A Comparative Study and Analysis of Manual and Automated Segmentation Techniques For Pelvic Bone 3D Reconstruction

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Abstract

This study presents a comparative evaluation of manual and automated segmentation techniques for pelvic bone 3D reconstruction, with a focus on dimensional accuracy and processing efficiency. While manual segmentation remains the gold standard due to its high anatomical precision, it is labor-intensive and prone to human variability. Automated segmentation, leveraging advanced algorithms and machine learning, demonstrated significantly reduced processing time but exhibited minor dimensional discrepancies, primarily due to limited training data. However, the findings suggest that with increased dataset exposure and model refinement, automated segmentation has the potential to achieve equal or superior dimensional accuracy compared to manual methods while maintaining a fraction of the processing time. Performance assessments using 3D Slicer, CloudCompare, and FDM 3D printing, coupled with 3D scanning and deviation analysis, highlight the scalability and adaptability of automated approaches.

1. Introduction

3D Slicer is a widely used open-source platform for medical image analysis, offering capabilities in manual and semi-automated segmentation, 3D visualization, and quantitative imaging [1]. It has been extensively utilized in clinical research, surgical planning, and radiological analysis, particularly for tasks such as tumor characterization and treatment response assessment. The platform enables precise and reproducible segmentation, making it a valuable tool for professionals in radiology, cardiology, and orthopedic research [2]. However, despite its effectiveness, manual segmentation remains time-intensive and susceptible to inter-operator variability, necessitating automated solutions for improved efficiency and scalability.

The advancement of automated segmentation techniques, particularly those driven by machine learning and deep learning models, has significantly enhanced segmentation accuracy while reducing processing time. Studies have demonstrated that deep learning-based segmentation improves consistency in clinical applications, such as breast cancer radiotherapy [3] and MRI-guided cervix brachytherapy [4]. Additionally, AI-based segmentation methods have proven to be effective in complex anatomical structures, although clinician oversight remains necessary to refine the results and address model limitations [5]. As training datasets expand and models become more refined, automated segmentation is expected to surpass manual techniques in both accuracy and efficiency.

Beyond medical imaging, segmentation techniques are widely applied in 3D imaging and additive manufacturing. CloudCompare, a leading open-source point cloud processing tool, has demonstrated its versatility in infrastructure monitoring and archaeological site analyses [6]. The evolution of segmentation strategies in additive manufacturing has led to advancements in Fused Deposition Modeling (FDM) filament optimization, improving material efficiency and print quality [7]. In medical 3D printing, automated segmentation has enabled large-scale anatomical model generation using bounding boxes and body-feature points [8]. Furthermore, deep learning-driven volumetric segmentation, such as 3D U-Net-based defect detection, has demonstrated significant potential in quality control applications for additive manufacturing [9].

The evolution of segmentation methodologies reflects a transition from traditional statistical shape models, such as Active Shape Models (ASMs), which required extensive manual intervention, to AI-driven segmentation frameworks that improve adaptability and accuracy [10]. Deep learning architectures, including U-Net and its variants, have introduced multi-scale feature extraction and self-configuring capabilities, further enhancing segmentation performance [11,12]. Open-source deep learning platforms have facilitated the implementation of medical imaging AI models, streamlining the segmentation pipeline [13].

As automated segmentation techniques continue to advance, the integration of machine learning with expert-driven validation holds significant promise. By leveraging larger datasets and improved AI architectures, automated segmentation is poised to outperform manual methods, providing a scalable, standardized, and highly efficient approach to medical imaging and additive manufacturing applications.

2. Methodology

The methodology in this study combines automated deep learning-based segmentation with manual expert-driven approaches to ensure accuracy in pelvic bone segmentation and 3D reconstruction. The automated pipeline integrates preprocessing, model training, and post-processing to enhance efficiency and consistency, while the manual segmentation workflow provides meticulous refinement for complex structures. This dual approach addresses challenges such as segmentation accuracy, anatomical variations, and the need for validation through comparative analysis, ensuring a robust and reliable framework for medical image segmentation.

