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The Image-to-Physical Liver Registration Sparse Data Challenge: Characterizing Inverse Biomechanical Model Resolution

Jon S. Heiselman[1,2] and Michael I. Miga[1,2]

[1] Department of Biomedical Engineering, Vanderbilt University, Nashville, TN
[2] Vanderbilt Institute for Surgery and Engineering, Vanderbilt University, Nashville, TN

ABSTRACT

Image-guided liver surgery relies on intraoperatively acquired data to create an accurate alignment between image space and the physical patient anatomy. Often, sparse data of the anterior liver surface can be collected for these registrations. However, achieving accurate registration to sparse surface data when soft tissue deformation is present remains a challenging open problem. While many approaches have been developed, a common standard for comparing algorithm performance has yet to be adopted. The image-to-physical liver registration sparse data challenge offers a publicly available dataset of realistic sparse data patterns collected on a deforming liver phantom for the purpose of evaluating and comparing potential registration approaches. Additionally, the challenge is designed to allow testing and characterization of these methods as a general utility for the registration community. Using this challenge environment, an inverse biomechanical method for deformable registration to sparse data was investigated with respect to how whole-organ target registration error (TRE) is impacted by a model parameter that controls the spatial reconstructive resolution of mechanical loads applied to the organ. For this analysis, this resolution parameter was varied across a wide range of values and TRE was calculated from the challenge dataset. An optimal parameter value for model resolution was found and average TRE across the 112 sparse data challenge cases was reduced to 3.08 ± 0.85 mm, an approximate 32% improvement over previously reported results. The value of the data offered by the sparse data challenge is evident. This work was performed entirely using information automatically generated by the challenge submission and processing site.

1. PURPOSE

The image-to-physical liver registration sparse data challenge, announced last year at SPIE 2019 (www.sparsedatachallenge.org, [1], [2]), aims to provide the registration community with a common dataset that allows quantitative assessment of registration accuracy given an expansive set of sparse data patterns collected on the surface of a deformable liver phantom. Furthermore, the challenge is designed to create an online testing environment where algorithmic approaches can be explored with a public dataset and methods can be validated according to a common standard. The goal of this work is to characterize the performance of a deformable registration algorithm based on a reconstructive inverse biomechanical modeling approach adapted from [3] and [4] using this public dataset. Specifically, in this work we aim to optimize a critical parameter of the inverse model that controls the resolution with which intraoperative deformations can be reconstructed. This investigation harnesses the full power of the challenge dataset to advance understanding of the registration method. Also, to assist wider participation of the image guidance community with developing alternative methods for the sparse data challenge, this year additional data has been added to the challenge site to allow users the option to quantitatively examine their approaches offline before submitting results to the publicly displayed dashboard.

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2. METHODS

2.1 Overview of the Sparse Data Challenge

The challenge data consists of 112 sparse data patterns collected on the liver surface representative of realistic intraoperative data acquisition in the operating room environment. Given an initial image mask and a tetrahedral mesh of the liver, the objective of the challenge is to determine a deformable registration to each sparse data pattern that most accurately predicts the whole-organ deformation based on the limited information provided. To permit quantitative validation of registration accuracy, these data were derived from a deformable silicone liver phantom with 159 embedded targets. To reproduce deformations similar to open liver surgery, surgical packing was placed under the posterior surface of the liver phantom. The sparse data patterns were obtained after these deformations were applied and the ground truth positions of the embedded targets were imaged for validation.

While the full validation data is hidden to participants, the challenge is hosted on an Amazon Web Services platform that is designed to allow rapid feedback about algorithm performance on a partial or full set of submitted results. For each of the 112 data patterns, participants submit a predicted displacement field sampled at each vertex of the tetrahedral grid that aims to most closely match the true deformation of the liver phantom. These submissions are automatically processed and output performance metrics are hosted on a public dashboard. These metrics include average target registration error (TRE) across all data sets, as well as TRE stratified over low, medium, and high levels of surface data coverage.

