# Joint Reconstruction and Registration of Bones from X-Ray Image Pragyan SHRESTHA Doctoral Program in Empowerment Informatics

### 1. Project Purpose

The aim of this project is to establish a framework for estimating 3D bone shape model and its pose from a single X-ray image. This task of joint reconstruction and registration is challenging because it is highly unconstrained as well as there is depth uncertainty in X-ray images. Thus, we tackle this problem in two phases. First, we establish the framework for registering X-ray image with known 3D model, then we extend it to estimate 3D shape as well. In this project, we develop deep learning architecture for both phases.



Figure 1. Overview of the proposed method in phase 1. Scene coordinate regression is utilized to run pose estimation algorithm.

In the first phase, we developed a framework to establish 2D and 3D correspondences using scene coordinates to register a known 3D model with an X-ray image. Scene coordinates are defined as the intersection in 3d space between back projected pixel rays and the 3d model. As shown in Figure 1., the scene coordinates are predicted from input X-ray image, which implicitly establishes 2d-3d correspondences. These correspondences are used to run perspective-n-point algorithm with random sample and consensus.

#### The Center for Computational Sciences, University of Tsukuba MCRP-2023 report



Figure 2. Overview of the proposed method in phase 2. Bothe shape points and image points are estimated to establish correspondences. Registration is done in 3d space as well as 2d-3d space.

In the second phase, we developed a framework to jointly predict the 3d shape as well as the corresponding points in the image (Figure 2.). This allows us to obtain the posed 3d shape from single X-ray image. In addition, it can be used to register the known 3d shape without preprocessing its coordinate system.

#### 2. Results



Figure 3. Contour overlays of 3d shape in estimated pose.

We show the qualitative results for the first phase (registration using scene coordinates) in Figure 3. The figure shows registration results for real X-ray images although the model was trained on synthetic images. The error metric is projected mean target registration error (mTRE) which is the mean L2 error between the re-projected and ground truth landmarks. We can see that the overlayed contours resemble the original contours in the X-ray image.



Figure 4. Examples of predicted point clouds (3d shapes in left) and registration results as reprojected points in image coordinates (right).

We show qualitative results for the second phase (reconstruction-based registration) in Figure 4. Two rows are examples of the predicted point clouds and its registration in 3d space along with reprojection of the estimated camera parameters. In the 3<sup>rd</sup> column we can identify that the reprojection of aligned target is closer to the x-ray image contours than the unaligned target.

## 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 consumergrade 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

In our upcoming project, we plan to enhance the framework to support patient-wide models. The current system's first phase achieves satisfactory registration outcomes but is limited to individual patients. The second phase, while applicable on a patient-

wide basis, does not match the accuracy of the first phase. To address this, we aim to integrate the strengths of both phases by estimating heatmaps for arbitrary landmarks in the next iteration of the project. This advancement will potentially improve both the scalability and precision of our models.

- 5. Publications and conference presentations
  - (1) Journal papers
  - (2) Presentations

[1] Shrestha, P., Xie, C., Shishido, H., Yoshii, Y., Kitahara, I. (2023). X-Ray to CT Rigid Registration
Using Scene Coordinate Regression. In: Greenspan, H., et al. Medical Image Computing and Computer
Assisted Intervention – MICCAI 2023. MICCAI 2023. Lecture Notes in Computer Science, vol 14229.
Springer, Cham. <u>https://doi.org/10.1007/978-3-031-43999-5\_74</u>

[2] Pragyan Shrestha, Chun Xie, Hidehiko Shishido, Yuichi Yoshii, and Itaru Kitahara 2d-3d Registration Method for X-Ray Image Using 3D Reconstruction Based on Deep Neural Network The 8th IIEEJ International Conference on Image Electronics and Visual Computing (IEVC 2024), 4 pages, 2024.

(3) Others

Supercomputer	Use	Allocated resources*	
		Initial	Additional
		resources	resources
Cygnus	Yes	3200	
Wisteria/BDEC-01	No		
*in units of node-hour product			