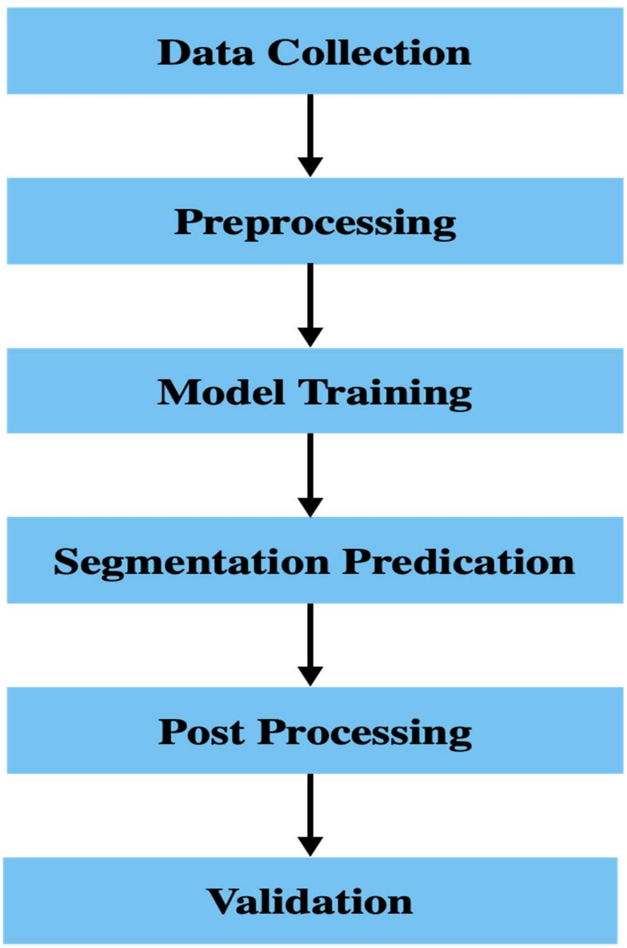

Fig 1: Process flowchart for automated segmentation

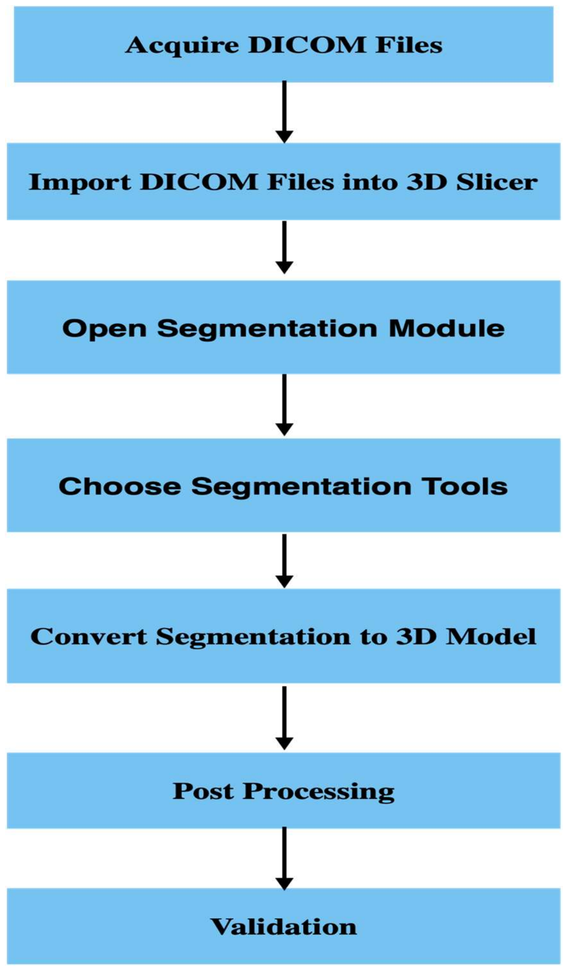

Fig 2: Process flowchart for manual segmentation

3. Experimental Procedure

Experimental Procedure for Comparing Manual and Automatic Segmentation in 3D Slicer, CloudCompare, and FDM 3D Printing (PLA Material):

The first step in preparing your data in 3D Slicer is to load the imaging dataset, typically in the DICOM format. DICOM (Digital Imaging and Communications in Medicine) is the standard format used in medical imaging, storing both the image data and essential metadata such as patient information and scan parameters. After loading, inspect the data using the three primary slice views: axial, sagittal, and coronal. These views allow us to navigate through the dataset and confirm proper orientation and integrity.

