2026 JULY 19–22 VANCOUVER, BC
JOINT AAPM | COMP MEETING

Fully Automated Contour-Regulated Deformable Registration Framework for Liver CT Perfusion

Zhan Xu, PhD[1]; Shanli Ding, MS[1]; Yao Zhao, PhD[1]; Jinyong Lin, PhD[1]; Chaan Ng, MD[1] and Jinzhong Yang, PhD[1]

[1]The University of Texas MD Anderson Cancer Center

IMPACT/INNOVATION

- Liver CTp imaging enables quantitative assessment of vascular dynamics but is highly susceptible to motion-induced artifacts.
- Misregistration between distinct regions of interest disrupts temporal signal consistency and perfusion estimation, underscoring the need for robust registration strategies tailored for liver CTp.
- An automated liver segmentation model and a two-stage, contour-regulated, deep-learning based deformable registration model were proposed to meet this urgent clinical need.
- The strategy of sequential deformable registration of neighboring time point CT scans successfully mitigated the impact of contrast variation to registration performance.

SUPPORTING INFORMATION

- The full manuscript of this work has been accepted by *Medical Physics*, for details of datasets and methods, please refer to the article titled: “Contour-Regulated Registration Framework for Liver CT Perfusion Images”
- Corresponding author: Jinzhong Yang
- Email: JYang4@mdanderson.org

POSTER PRESENTATION

- Date: Sunday, July 19, 2026
- Time: 3:15 PM - 4:00 PM
- Location: Poster Lounge Area, Exhibit Hall
- Poster Board ID: SU-315-GPD-D-28

UT MD Anderson Cancer Center

INTRODUCTION

Liver computed tomography perfusion (CTp) imaging enables quantitative assessment of vascular dynamics but is highly susceptible to motion-induced artifacts arising from breath-hold variability and involuntary patient motion[1]. These effects cause different liver segments to appear across time frames and introduce in-plane deformation, creating substantial challenges for image registration. Misregistration between distinct regions of interest disrupts temporal signal consistency and perfusion estimation, underscoring the need for robust registration strategies tailored for liver CTp.

This work developed and evaluated a contour-regulated automated registration framework for correcting motion artifacts and aligning time-resolved images in liver CTp series.

METHODS AND MATERIALS

Forty-six CTp datasets from 23 patients were analyzed; each dataset consisted of a pre-contrast static scan (full liver craniocaudal coverage of 20-30 cm), a post-contrast high–temporal-resolution cine scan (narrow craniocaudal coverage of approximately 4 cm, 60–80 time frames), and a post-contrast low–temporal-resolution helical scan (craniocaudal coverage of 10 cm, 8–10 time frames). The acquisition protocol is illustrated schematically in **Figure 1**.

A 2D liver auto-segmentation nnU-Net model was trained on 23 whole liver contours that had been manually delineated on pre-contrast static images and applied to all 46 cine and helical series. The auto-segmented contours were used to regulate downstream registration. The workflow of segmentation and registration is shown in **Figure 2**.

A two-stage registration pipeline was built consisting of affine registration followed by TransMorph-based[2] deformable registration. The registration was first accomplished with intensity-corrected images to mitigate intensity distribution bias introduced by sharp air–tissue transitions in abdominal regions, as shown in **Figure 3**.

The registration framework was separated into two sequential steps. First, an affine registration was applied to the intensity-corrected dynamic images to correct for large craniocaudal displacements caused by breath-hold variability. In this step, a module was incorporated to automatically detect and compensate for missing slices in cases of excessive motion. The same transformation matrix was then applied to the automatically segmented liver contours. In the second step, a deformable registration, implemented with the TransMorph framework and a *liver-contour–regulated module*, was performed to achieve finer in-plane alignment of local deformations.

The models with different parameters were trained by using intensity-corrected images on 36 randomly selected cases and tested on the remaining 10. Multiple registration variants were evaluated against the unregistered series.

