Joint Reconstruction and Registration of Bones from X-Ray Image

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1. Project Purpose

This research project aims to design a deep learning-based pipeline specifically aimed for joint 3D reconstruction and registration tasks using X-Ray images. In orthopedic surgeries, a frequently used technique for helping the surgeons visualize the operation target is overlaying the intra-operatively acquired X-Ray image to a preoperatively acquired CT scan. This task is called 2D-3D registration, and the state-of-the-art method is to embed fiducial markers onto the bones for identifying the 2D-3D correspondences in the X-Ray image and the CT volume. We propose a method for registering the image with the CT volume without using any externally implanted markers. To make the method work with patient wide CT, we utilize subspaces of ray features pertaining to a 3D landmark. Then, the problem of finding the corresponding 2D landmark would be to find the ray feature similarity with subspaces from 3D landmarks. Figure 1 presents the overview of our method RayEmb [2].

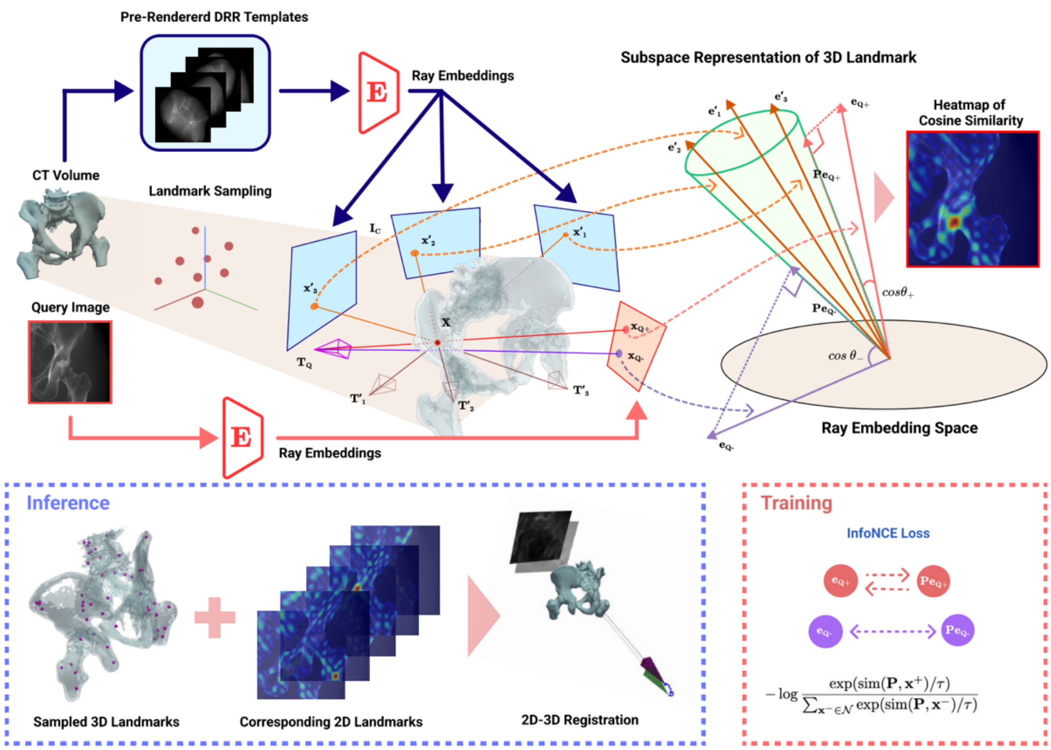

Figure. 1. Overview of the method RayEmb.