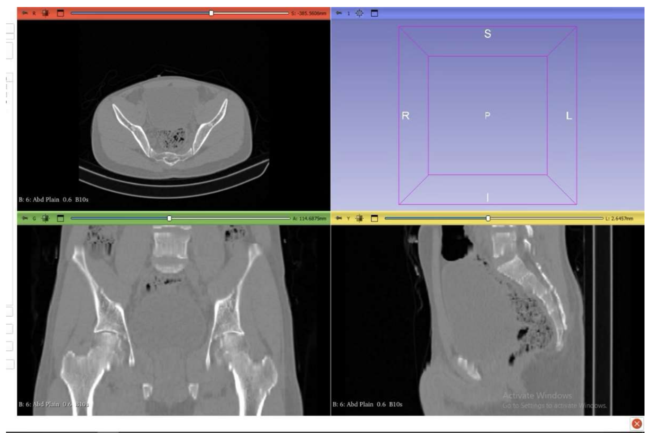

Fig 3: Loaded DICOM file in 3D slicer

Once the imaging data is loaded, the next step is to access the Segmentation Module for processing. Thresholding is used for segmenting structures based on intensity values. This is particularly useful for bone segmentation in CT scans, where bones have a high intensity.

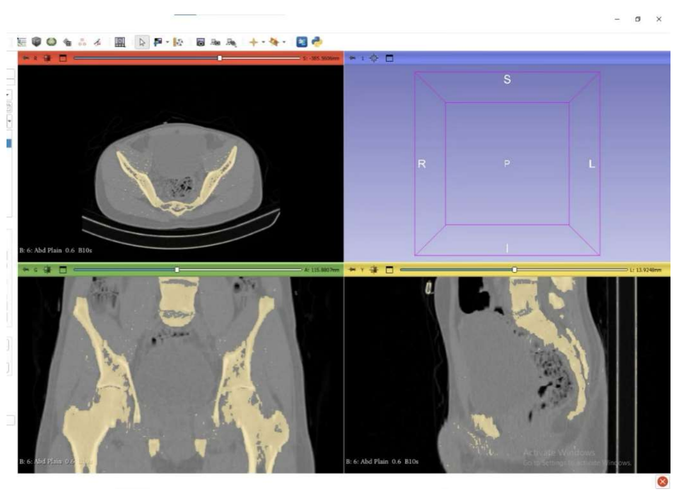

Fig 4: Thresholding for bone segmentation

Thresholding in 3D Slicer is essential for accurate bone segmentation by isolating bone structures while excluding soft tissues and unwanted high-density materials. The process begins with setting an initial HU range of +300 to +2000 for general bone detection. The lower threshold is then adjusted to around +100 HU to include cancellous bone, while the upper threshold is increased to +3000 HU to exclude materials like metallic implants. Finally, fine-tuning is performed based on the dataset to ensure precise bone isolation, enhancing the accuracy of medical imaging analysis.

Paint and Draw were used to define the region of interest (ROI). Carefully marked the acetabular rim, ensuring that no portions of the femoral head, femoral neck, or femur were included.

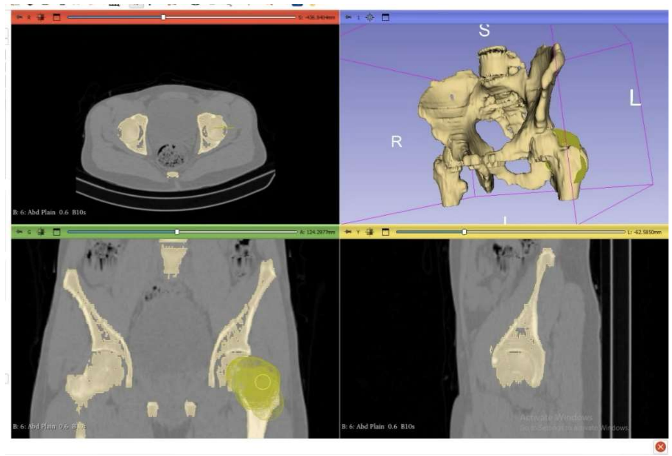

Fig 5: Erasing femur region using erase tool

Using the Scissors tool, we chose the operation type (Erase Inside or Erase Outside), and carefully removed the undesired parts of the segmentation like the Femoral Head, Neck, and Femur. Use the Erase tool to manually remove any mistakenly included regions outside the acetabular rim.