2.2 Additional Offline Testing Data for Participants

To promote further participation in the challenge, additional data has been offered for participants to more closely validate potential algorithms offline. Positions for a partial set of 35 of the 159 targets have been provided in the same space as the undeformed tetrahedral grid. Furthermore, the ground truth positions of these targets have been provided for four of the sparse data patterns: Sets 044, 057, 067, and 084. These additional data, shown in **Figure 1**, are intended for users to be able to more closely analyze the behavior of their methods as they are being developed.

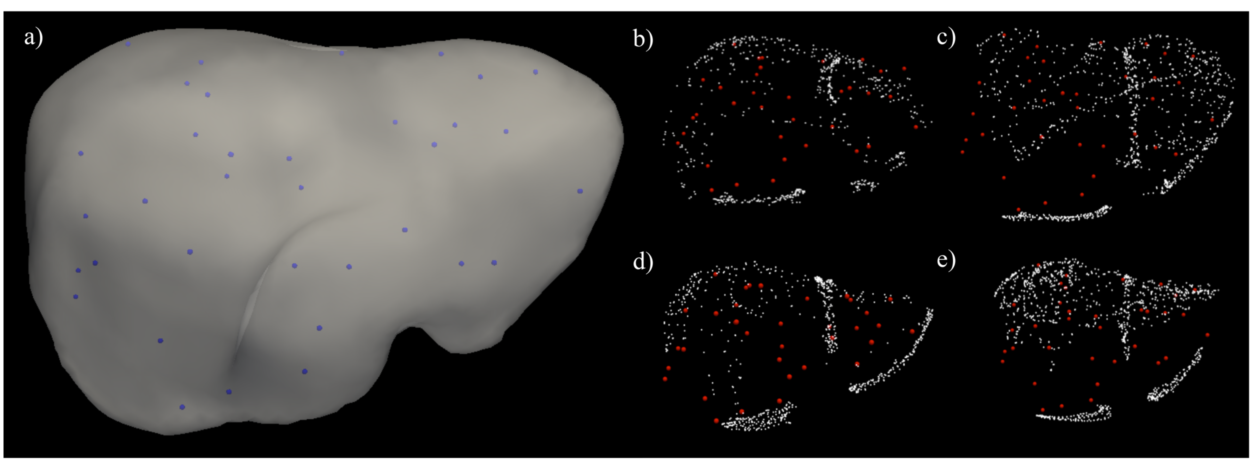

Figure 1. Additional offline testing data for challenge participants. **(a)** Initial positions of the 35 provided targets (blue) from the total 159 targets inside the liver. **(b–d)** Deformed positions of the 35 provided targets (red) for the four selected sparse data patterns (white).

2.3 Overview of In-House Nonrigid Registration Algorithm

As sparse intraoperative data does not necessarily provide complete constraints to the unique solution, in general the sparse data registration problem is ill-posed. It is imperative to note that ill-posed problems are still solvable. However, regularization methods and attention to the conditioning of the problem are important because it can become difficult to define how well determined a configuration of sparse data makes the underlying numerical problem. Often, algorithms can be parameterized to control performance in these situations. In this work, we show that the sparse data challenge can be used to characterize such performance-tuning parameters for registration algorithms, including our own, with a realistic dataset.

Our registration approach utilizes a linear elastic biomechanical model of the liver to minimize error between the observed sparse surface data and a deformable model of the organ described by a series of simulated superimposed deformations. This algorithm is represented by the nonrigid registration method described in [4], wherein deformations mirroring the mechanical loading configurations present during surgery are simulated by perturbing control points placed across the surface of the liver. Perturbing each control point creates a local mode of deformation that can be used to iteratively reconstruct an unknown distributed load placed on the boundary of the liver. This reconstruction minimizes the model-data error regularized by a strain energy penalty function. In this work, the algorithm is modified to match the mechanical loading configuration of open liver surgery represented by the sparse data challenge by limiting control point placement to the posterior surface only, where surgical packing imparts mechanical excitation to the system.

