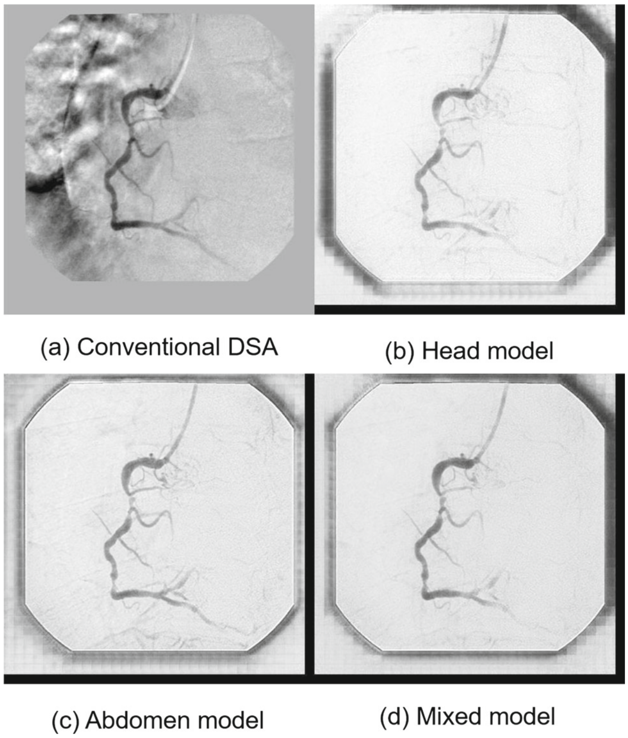

Fig. 2 Result images: **a** is conventional DSA image. This has heavy motion artifacts caused by hart beating and breathing. **b** is the clearest vessel image of 4 images

Acknowledgements

This work was supported by JSPS KAKENHI Grant Number JP 17K18291.

References

[1] Yamamoto M, Okura Y, Kawata N, Yamamoto N (2019) A new method for reducing large motion artifacts of DSA vased on deep learning technique, Int CARS Suppl 1: S4

[2] Ronneberger O, Fischer P, Brox T (2015) U-net: Convolutional networks for biomedical image segmentation, Lecture Notes in Computer Science 9351: 234–241

Deformable registration of the liver using sparse intraoperative data: Incorporating hepatic feature constraints from tracked intraoperative ultrasound

J. S. Heiselman[1], W. R. Jarnagin[2], M. I. Miga[1]
[1]Vanderbilt University, Dept. of Biomedical Engineering, Nashville, United States [2]Memorial Sloan Kettering Cancer Center, Dept. of Surgery, New York, United States

Keywords: Liver, Registration, Image-guided surgery, Ultrasound

Purpose

During liver surgery, successful delivery of treatment depends on a comprehensive understanding of the spatial relationships between interventional targets, hepatic vessels, and surgical instruments. Image guidance aims to localize these components by registering information from preoperative imaging with the intraoperative anatomy of the patient. However, accurate registration of subsurface structures remains challenging due to organ deformation that compromises the fidelity of image-to-physical registration. To compensate, many liver registration techniques rely on the shape of the organ surface to predict the underlying state of deformation. However, the visible extent of surface coverage is often limited and can be insufficient for achieving accurate registrations throughout the depth of the liver. Tracked intraoperative ultrasound (iUS) can extend the coverage of intraoperative data available for registration; however, limitations in lesion detection, interpretability, and workflow encumber iUS as the principal means of intraoperative guidance. In this work, we evaluate how information from very sparse iUS data can be applied to best improve the performance of deformable liver registration by examining and comparing iUS feature constraints visible within individual iUS planes.

Methods

A simulation study was performed to compare registrations to subsurface features from 16 orientations of 2D tracked iUS imaging data. Models of the liver parenchyma and portal and hepatic veins were created from a contrast-enhanced preoperative CT of a deidentified human patient. A linear elastic finite element model was then used to deform the liver to a known intraoperative organ presentation using the data generative method from [1]. Intraoperative features from tracked iUS were simulated by intersecting 16 potential image plane orientations with the ground truth deformed model. In each iUS image plane, these features described the posterior surface of the liver typically visible in iUS and intrahepatic vessel contours with associated centerline positions approximated by feature centroids. Additionally, sparse anterior surface data were derived from a clinical pattern of digitization on the ground truth model for registration purposes. Figure 1 shows one of the 16 configurations of data.