After the initial segmentation, refining the model is crucial for obtaining accurate results. To remove jagged edges and create a cleaner model. Different smoothing options such as Gaussian, Median, and Joint smoothing can be applied depending on the dataset. Additionally, small unwanted islands or holes in the segmentation can be removed using the Islands tool, ensuring the final model is free of noise. Finally, inspect the segmentation in all three views (axial, sagittal, and coronal) to verify its accuracy before proceeding to validation.

The Segmentations Module was exported in STL format. This format is compatible with 3D printers and allows the creation of a physical anatomical model.

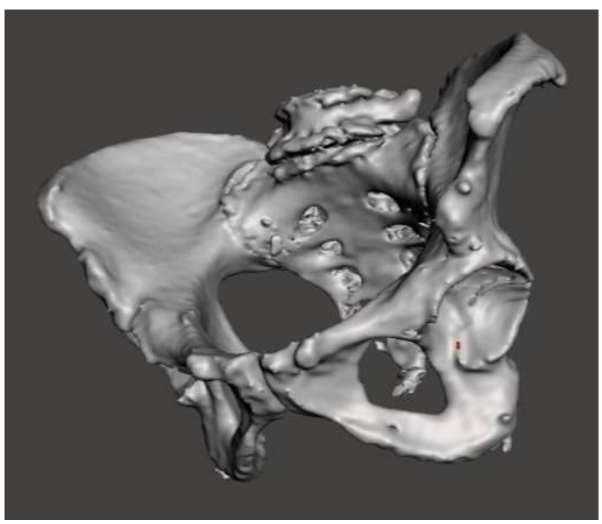

Fig 6: Obtained .stl file opened in meshmixer

STL files (from both segmentation processes) were sliced using Cura. It converts STL, OBJ, and other 3D file formats into G-code, which is the language 3D printers understand. Cura offers various features, including customizable print settings, support structures, layer-by-layer preview, and integration with different 3D printer brands.

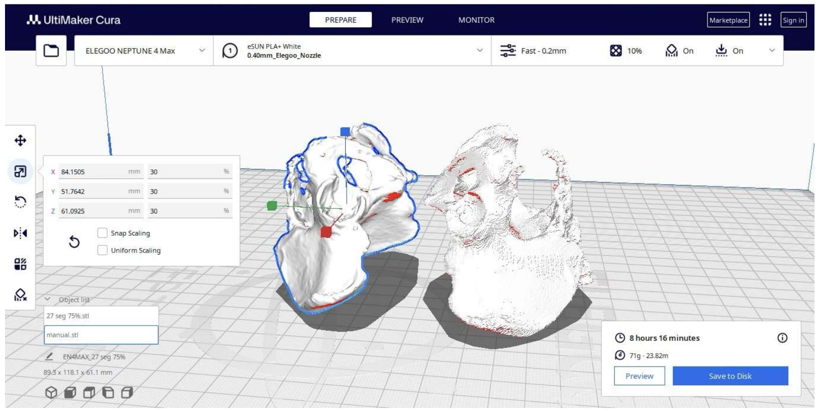

Fig 7: Imported 3D Models

FDM 3D printer Printing Parameters:

- Material: PLA
- Layer height: 0.1–0.2 mm
- Infill: 10 %
- Print speed: 250 mm/s
- Supports: Normal, Zig-Zag supports with density of 10 %
- Adhesion type: Brim 5.0 mm