Although it may be algorithmically tempting to apply boundary conditions directly on the anterior surface of the liver where data can be collected, this practice may give rise to substantial error compared to the underlying deformation of the organ. As demonstrated in **Figure 2**, the internal displacements of simulations driven off the anterior surface can differ by approximately 50% of the RMS magnitude of the actual excitatory displacements applied to the posterior. Therefore, we contend that a reconstructive approach that attempts to solve for the unknown distributed loads applied to the liver is a preferable approach that can allow for better predictions of the internal and far-field displacements.

An important parameter in the reconstructive registration approach is the number of control points, which regulates the resolution with which the mechanical load applied to the organ can be represented. While a compromise between registration accuracy and computation time is to be expected, the nature of sparse data registration gives rise to an additional layer of complexity. Notably, a tradeoff exists between the number of control points and how well the control point motions can be resolved by sparse data. The objective of this paper is to characterize the performance of the algorithm across a wide range of control point densities to determine what level of numerical complexity is sufficiently constrained by typical extents of sparse surface data coverage.

2.4 Characterization of Control Point Density

Full submissions were made to the image-to-physical liver registration sparse data challenge for varying numbers of control points in the reconstructive algorithm. Control points were sampled using k-means clustering on the posterior surface of the liver mesh at the following values of k: 2, 3, 5, 7, 10, 15, 20, 30, 50, 70, 100, and 150. These values were selected to explore performance of control point density on a logarithmic scale. **Figure 3** shows several control point distributions on the challenge liver mesh. Challenge submissions were made for each value of k, and the resulting TRE values were downloaded from the sparse data challenge website.