The linearized iterative boundary reconstruction method [1] was used for deformable registration of the original model to simulated data. While [1] aimed to understand how data from multiple iUS planes could be combined to improve registration accuracy, the focus of this work is to characterize how incorporating distinct feature constraints from a single iUS plane can impact registration accuracy. For each of the 16 iUS views, target registration error (TRE) was evaluated to determine: (I) whether informational redundancy might exist between vessel and posterior surface features when they are derived from the same image plane, (II) the potential need for manually defining correspondence of iUS vessel features to the correct branch of the 3D vessel model, and (III) the tradeoffs between centerline and contour representations of vessel features. TRE was computed as the average nodal distance between the ground truth and registered mesh, and differences in average TRE were statistically

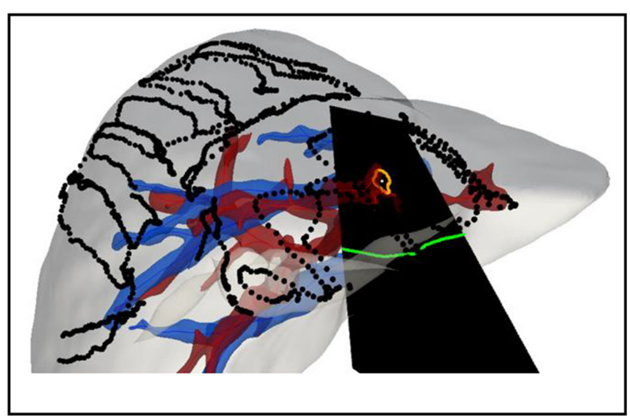

Fig. 1 Preoperative liver model (gray), portal vein (red) and hepatic vein (blue) with rigidly registered data consisting of sparse anterior surface points (black) and iUS features including the posterior surface (green), vessel contour (orange), and vessel centerline point (white)

tested against zero mean using a two-tailed, one-sample t-test at significance α = 0.05.

Results

(I): Close spatial proximity of features within an iUS image plane may suggest that registering to only a subset of these features might be necessary for accurate alignment. To test this possibility, average TRE was computed for the 16 iUS registration scenarios in three conditions: using only vessel contour features (8.6 ± 1.8 mm), using only posterior surface contours (8.9 ± 1.7 mm), and using both posterior and vessel contours (7.6 ± 1.9 mm). Significant improvements in average TRE were observed when using both features, with average improvement of 1.0 ± 1.4 mm ($p = 0.01$) compared to using only vessels and 1.3 ± 1.5 mm ($p = 0.005$) compared to using only posterior, suggesting that vessel and posterior surface features visible in iUS offer partially independent constraints best leveraged together to improve registration accuracy. Overall distributions of the differences in TRE are shown in the first two columns of Fig. 2. The largest improvement in average TRE across the mesh was 5.0 mm when using both features instead of a single feature in one of the 16 configurations of data, decreasing TRE from 11.4 ± 7.1 mm to 6.4 ± 4.5 mm. Reciprocally, it is possible that posterior surface data may help direct vessel features towards the correct branch of the vessel model, and vessel data may assist with regularizing the posterior constraint that can traverse across the rear surface of the liver.

(II): During registration, correspondence between iUS vessel features and the full 3D vessel model can be estimated by closest point distance. However, these correspondences can become incorrect when features are located near bifurcations or in regions with large deformation compared to the inter-branch distances of the vessel tree. In these cases, directing a skilled sonographer to manually label the vessel branch of correspondence during data collection can ensure correct alignment between the iUS feature and the model. With manual designation of centerline branches, average TRE improved by 0.4 ± 1.2 mm over unconstrained closest point correspondences (Fig. 2 third column), from 8.0 ± 2.2 mm to 7.6 ± 1.9 mm. While this difference was not statistically significant ($p = 0.17$), in one case the manual constraint improved TRE from 12.5 ± 6.1 mm to 7.8 ± 4.4 mm when a vessel feature had initially been misregistered to an incorrect branch. Steps to address vascular feature correspondence between 2D iUS planes and 3D models therefore may improve robustness of registration algorithms.