2． Results

Figure 2 presents two representative test cases from the dataset. In the left panel, ground truth landmarks are depicted in **magenta**, while the estimated landmarks generated by each method are shown in **cyan**. The upper example illustrates that the proposed method yields a pose estimate that is notably closer to the ground truth compared to the *Fixed Landmark* method. The lower example further highlights the robustness of the proposed approach, showing that it is capable of producing plausible pose estimates even in challenging scenarios where both *DiffDRR* and *Fixed Landmark* methods fail to converge. Notably, *RayEmb* achieves substantially improved alignment with the ground truth, attaining mean projection distance (mPD) values of **3.77 mm** and **4.06 mm**, significantly outperforming the other baselines. In the right panel, the initial pose estimates are visualized in **green**, while the ground truth poses are shown in **red**. The connecting trajectories between estimated and true poses illustrate the deviation of each method from the optimal alignment. *RayEmb* exhibits the smallest deviations, underscoring its superior precision in initial pose estimation.

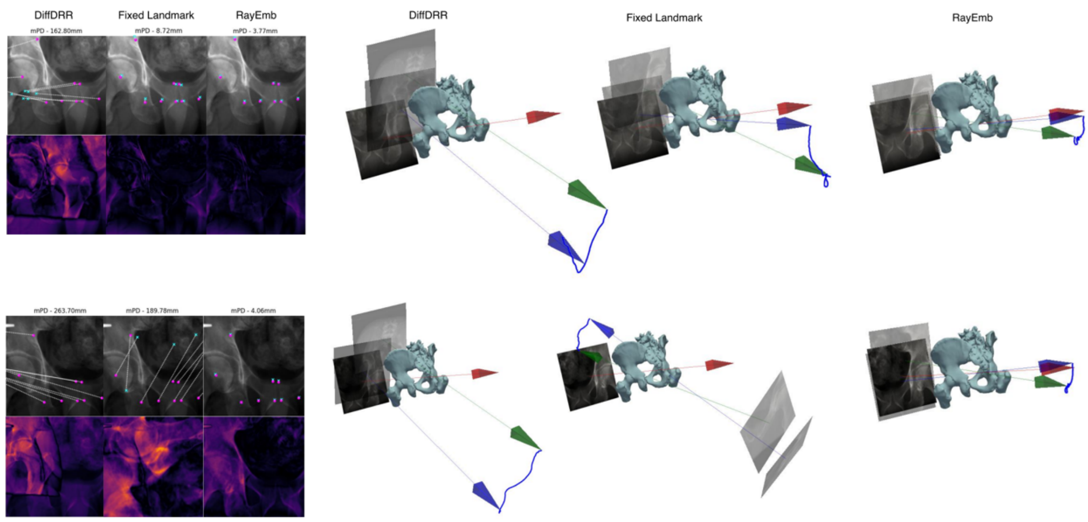

Figure. 2. Qualitative results with DeepFluoro dataset

3． Roles of the MCRP and its significance

The GPU resources provided by the MCRP significantly enhance our capability to conduct multiple experiments using large datasets. Training models on consumer-grade hardware can be challenging due to the extensive time requirements. Moreover, the computational demands extend beyond training deep learning models; for instance, Monte Carlo simulations for X-ray imaging also require substantial computational power. Therefore, MCRP is a vital resource that facilitates these advanced computational tasks.

4．Future plan

The next step would be to reconstruct 3D volume from single X-ray image so that we simultaneously update the volume.

5．Publications and conference presentations

(1) Journal papers

[1] Shrestha P, Xie C, Yoshii Y, Kitahara I. 2D-3D Registration Method for X-Ray Image Using 3D Reconstruction based on Deep Neural Network, IIEEJ Transactions on Image Electronics and Visual Computing, vol.12, no.2, pp.60-67, 2024.

(2) Presentations

[2] Shrestha, Pragyan & Xie, Chun & Yoshii, Yuichi & Kitahara, Itaru. (2024). RayEmb: Arbitrary Landmark Detection in X-Ray Images Using Ray Embedding Subspace, Proceedings of the 17th Asian Conference on Computer Vision, 2024.

Supercomputer	Use	Allocated resources*		
		Initial resources	Transferred resources**	Additional resources
Cygnus	No			
Pegasus	Yes	2240		
Wisteria/BDEC-01	No			
	*in units of node-hour product ** If the budget transfer was performed, fill in here, such as “+2000” and “−1000”.			