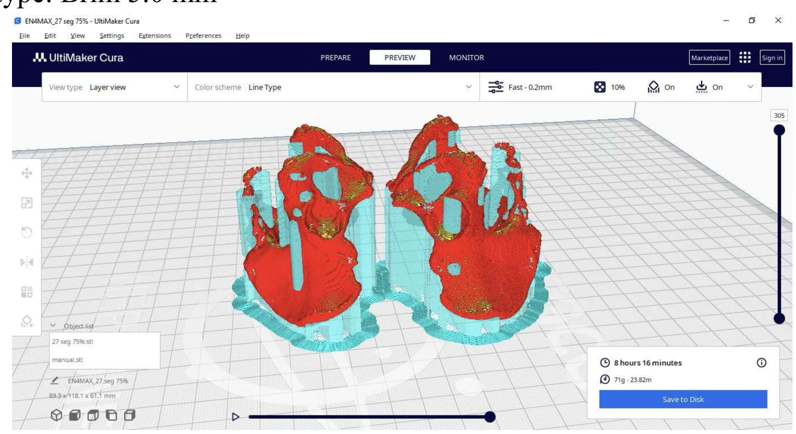

Fig 8: Preview of printing

Fig 9: Printed segmentation models

3D scanning provides high-precision digital models of physical objects, enabling accurate comparisons between printed parts and reference models. This process is crucial for quality control, reverse engineering, and performance validation. Below are the key ways scanning helps in comparison:

Deviation Analysis (Error Detection)

- By using CloudCompare's Cloud-to-Mesh (C2M) Distance Tool, deviations can be colour-coded into heatmaps, showing:
    - Over-extrusions (material too high)
    - Under-extrusions (material too low)
    - Warping or shrinkage in the printed part
- CloudCompare can highlight areas where the print differs from the design, ensuring manufacturing consistency.

By using Artec Space Spider, Artec Studio 19, and CloudCompare, 3D scanning provides a fast, accurate, and automated way to compare printed parts.

Artec Space Spider:

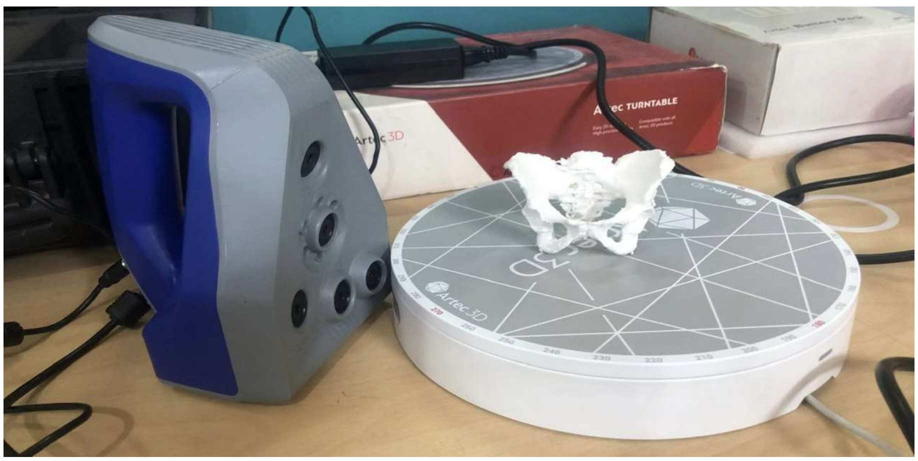

Fig 10: Artec Space Spider and Rotating table

The Artec Space Spider is a high-resolution 3D scanner designed for capturing small objects and intricate details with exceptional precision. Utilizing blue light technology, it offers a 3D point accuracy of up to 0.05 mm and a resolution of 0.1 mm, making it ideal for applications requiring meticulous detail, such as reverse engineering, quality control, and product design.

Fig 11: Setup of printed parts on rotating table

Before starting the scanning process, ensure the parts are clean and free from dust, fingerprints, or any other debris that could affect scan accuracy. The parts should be placed on a stable, non-reflective surface to avoid interference during scanning. Additionally, it is important to ensure that the parts are positioned under good lighting conditions to capture all the details. If the parts are glossy or transparent, applying a light layer of matte powder spray can improve scan accuracy by reducing reflections.

