DEEP LEARNING-BASED POINT CLOUD REGISTRATION FOR AUGMENTED REALITY-GUIDED SURGERY.

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We investigate the feasibility of using deep learning for point cloud registration in augmented reality-guided surgery.

METHOD

Research question

Is there currently a deep learning-based point cloud registration method that exhibits an "out-of-the-

box" characteristic for seamless integration with AR-GS?

Dataset

- CT scans from real patients and corresponding 3D-printed heads [1]
- Source point cloud
 - Segmenting skin surfaces from PET/CT scans \bullet
 - Extracting points using the Marching Cubes
 - Sub-sampling and cutting \bullet
- Target point cloud
 - Reconstructed from depth images of 3D-printed head phantoms
 - Captured from different perspectives using HL2's depth sensor



Source point cloud



Target point cloud

MOTIVATION

- **Point cloud registration** is crucial in various computer vision applications, such as augmented reality (AR), medical imaging, or **AR-guided surgery** (AR-GS).
- Traditional **image-to-patient registration** methods on AR devices face challenges in precision, efficiency, user-friendliness, and patient comfort.
- **Deep learning** holds potential for point cloud registration.

CONTRIBUTION

- Study deep learning-based point cloud registration for AR-GS.
- A dataset with real medical data and point clouds from

- Artifact and outlier removal
- Total of 30 data pairs

Benchmark method

- Traditional registration pipeline
- Global registration using FPFH features [2] and RANSAC [3]
- Refinement using ICP [4]

Deep learning-based methods

- Feature-metric registration (FMR) [5] \bullet
- PointNetLK Revisited [6]
- Deep Global Registration (DGR) [7]

the HoloLens 2 (HL2).

Compare three deep learning-based registration \bullet methods with a traditional method.

DISCUSSION AND CONCLUSION

- Our dataset is challenging due to variations in noise, \bullet density, and distribution patterns.
- Deep learning shows promise but cannot outperform

traditional image-to-patient registration methods.

REFERENCES

[1] C. Gsaxner et al., "Facial model collection for medical augmented reality in oncologic cranio-maxillofacial surgery," SciData, vol. 6, 2019. [2] R. B. Rusu et al., "Fast point feature histograms (fpfh) for 3d registration," in ICRA, 2009, pp. 3212-3217. [3] M. A. Fischler and R. C. Bolles, "Random sample consensus: A paradigm for model fitting with applications to image analysis and automated cartography," CACM, vol. 24, no. 6, pp. 381–395, 1981. [4] D. Holz et al., "Registration with the point cloud library: A modular framework for aligning in 3-d," IEEE RA-M, vol. 22, no. 4, pp. 110–124, 2015 [5] X. Huang et al., "Feature-metric registration: A fast semi-supervised approach for robust point cloud registration without correspondences," in CVPR, 2020, pp. 11 363–11 371.

RESULTS



Method	Recall	TE (cm)	RE (°)	T (s)
DGR	0.27	0.08	4.7	4.3
DGR FT	0.41	0.09	5.8	4.4
Global	0.3	0.18	8.0	1.6
GI + ICP	0.6	0.05	2.0	1.6

[6] X. Li et al., "Pointnetlk revisited," in CVPR, 2021, pp. 12 763–12 772. [7] C. Choy et al., "Deep global registration," in CVPR, 2020, pp. 2514–2523





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DGR

