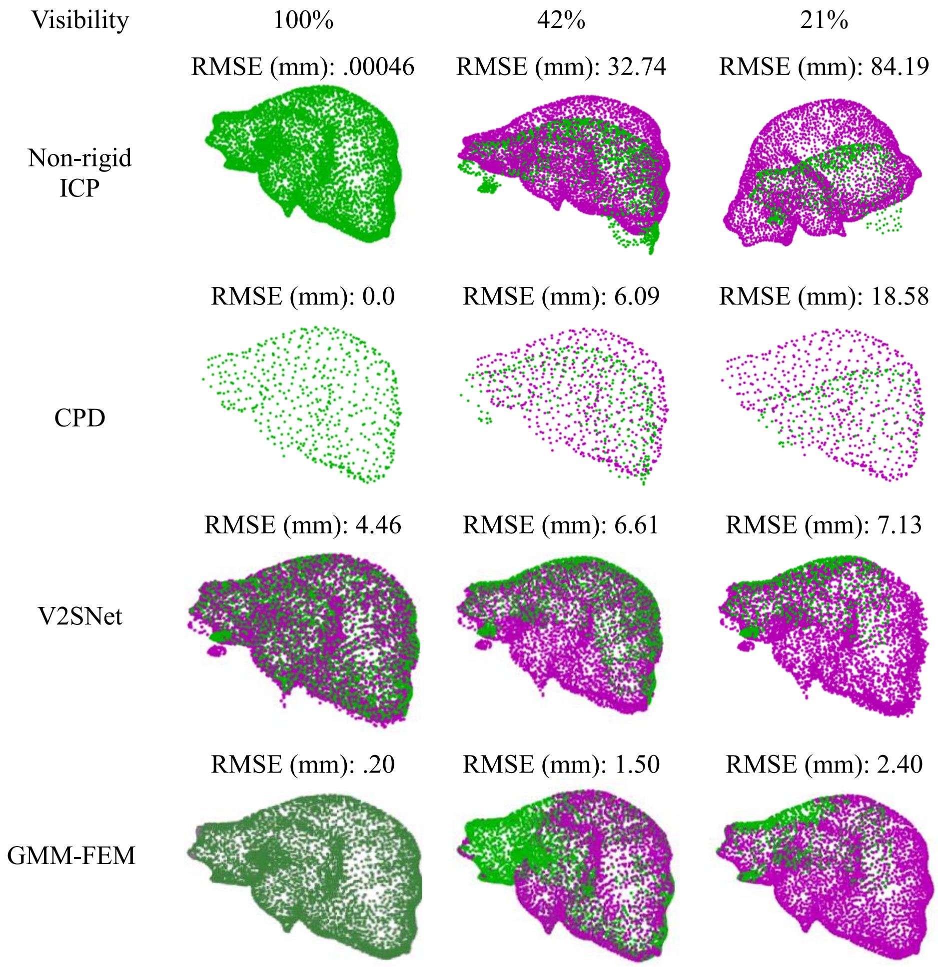

Figure 1. Effect of the limited intra-operative partial views (21%, 42% and 100%) on the performance of the four registration methods under consideration quantified according to the root-mean-squared error (RMSE) computed between the registered results and the ground truth, pre-operative (i.e., source) surface shown in magenta and intra-operative (i.e., target) surface shown in green after registration.

V2S-Net is a learning-based method that highly relies on the diversity and quality of the data on which it was trained. It leads to poor performance if it has not been exposed to data undergoing extensive deformations. This limitation is contrasted by GMM-FEM, a probabilistic approach that provides a more robust and physics-based framework to deal with incomplete data, ensuring that the registration is not adversely affected by missing mesh portions.

The non-ICP method aligns each data point of the pre-operative mesh to the closest point in the intra-operative mesh. It highly relies on finding correspondence between pre- and intra-operative surfaces. In the case of partial surface, the regularization term inadvertently biases the solution due to a significantly missing portion of the surface, leading to an incorrect alignment. Conversely, with a variation in the data density, the CPD registration method converges to a local minimum or maximum. Hence, it needs to improve dealing with partial views and mean displacement.[9]

We also study the robustness of the four methods to increase levels of mean displacement (deformation) in the data. Fig 2 illustrates the registration outcomes of the four methods under consideration in response to varying mean displacements. For this experiment, we used partial visibility of 42% (i.e., only 42% of the liver surface is visible intra-operatively) to mimic a typical clinical scenario where only a limited portion of the liver

