# A General Computationally-Efficient 3D Reconstruction Pipeline for Multiple Images with Point Clouds

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## Introduction

Traditional 2D images may lose important spacial information, and current precise 3D reconstruction systems for images such as CT and WSI are not general enough because:

- Manually collected WSIs require registration, which is one of the the bottlenecks for real-time visualization
- Gigabytes images require extensive computational resources and are extremely time-consuming

In this task we combined the idea from current 3D systems of WSI[1] and CT images[2] and proposed a general 3D reconstruction pipeline which greatly reduced the computational and time costs required for the registration process.

## Methodology

The pipeline consists of four reletively independent parts:

- Segmentation
- Layered Point Cloud Sampling
- Registration
- 3D Modeling and Rendering

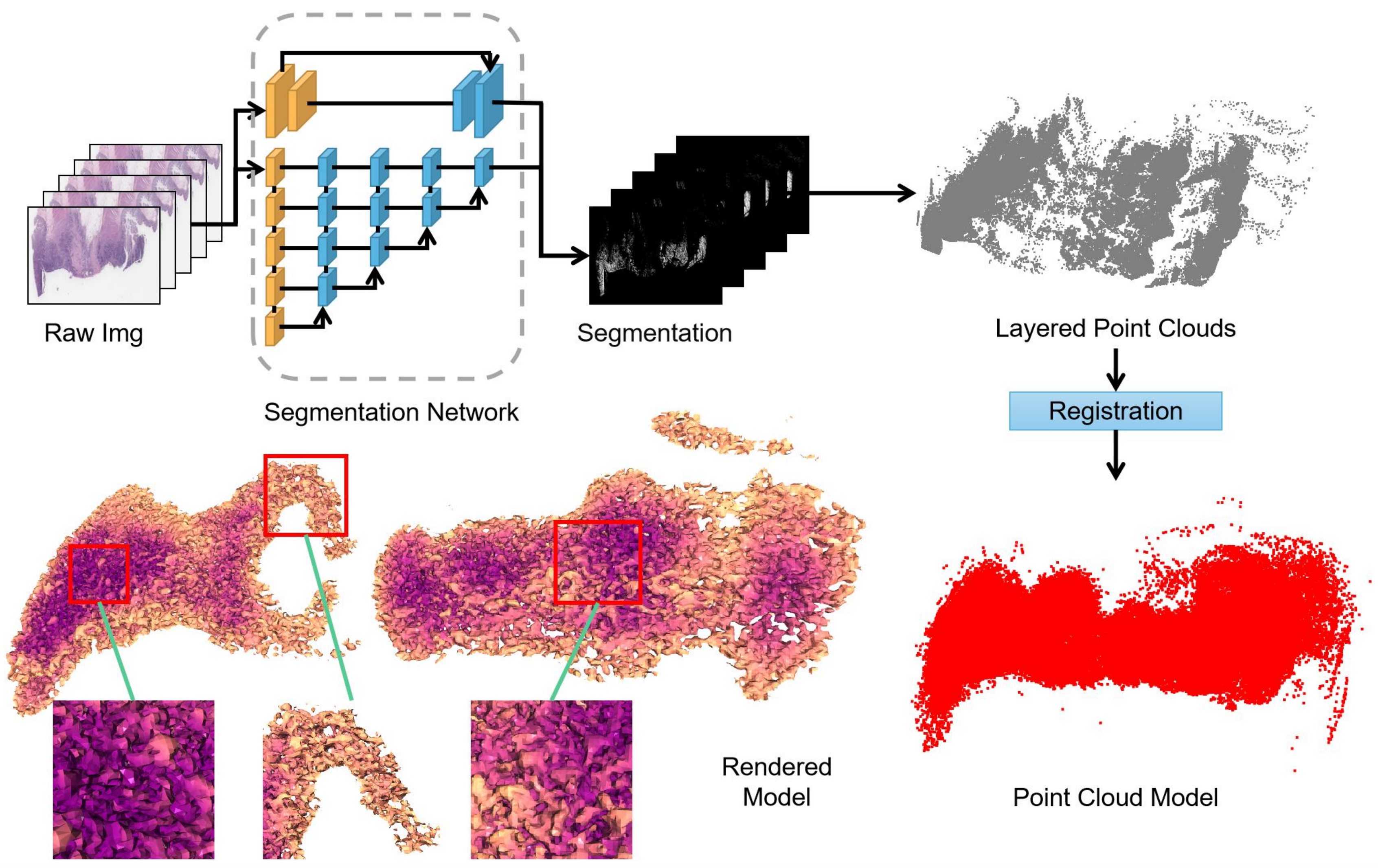



Fig 1: An Overview of the 3D reconstruction pipeline

- The segmentation part is modified from a medical-transfromer network[3].The network consists of two braches to train for global and local features. Each uses axial-transformer as backbone for encoders(yellow in fig.1) and CNN as backbone for decoders(blue in fig.1).

- The registration part adopts point to point ICP (iterative closest point) strategy[4]. The main idea is to calculate the transformation vectors (R,T) to get the least loss value of the fixed and moving point clouds.

$$\mathscr{L}(R,T) = \frac{1}{N}\sum_{i=1}^{N} ||P_{i,fixed} - RP_{i,mov} - T||^2 \quad (1)$$

- We further improved the performance through axial-registration. By calculating the transformation vectors with a cross-like band area(blue parts in fig.2), the time cost could be further decreased.