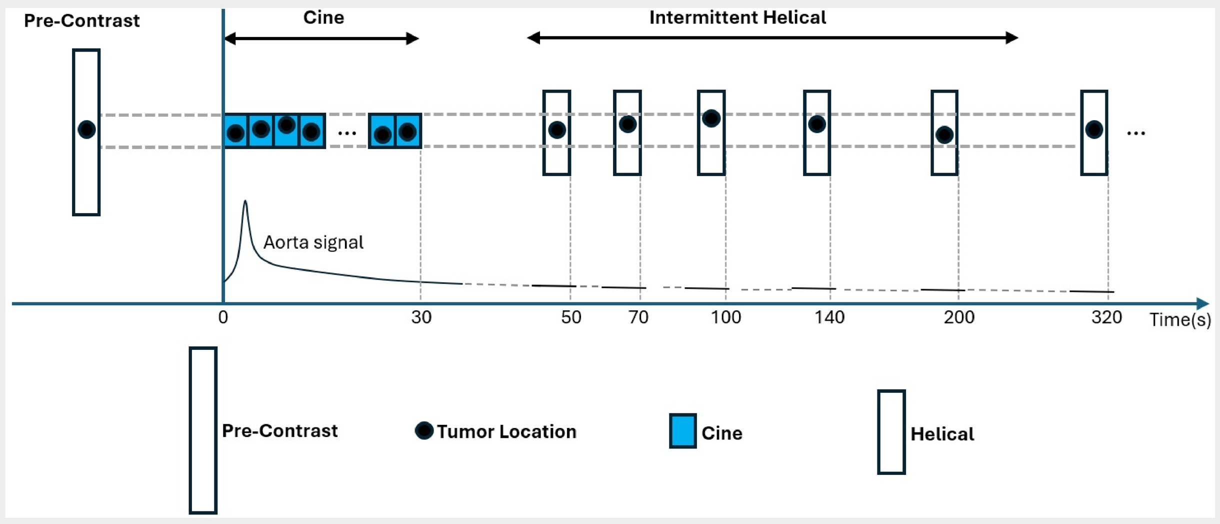

Figure 1. Timeline for obtaining CTp images

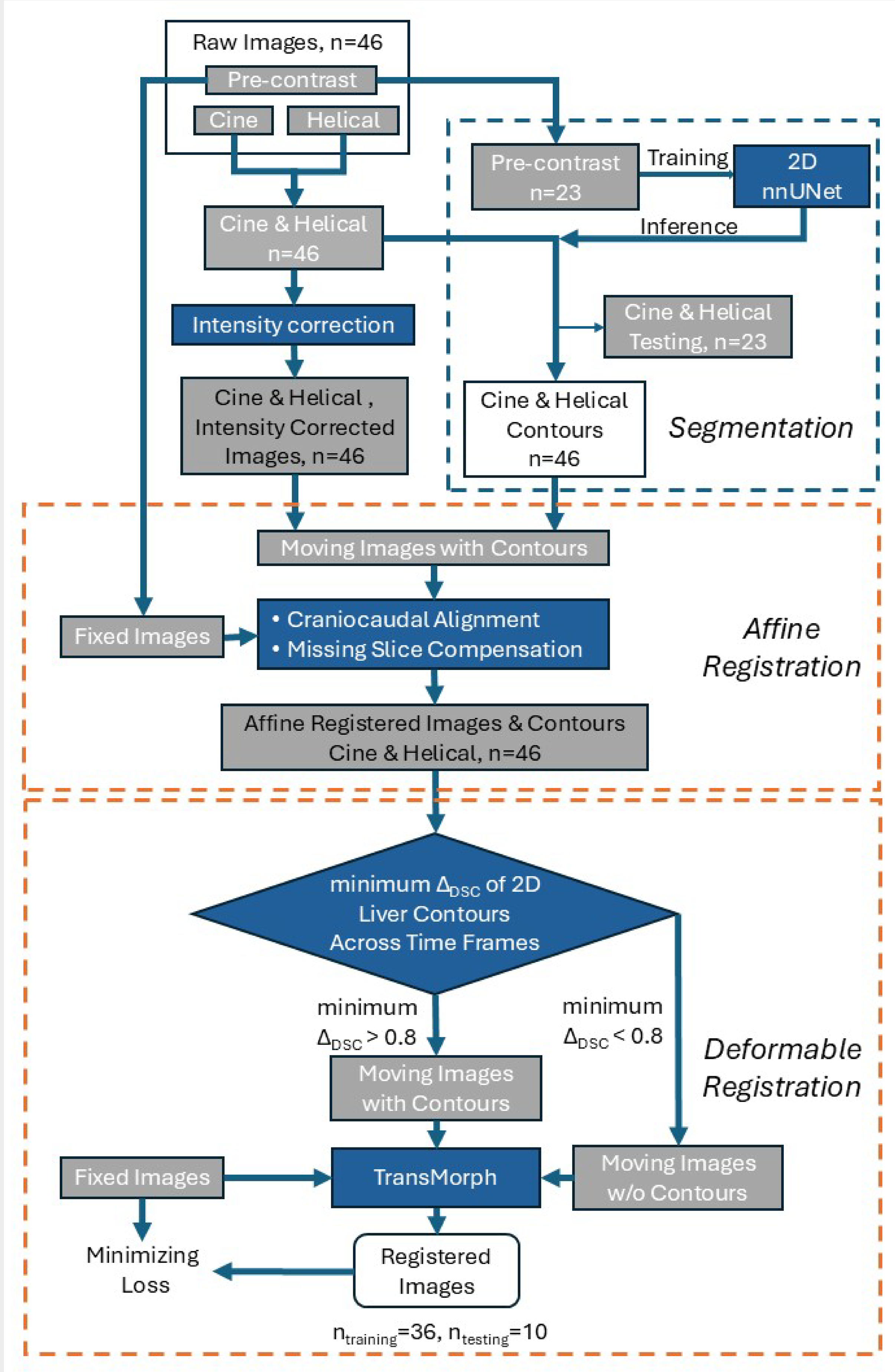

Figure 2. Workflow of segmentation and two-stage registration

RESULTS

Liver auto-segmentation achieved mean Dice similarity coefficients of 0.92 (SE=0.03) for helical scans and 0.89 (SE=0.05) for cine scans. Structure alignment was improved significantly compared with raw data after registration, which assessed by mean surface distance (MSD) and 95th percentile Hausdorff distance (HD95).

At a stronger regularization level at which λ_S=0.8, the registration accuracy improved compared with λ_S=0.2. The best-performing model had an auto-determined contour regularization weighting factor (λ_S) of 0 or 0.8, reduced the MSD from 5.1 ± 1.4 mm to 1.0 ± 0.3 mm (P < 0.01) and HD95 from 9.7 ± 2.2 mm to 3.0 ± 0.9 mm (P < 0.01) in cine scans. In helical scans, MSD decreased from 3.2 ± 0.9 mm to 1.0 ± 0.3 mm (P < 0.01) and HD95 from 6.6 ± 1.9 mm to 2.9 ± 1.0 mm (P < 0.01). Qualitative and quantitative results are shown in **Figure 4** and **Table 1**, respectively.