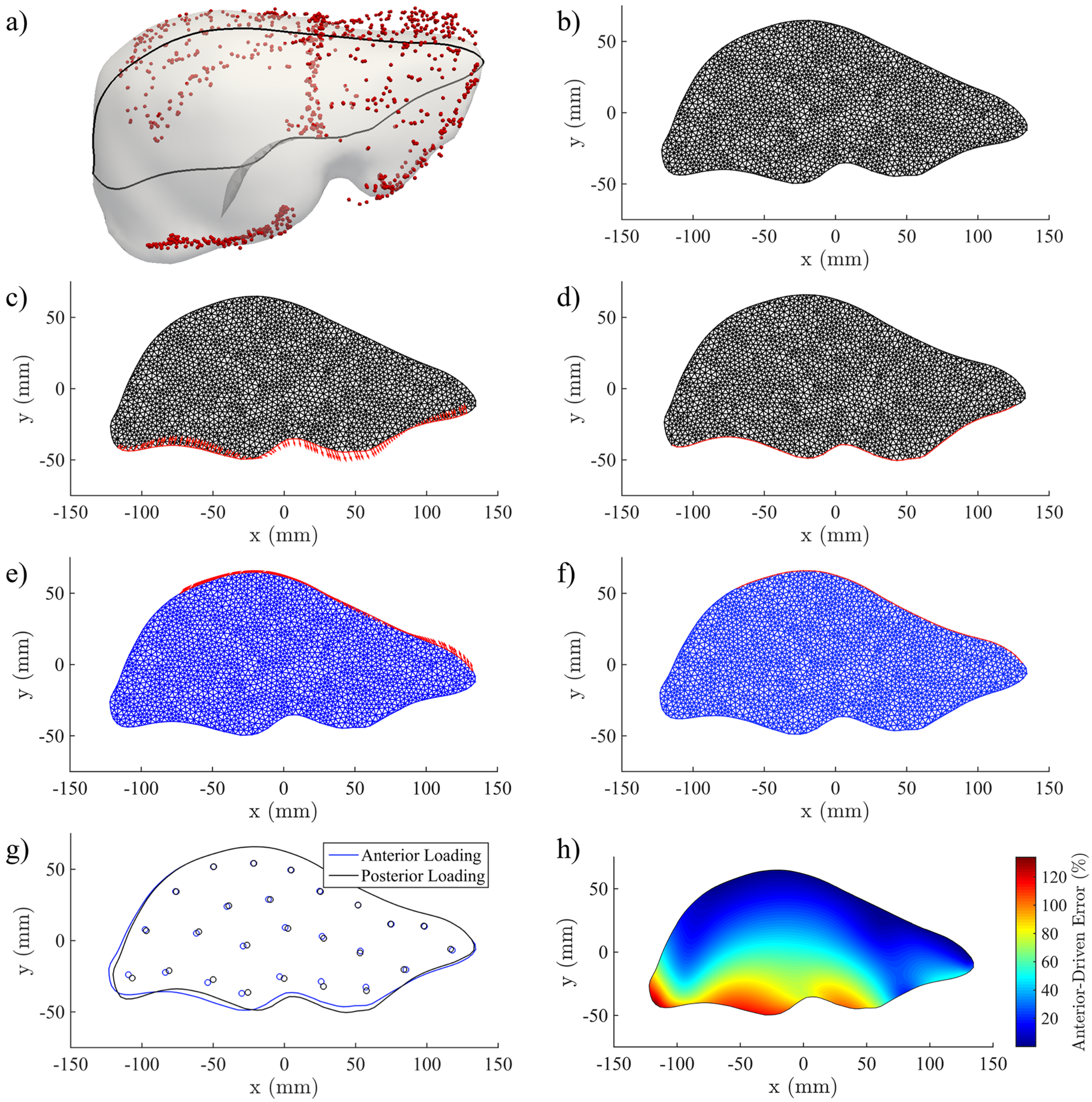

Figure 2. Comparison of plane-strain linear elastic responses to loading conditions placed on the posterior and anterior surfaces of the liver. **(a)** A 2D slice (black contour) is taken from the sparse data challenge liver mesh. Rigidly registered anterior surface data from Set 057 (red points) shows approximate data coverage on the slice. **(b)** The 2D slice is triangulated into a finite element mesh with edge lengths under 4 mm. **(c)** A sinusoidal displacement profile with 6 mm amplitude is applied to the posterior aspect of the liver as boundary conditions to simulate an unknown mechanical load from surgical packing applied to the liver. All other boundary nodes are stress free. **(d)** The finite element response to the posterior displacement boundary conditions. **(e)** Exact displacements from the posteriorly-driven solution in (d) are applied to the original mesh from (b) as boundary conditions on the anterior surface where data coverage exists. All remaining boundary nodes are stress free. **(f)** The finite element response to the anterior displacement boundary conditions. **(g)** A comparison of the liver boundary between the posteriorly-driven deformation from (d) and the anteriorly-driven deformation from (f), with the positions of 25 internal nodes shown as mock targets. **(h)** The error in displacement solutions between the anteriorly- and posteriorly-driven deformations relative to the RMS of posterior displacements.