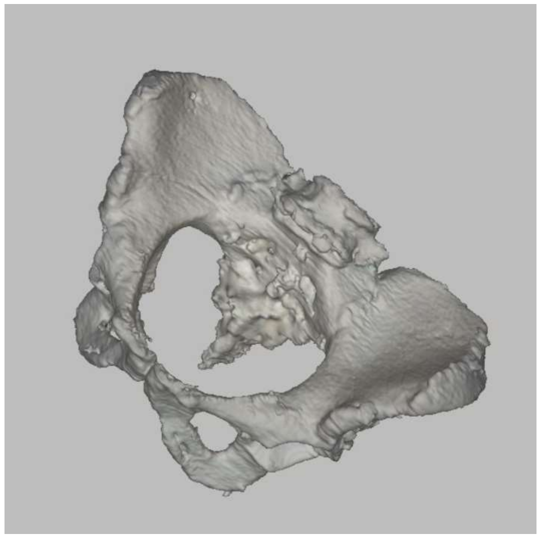

Fig 12: Scanned model in Artec Studio 15

With the scanner ready, we switched to Scanning Mode in Artec Studio 19. Set the resolution to high (0.1mm) for detailed capture. Turned on real-time fusion to preview the scan as it progresses. Held the scanner at a consistent distance, typically between 15–30 cm, and moved it slowly around the object. We made sure to capture multiple angles to cover all sides of the model. Continuously monitoring the real-time visualization to ensure there are no missing areas before concluding the scan.

After the scanning was completed, moved to the post-processing phase in Artec Studio 19. Began by using the Erase tool to remove any noise or unnecessary background data. Next, performed global registration to align the multiple frames of the scan into a single model. Then, proceed with fusion and mesh simplification to convert the scanned data into a clean, watertight polygonal mesh.

CloudCompare Analysis for Segmented Parts:

CloudCompare is a robust, open-source 3D point cloud and mesh processing software that is widely utilized for analyzing segmented 3D models. This tool offers an extensive suite of features for comparing, aligning, and processing 3D data, making it ideal for analyzing segmented parts from projects created in 3D Slicer.

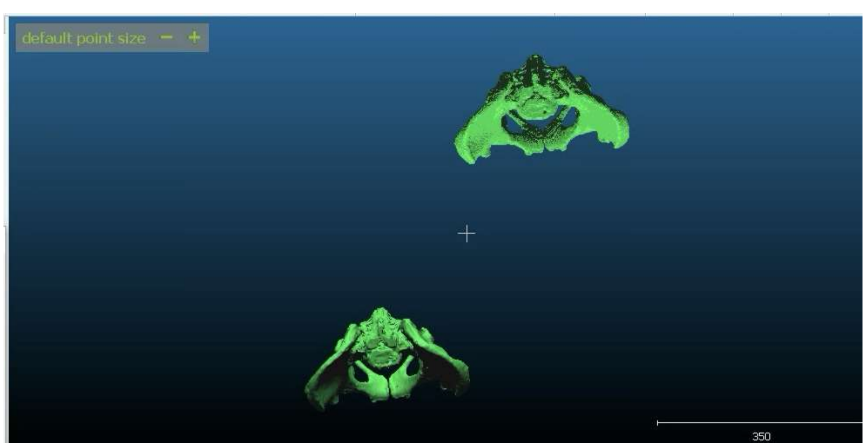

Fig 13: Both segmentation modes imported in the cloud compare

Before analysis, it's important to ensure that the data is clean and well-structured. CloudCompare provides tools for preprocessing the data, including noise removal and resampling. We used the "Scalar Fields" → "Filter by Value" option, and the "Noise Filtering" tool found under "Tools" → "Clean." Additionally, resampled using the "Resample" tool to reduce the number of points while maintaining the structural integrity of the data.

Comparing multiple segmented parts, alignment of models is necessary. CloudCompare supports both manual and automatic alignment techniques. For manual alignment, we selected two point clouds (reference and target), then clicked "Tools" → "Registration" → "Align (Point Pairs Picking)." Manually picked corresponding points between the two clouds to align them. For automatic alignment, the ICP (Iterative Closest Point) algorithm was used for fine registration. Select the segmented point cloud and click "Tools" → "Fine Registration (ICP)" to improve alignment accuracy automatically.