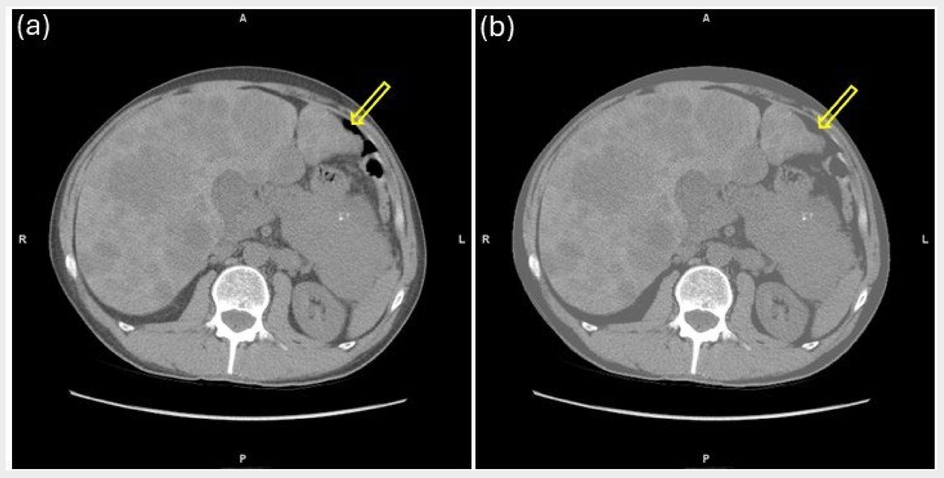

Figure 3. Representative cine images before (a) and after (b) intensity correction