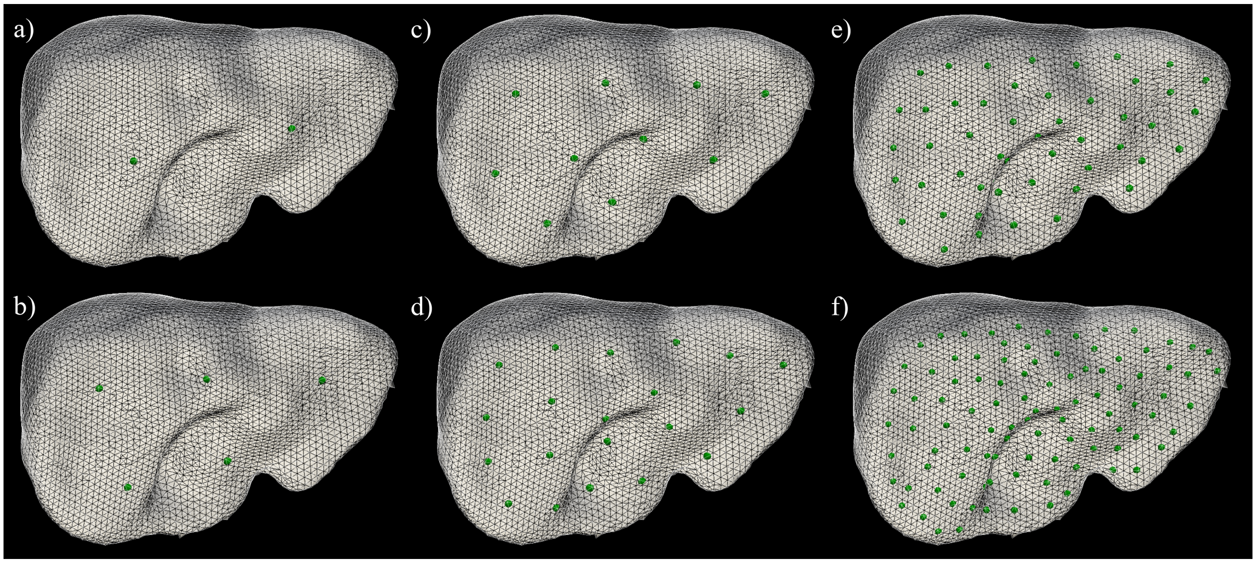

Figure 3. Distribution of control points across the liver: **(a)** 2, **(b)** 5, **(c)** 10, **(d)** 20, **(e)** 50, **(f)** 100.

3. RESULTS

In **Figure 4**, average target registration error is plotted for each value of k. The shape of the semilogarithmic curve suggests an optimal value of k exists that minimizes TRE. **Table 1** shows the automatically generated results from the sparse data challenge for the optimal number of control points, $k = 20$, that produces the minimum average TRE on the challenge dataset. With this value of k, the overall TRE across the whole organ averaged over all 112 challenge cases was 3.08 ± 0.85 mm, showing that highly accurate registrations to sparse surface data can be made using a modest number of control points. This TRE represents a 32% improvement over the value reported in [1]. It is interesting to note that the algorithm performance degrades when the number of control points is too small or too large. In the former case, an insufficient number of control points likely prevents sufficiently detailed reconstruction of the mechanical loads applied to the organ. In the latter case, it is possible that the amount of data provided becomes insufficient to be able to resolve the behavior of each control point, leading to an underdetermined system that is more susceptible to local minima. It is important to note that the most suitable number of control points may change depending on the amount of available intraoperative data. Information from additional subsurface, posterior surface, or more complete anterior surface data may shift the optimal value of k by improving the ability to resolve a greater number of control points.

Surface Coverage	Average TRE (mm)	Median TRE (mm)
20–28%	3.27 ± 1.07	2.89
28–36%	3.00 ± 0.67	2.97
36–44%	2.99 ± 0.78	2.73
All Data Sets	3.08 ± 0.85	2.89

Table 1. Sparse data challenge target registration error for the best control point sampling, found to be $k = 20$.