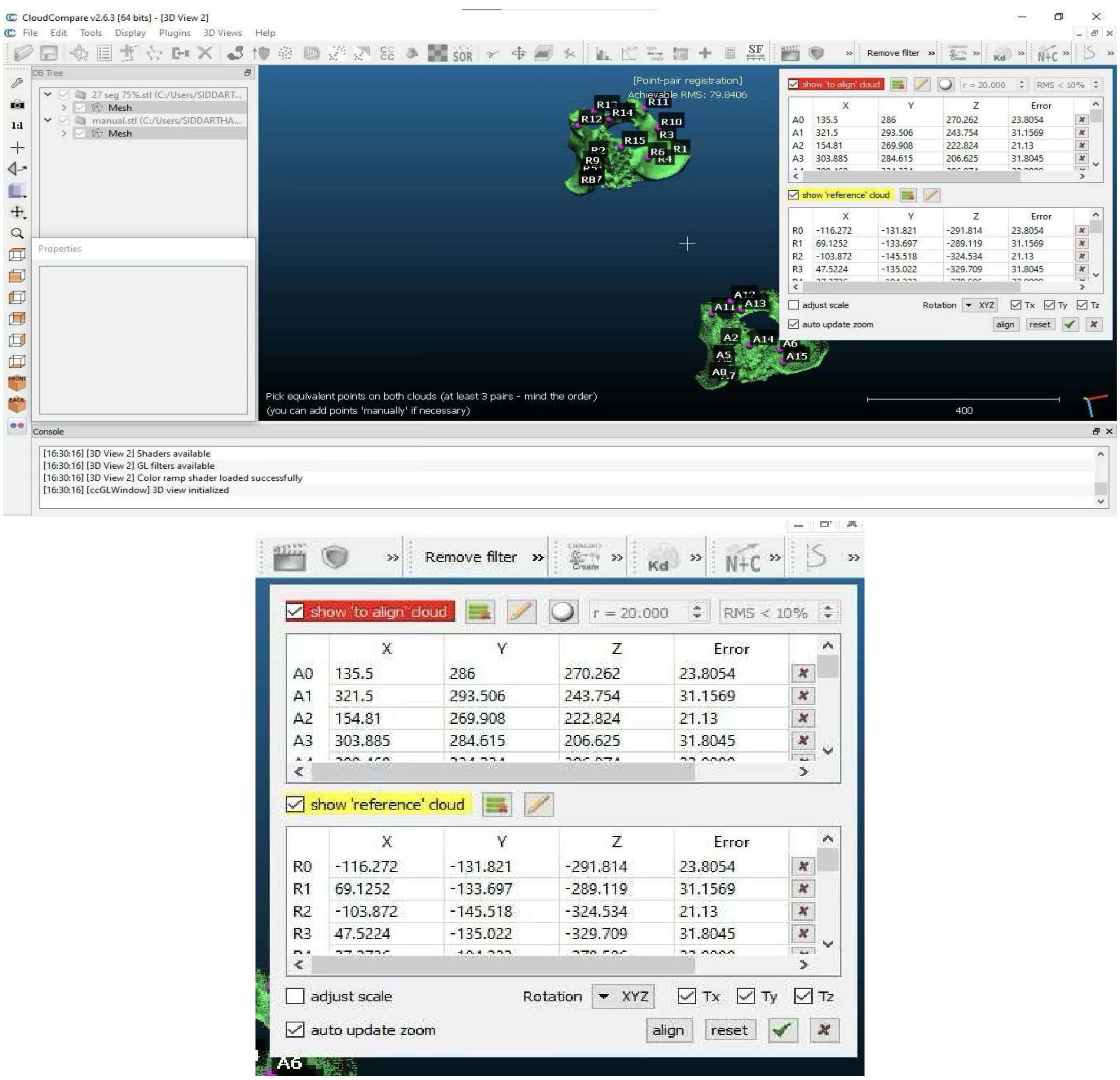

Fig 14: Point cloud alignment and mesh distance analysis using CloudCompare.