(III): Whereas vessel centerline representations have reduced dimensionality that may smooth the optimization landscape and obscure physiological changes to vasculature during registration, centerline approximations from iUS image planes may not be accurate when vessels are imaged obliquely or near bifurcations.

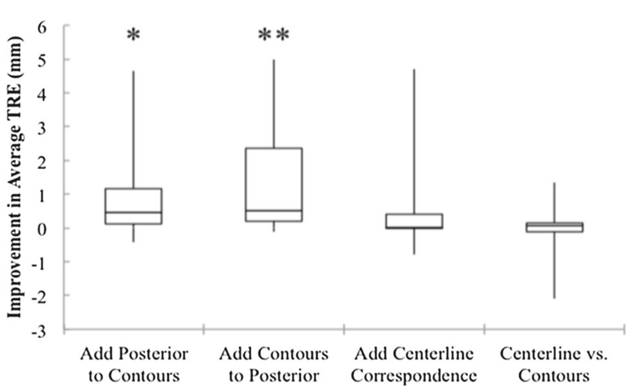

Fig. 2 Quartile distributions of the change in average TRE comparing iUS feature constraints across 16 registrations to simulated data (*$p = 0.01$; **$p = 0.005$)

Additionally, information encoding the orientation of the vessel is lost. Although registration using vessel contours may avoid these shortcomings, the apparent diameter of the intrahepatic blood vessels may change based on segmentation, pulsatility, and vasoregulation. To compare, differences in average TRE were computed for registrations to vessel contour and centerline approximations of the portal and hepatic vein features in the simulated iUS planes. No significant difference in average TRE was found between using the unlabeled contour or the correspondence-labeled centerline representations of vessels ($p = 0.99$), with an average difference of 0.0 ± 0.7 mm (Fig. 2 fourth column). While this comparison was performed using simulated data free from noise, it is possible that combining contour and centerline feature constraints in more realistic registration scenarios may complement the shortcomings of each and improve overall registration robustness.

Conclusion

Feature constraints from tracked iUS were investigated for application in image-to-physical liver registration. Significant improvement in average TRE was found when registering to a combination of hepatic vessel features and posterior surface features detectable within single iUS images. Non-significant improvement was found when model-data correspondences of vessel features were manually constrained, and no difference in average TRE was found between registrations to unconstrained contour and manually constrained centerline representations of vessel features.

References

[1] Heiselman JS, Jarnagin WR, Miga MI (2020) Intraoperative correction of liver deformation using sparse surface and vascular features via linearized iterative boundary reconstruction. IEEE Transactions on Medical Imaging, *in press*.

Heterogeneous large-scale CT database analysis for mining knowledge of musculoskeletal anatomy

Y. Otake[1], Y. Hiasa[1], M. Takao[2], Y. Tanaka[1], K. Aida[3], S. Sato[3], A. Nishie[4], N. Sugano[2], Y. Sato[1]
[1]Nara Institute of Science and Technology, Graduate School of Science and Technology, Ikoma, Japan [2]Osaka University, Suita, Japan [3]National Institute of Informatics, Chiyoda-ku, Japan [4]Kyushu University, Nishi-ku, Japan

Keywords Large-scale database managemen, Musculoskeletal anatomy, Knowledge mining, Segmentation

Purpose

Medical images stored in hospitals" picture archiving and communication systems (PACS) are unsorted and lack semantic annotations such as types of patients, scanned body parts, and field-of-view (FOV), thus are hard to use directly in machine learning studies. Our group has been constructing a data cloud that exhaustively collects all CT scans obtained in routine practice every day from PACS of multiple hospitals in Japan. The cloud contains more than 300 K examinations (as of January 2020) each of which has multiple series of CT scans and a radiology report. The purpose of this study was to develop a pipeline using deep neural networks (DNNs) to organize the significantly heterogeneous (i.e., including multiple scanners, diverse patient cohorts, target body parts, scan protocols, etc.) CT database and extract knowledge about human anatomy. This study specifically targeted understanding of musculoskeletal anatomy in the pelvis region that is important, for example, in the analysis of body posture changes as a natural consequence of aging.