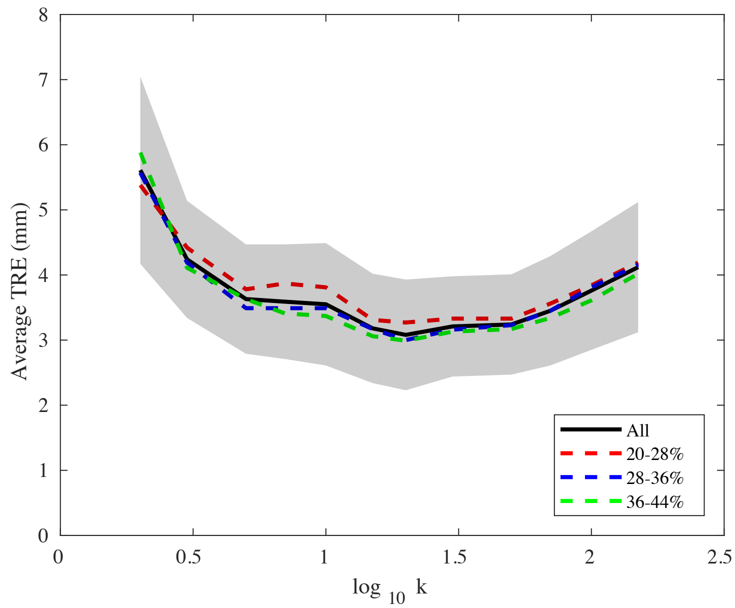

Figure 4. TRE vs. number of control points plotted on logarithmic scale. The black line represents the mean value of TRE across all 112 challenge cases surrounded by one standard deviation in the gray region. The red, blue, and green dashed lines represent the mean TRE across the subset of cases in the low, medium, and high extent brackets, respectively.

4. CONTRIBUTIONS

In addition to serving as a common benchmark for sparse data registration methods, the dataset made available with the image-to-physical liver registration sparse data challenge is a powerful tool for identifying useful information about potential algorithmic approaches. In this work, our algorithm for nonrigid sparse data liver registration was analyzed for its ability to reconstruct mechanical deformations at varying levels of control point resolution. These findings were used to characterize and tune performance of the algorithm within the expected range of intraoperative surface data available in the clinical setting. The presented results represent an effort towards understanding the influence of how the nature of data sparsity influences registration methodology.

5. CONCLUSIONS

Registration to sparse data becomes a difficult problem if accurate and robust results are desired. In general, sparse data registration requires solution methods that simultaneously consider interpolative and extrapolative model effects in relation to the data made available, in addition to intraoperative considerations such as computation time. These methods can sometimes require careful characterization to understand how model parameters interact with sparse data and influence registration results. The image-to-physical liver registration sparse data challenge is designed to facilitate this characterization for developing new methods and to offer a public comparator of algorithm fidelity. In this work, the challenge data was used to characterize an essential parameter of the registration algorithm used by our group. This parameter, which controls the spatial resolution with which deformations applied to the organ can be reconstructed, was found to have an optimal value for registration to realistic patterns and extents of intraoperative sparse surface data collected during open liver surgery.

REFERENCES

[1] E. L. Brewer, L. W. Clements, J. A. Collins, D. J. Doss, J. S. Heiselman, M. I. Miga, C. D. Pavas, and E. H. Wisdom, "The image-to-physical liver registration sparse data challenge," *Proc. SPIE Med. Imaging 2019 Image-Guided Proced. Robot. Interv. Model. Conf.*, vol. 10951, 2019. doi: 10.1117/12.2513952

[2] J. A. Collins, J. A. Weis, J. S. Heiselman, L. W. Clements, A. L. Simpson, W. R. Jarnagin, and M. I. Miga, "Improving registration robustness for image-guided liver surgery in a novel human-to-phantom data framework," *IEEE Trans. Med. Imaging*, vol. 36, no. 7, pp. 1502–1510, 2017. doi: 10.1109/TMI.2017.2668842

[3] J. S. Heiselman, L. W. Clements, J. A. Collins, J. A. Weis, A. L. Simpson, S. K. Geevarghese, T. P. Kingham, W. R. Jarnagin, and M. I. Miga, "Characterization and correction of soft tissue deformation in laparoscopic image-guided liver surgery," *J. Med. Imaging*, vol. 5, no. 2, pp. 1–13, 2018. doi: 10.1117/1.JMI.5.2.021203

[4] J. S. Heiselman, W. R. Jarnagin, and M. I. Miga, "Intraoperative correction of liver deformation using sparse surface and vascular features via linearized iterative boundary reconstruction," *IEEE Trans. Med. Imaging*, 2020. (in press) doi: 10.1109/TMI.2020.2967322