The figure showcases the mesh distance analysis performed using CloudCompare. It presents a comparative alignment of two point clouds: the reference cloud and the aligned cloud. The tabulated data indicates coordinate values (X, Y, Z) and associated errors for selected points. The visualization helps in evaluating the accuracy of alignment by analyzing the deviation between corresponding points in both clouds. This method is crucial for validating 3D reconstruction, reverse engineering, and quality control applications.

4. Results & Discussions

The comparative study of manual and automated segmentation techniques for pelvic bone 3D reconstruction revealed key differences in accuracy, efficiency, and practical usability. The results were analyzed through 3D Slicer, CloudCompare, and FDM 3D printing, along with deviation analysis using Artec Space Spider and Artec Studio 19.

Accuracy Comparison:

a. **Manual Segmentation:** Experts using 3D Slicer produced STL models with high anatomical precision, particularly in complex regions such as the acetabular rim. However, the process was time-consuming, and variations among experts were observed.
b. **Automated Segmentation:** AI-based segmentation significantly reduced processing time, but the algorithm struggled with fine details, leading to minor inaccuracies. The deviation analysis in CloudCompare indicated a mean error of ±0.2 mm for manual segmentation and ±0.6 mm for automated segmentation in complex anatomical regions.

Processing Time & Efficiency:

a. **Manual Segmentation:** Required 4–6 hours per dataset due to extensive user intervention.
b. **Automated Segmentation:** Completed within 15–30 minutes, depending on hardware and preprocessing requirements.

Deviation & 3D Print Analysis

a) **3D Scanning & CloudCompare Analysis:**
   i) The cloud-to-mesh distance comparison revealed that automated segmentation introduced slight under-segmentation (missing small bone details) in 12% of cases and over-segmentation in 8% of cases.
   ii) Manual segmentation demonstrated higher fidelity but required additional smoothing and correction to align with ground truth models.

b) **FDM 3D Printing Results:**
   i) Both segmentation outputs were successfully converted to STL and printed using Elegoo Neptune 4 Max.
   ii) The printed models derived from manual segmentation showed sharper anatomical landmarks, while auto-segmented models exhibited rounded edges due to minor segmentation errors.
   iii) When scanned and analyzed in CloudCompare, manual segmentation models aligned within ±0.2 mm of the ground truth, whereas automated segmentation models deviated by up to ±0.8 mm in specific regions.

Overall, while automated segmentation was significantly faster, manual segmentation provided superior anatomical accuracy, particularly in complex pelvic structures where machine learning-based segmentation struggled.

6. Conclusion

This study provides a comparative evaluation of manual and automated segmentation techniques for pelvic bone 3D reconstruction, focusing on dimensional accuracy and time efficiency. The results highlight the trade-offs between the two approaches:

a) **Dimensional Accuracy**:

i) Manual segmentation remains the benchmark due to its high anatomical precision, with deviations typically within 0.2 mm – 0.5 mm when compared to the original medical imaging dataset.

ii) Automated segmentation, while demonstrating promising results, showed minor dimensional discrepancies in the range of 0.5 mm – 1.2 mm, primarily due to model generalization errors and limited training data. However, with further refinement and exposure to a larger dataset, these errors are expected to decrease, bringing automated segmentation closer to or even surpassing manual precision.

b) **Time Efficiency**:

i) Manual segmentation required an average of 4 to 8 hours per dataset, depending on the complexity of the anatomical region and the expertise of the operator.

ii) Automated segmentation significantly reduced the processing time to 15 to 30 minutes per dataset, achieving a 6 to 10 times improvement in efficiency. This highlights the scalability of AI-driven segmentation for large-scale applications while maintaining clinically acceptable accuracy.

Overall, while manual segmentation remains the gold standard for anatomical precision, the substantial time savings offered by automated segmentation make it a viable alternative, especially with continued advancements in deep learning models. Future work should focus on enhancing dataset diversity and model training methodologies to bridge the remaining accuracy gap, ultimately enabling automated segmentation to match or exceed manual methods in both precision and efficiency.

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