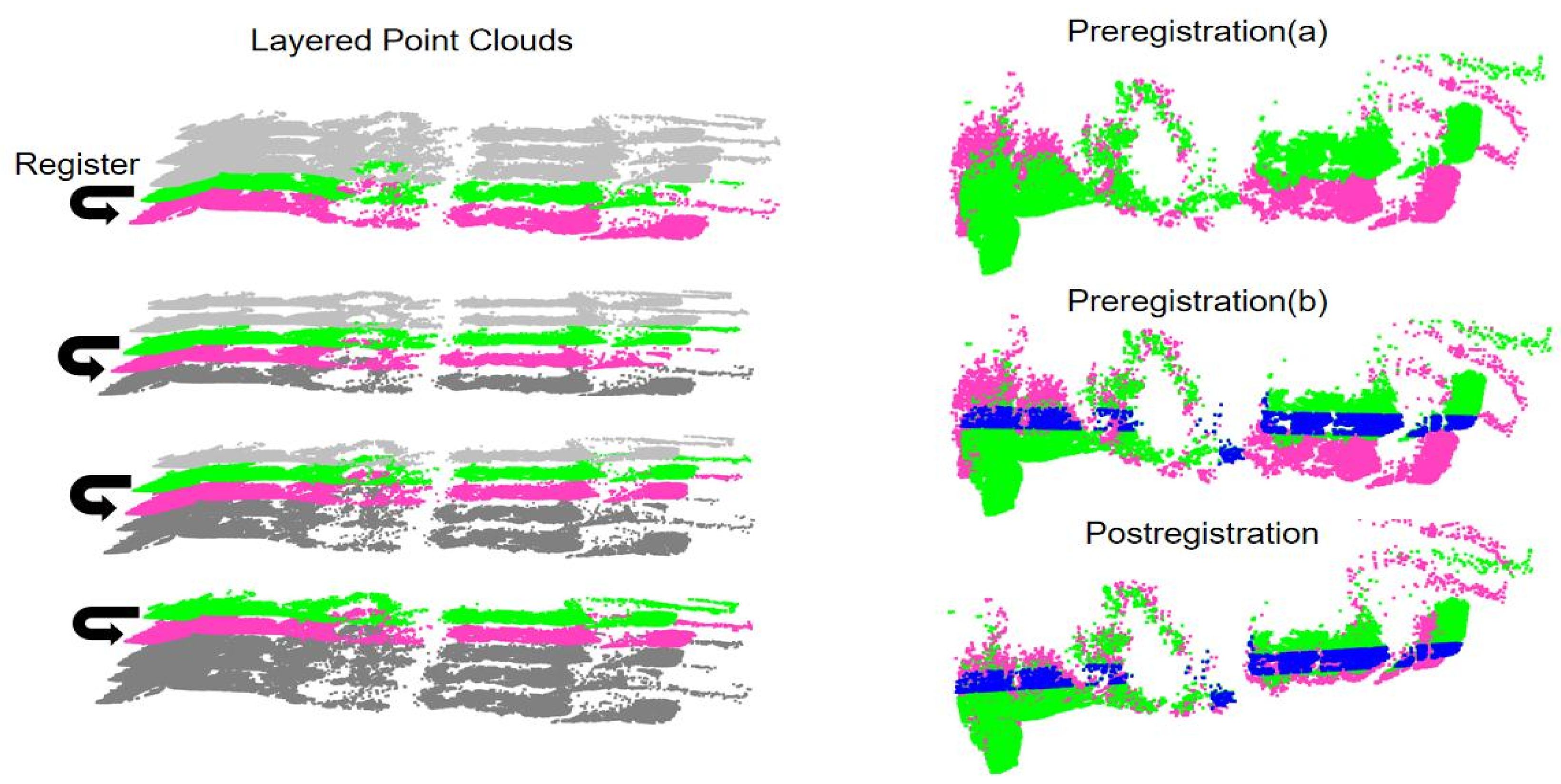
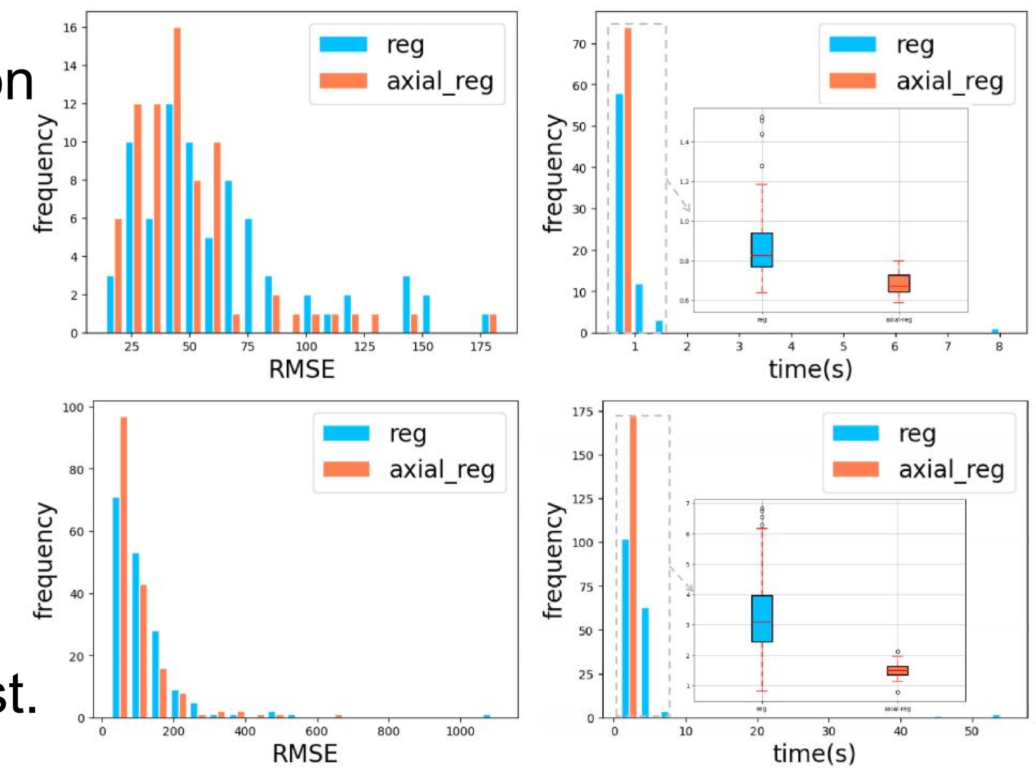



Fig 2: The registration process with the pink parts as fixed layers and green parts as moving layers.