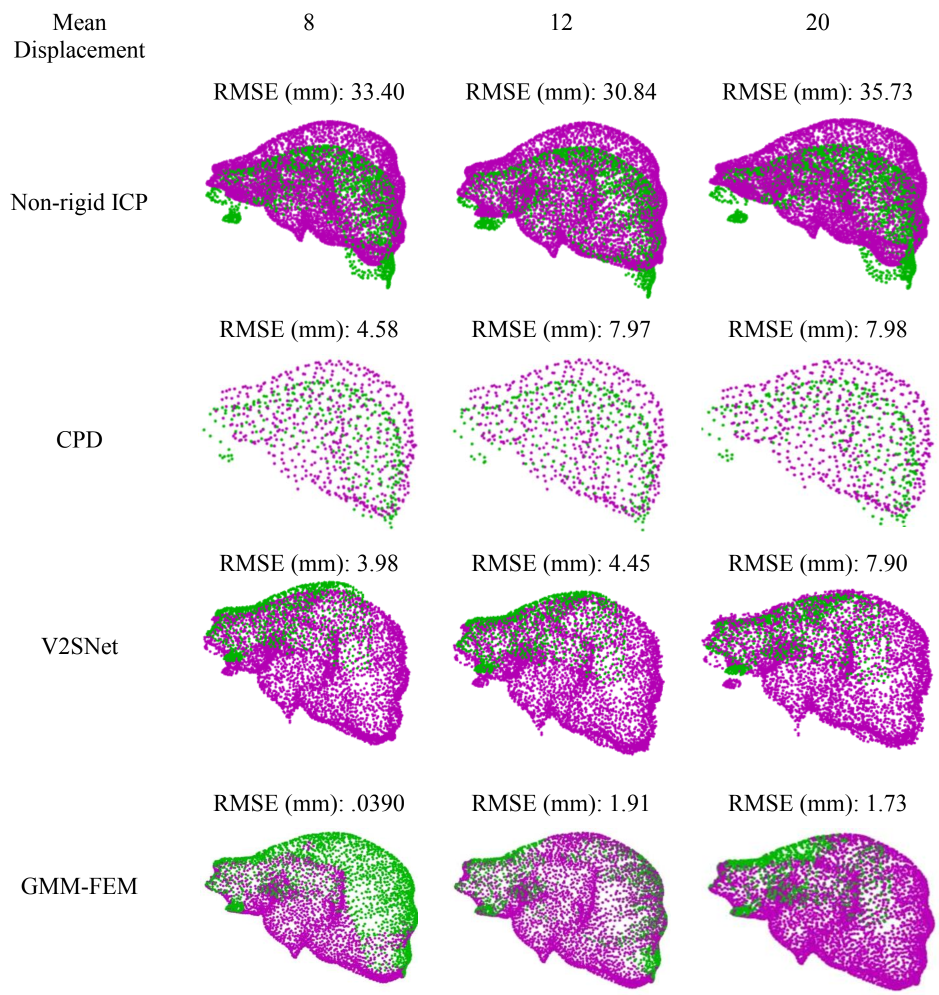

Figure 2. Effect of the increasing level of mean displacement associated with the intra-operative (i.e., target) surface representing 42% of the entire liver surface on the performance of the four registration methods under consideration quantified according to the root-mean-squared error (RMSE) computed between registered results and the ground truth, the pre-operative (i.e., source) surface shown in magenta and intra-operative (i.e., target) surface shown in green after registration.

surface is exposed. Visually, GMM-FEM registration yields the lowest error for all mean displacement levels, whereas the other three methods show an increased error. This illustration implies that the GMM-FEM method can also lead to a more accurate and robust registration in the presence of displacement/ deformation in the intra-operative partial surface.

We present comprehensive quantitative results for an increased number of samples using all four methods, illustrating the mean root mean square error (RMSE) along with the standard deviation. Table 1 reports the average RMSE (mm) value for each method under varying partial view and mean displacement. These findings indicate that the GMM-FEM nonrigid registration method provides a statistically significant ($p < .05$) lower RMS error than the other methods, underscoring the effectiveness of the GMM-FEM method in achieving a more robust alignment of the pre- and intra-operative liver meshes in terms of both the limited intra-operative partial views and the presence of increased levels of surface displacement in the data, which were two of the nonrigid registration challenges outlined in this study.

Considering the aforementioned challenges (partial intra-operative organ surface visibility, presence of deformations, varying tissue properties, and noisy data) associated with liver surface registration, our study presents a

Table 1. RMS Error (mm) post-registration under different visibility ratios (%) and mean displacement (mm). * $p < .05$ indicates statistically significant method

Visibility Ratio (%)	**(0 - 25)%**	**(25 - 50)%**	**(50 - 75)%**	**(75 - 100)%**
Non-ICP	58.87±24.24	44.50±15.98	24.93±10.09	7.09±4.83
CPD	17.19±12.3	15.54±4.53	14.44±5.36	10.38±4.80
V2S-Net	5.23±2.16	6.86±3.55	5.78±3.67	4.15±2.00
*GMM-FEM	**1.95±2.04**	**3.55±2.28**	**3.57±2.98**	**2.54±1.62**
Mean Displacement (mm)	**(0 - 6)mm**	**(6 - 12)mm**	**(12 - 18)mm**	**(18 - 25)mm**
Non-ICP	22.03±18.23	25.36±22.38	27.42±20.46	29.56±17.61
CPD	7.94±4.30	11.88±3.60	15.20±2.95	19.88±3.20
V2S-Net	2.49±1.18	4.17±1.38	5.64±2.28	8.51±3.50
*GMM-FEM	**1.32±1.06**	**2.18±1.03**	**3.51±1.90**	**5.35±3.4**

comprehensive comparative analysis of several optimizations and deep learning-based non-rigid liver surface registration methods. Our comparative study is intended to contrast and highlight the strengths of the investigated methods while offering insights into the most appropriate approach for liver surface alignment that addresses as many of the outline challenges.

4. CONCLUSION

In this study, we analyze three optimization-based algorithms and one deep learning algorithm for surface-based registration of implemented 3D liver meshes, optimizing their default configuration parameters disseminated in the open-source implementation. We have evaluated the robustness and performance of different intra-operative liver surface visibility ratios and mean displacements. According to our implementation and results, the GMM-FEM method consistently outperforms Non-ICP, CPD, and V2S-Net under both limited intra-operative surface visibility and increasing deformation, with the ICP method yielding the worst performance. We have fine-tuned the default parameters of the optimization-based techniques. We have used the pre-trained model for a data-driven method to generate a displacement field. In our analysis, we have used the displacement field to generate a deformable mesh. This iterates over all points in the pre-operative mesh, interpolates the displacement field at their position, and deforms the mesh based on the estimated displacement field.
The significance of this study lies in helping the community understand the performance of existing open-source methods for non-rigid liver surface registration, potentially impacting the advancement of medical image registration as a precursor for surgical navigation applications. As the research landscape advances, our study will have the potential to help and guide researchers when developing and exploring new open-source liver registration methods.

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