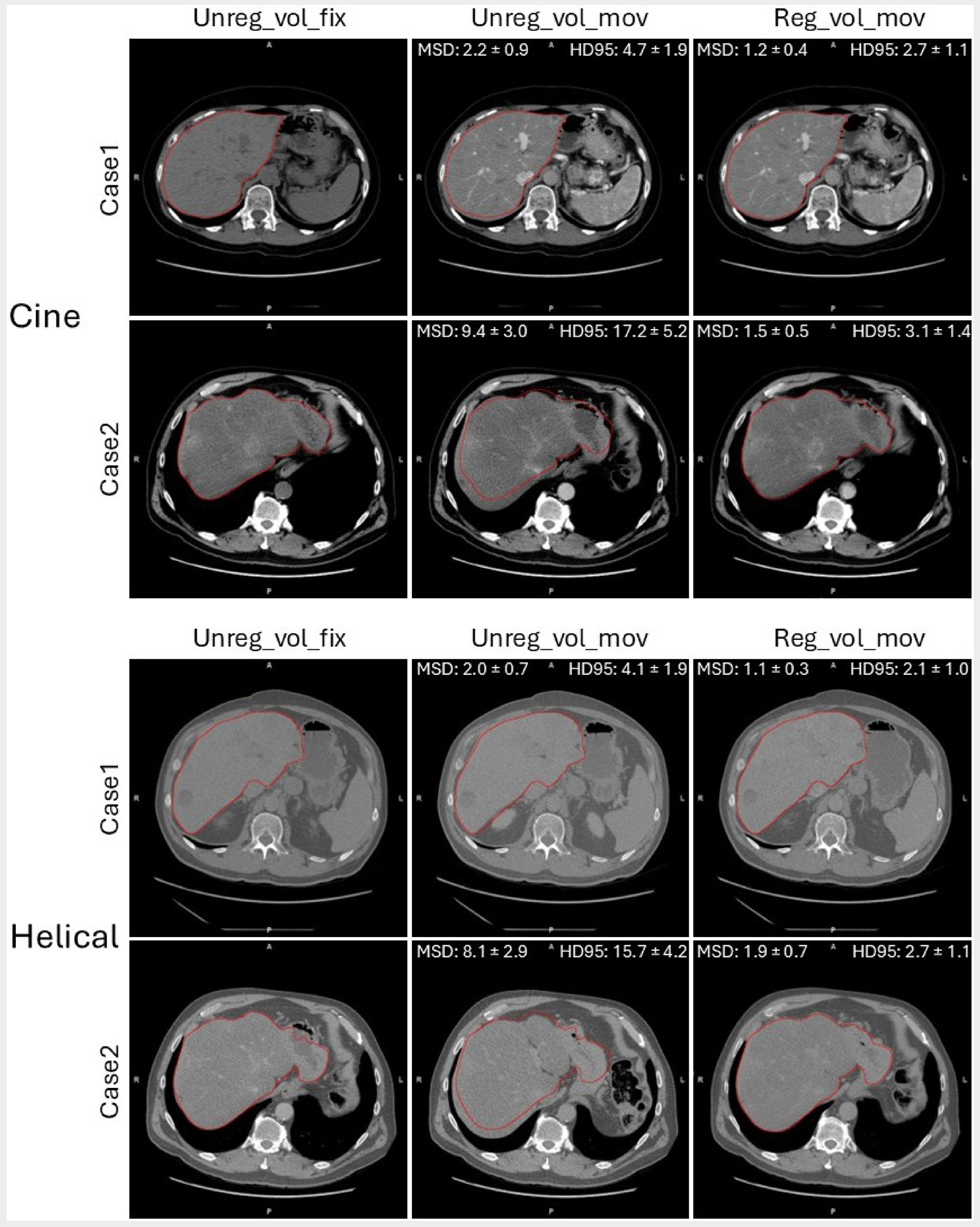

Figure 4. Qualitative results of the proposed registration methods

Table 1. Performance of the registration model variants

Models	Mean Surface Distance (mm)		HD95 (mm)	
	Cine Scans	Helical Scans	Cine Scans	Helical Scans
Unregistered	5.1 ± 1.4 (1.2, 9.6)	3.2 ± 0.9 (1.1, 9.1)	9.7 ± 2.2 (3.1, 19.7)	6.6 ± 1.9 (2.7, 15.4)
Affine-only	3.2 ± 1.0* (1.2, 5.1)	2.0 ± 0.9* (1.1, 4.4)	6.7 ± 1.6* (2.9, 11.2)	5.1 ± 1.7* (2.2, 6.7)
Affine + Deformable, λ_S = 0	2.0 ± 0.9*# (1.1, 3.4)	1.9 ± 0.7*# (1.2, 3.1)	4.7 ± 1.5*# (2.4, 7.1)	4.4 ± 1.6*# (2.2, 6.3)
Affine + Deformable, λ_S = 0.2	2.1 ± 1.0*# (1.1, 3.2)	1.7 ± 0.7*# (1.2, 2.9)	4.5 ± 1.5*# (2.3, 6.5)	4.2 ± 1.5*# (2.1, 6.2)
Affine + Deformable, λ_S = 0 or 0.2	2.0 ± 1.0*# (1.1, 3.2)	1.7 ± 0.6*# (1.2, 2.9)	4.5 ± 1.4*# (2.3, 6.5)	4.1 ± 1.4*# (2.1, 6.2)
Affine + Deformable, λ_S = 0.8	1.5 ± 0.6*# (0.8, 2.4)	1.3 ± 0.7*# (0.6, 1.9)	3.2 ± 1.0*# (1.2, 5.1)	3.2 ± 1.1*# (1.2, 5.1)
Affine + Deformable, λ_S = 0 or 0.8	1.0 ± 0.3*#$ (0.8, 1.9)	1.0 ± 0.3*#$ (0.6, 1.4)	3.0 ± 0.9*#$ (1.2, 4.7)	2.9 ± 1.0*#$ (1.1, 4.9)

CONCLUSIONS

The proposed contour-regulated, two-stage registration framework improved temporal alignment in dynamic liver CTp images, providing a robust foundation for subsequent analysis and clinical assessment.

REFERENCES

1. Ng CS, et al. CT perfusion in normal liver and liver metastases from neuroendocrine tumors treated with targeted antivascular agents. *Abdominal Radiology*. 2018;43(7):1661-1669. doi:10.1007/s00261-017-1367-1
2. Chen J, et al. TransMorph: Transformer for unsupervised medical image registration. *Med Image Anal.* 2022;82(September). doi:10.1016/j.media.2022.102615