## Results

- We value our axial-regisrtaion method through accuracy and speed. For datasets in our experiments, the axial-registration outperforms the traditional method with less average RMSE and time cost.




- We employ Open3D library [5] to generate point clouds to visualize spatial tissue distribution. The area with eeper areas in the 3D mesh represents areas with higher point density, which indicates higher possibility to be tumor tissiues,

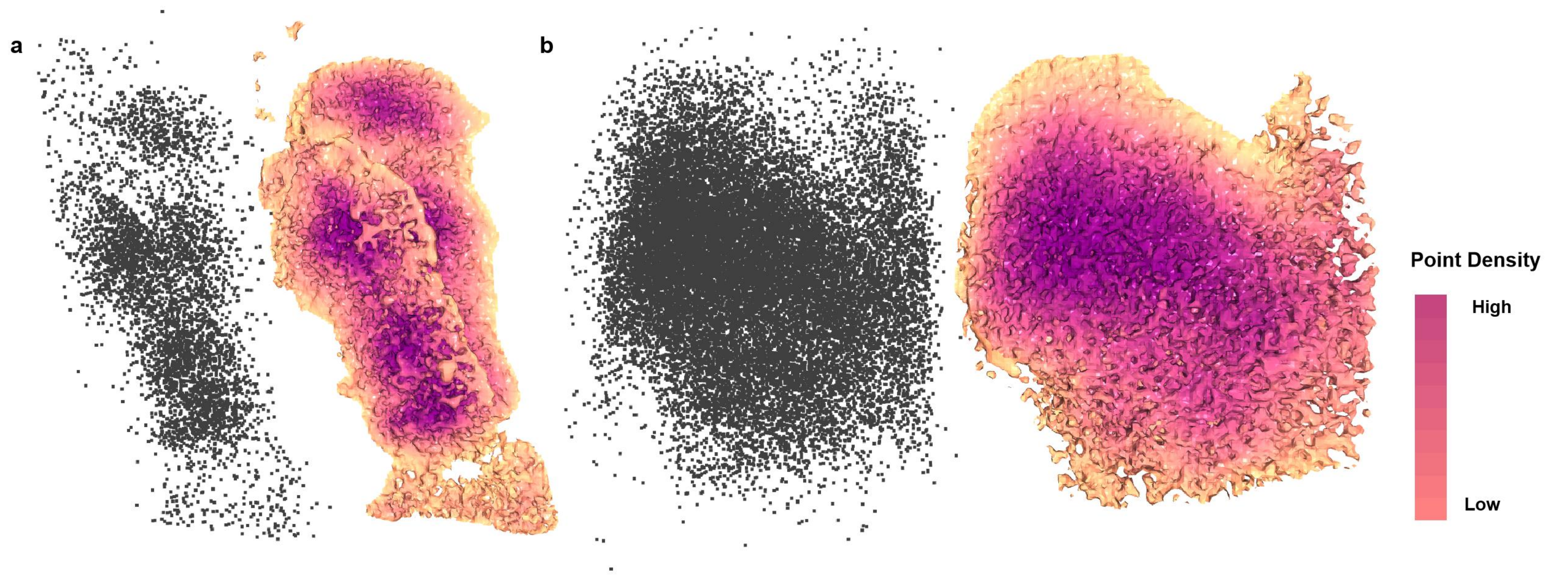



Fig 3: 3D rendered models for different datasets.

## Conclusion & Future Work

- **Efficiency**: Our pipeline accelerate the process through reducing the computation and time cost for registration through the following methods：
  - Register for point clouds instead of the gigabyte images.
  - Modify the registration method to improve the performance.
- **Generality**: The relatively independent blocks in the pipleline is replacable and the segmentation part has the potential to be modified to suit other kinds of images and deseases.
- **Future Goals:** We plan to modify the pipeline for more diseases, more datasets, and make the 3D reconstrctuion process more accurate and more user friendly to help open a grand new door for 3D medical diagnosis and analysis.

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