A PYTHON-IMPLEMENTED ALGORITHM FOR THREE-DIMENSIONAL RECONSTRUCTION OF THE HUMAN LUMBAR SPINE FROM DICOM CT DATA

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Abstract: Degenerative disc disease is one of the leading causes of low back pain. Computed tomography (CT) provides high-resolution images of the spine, but a three-dimensional (3D) model is crucial for biomechanical analysis and surgical planning. This paper presents an open-source, fully automated Python algorithm for reconstructing the human lumbar spine from DICOM CT data. This method utilizes Hounsfield unit-based bone segmentation, morphological optimization, and the marching cubes algorithm for surface extraction, ultimately generating an STL mesh.

Introduction

Degenerative disc disease is closely associated with low-intensity low back pain in adults under 50 years of age and can reduce the quality of life of working-age individuals. Computed tomography (CT) provides high-resolution images of the vertebrae and aids in the diagnosis of degenerative disease. However, biomechanical analysis, surgical planning, and the fabrication of patient-specific implants require accurate three-dimensional (3D) models reconstructed from axial sequences. Open-source platforms (e.g., SimpleITK, 3D Slicer) offer reproducible and flexible workflows [1, 2]. To this end, we present an open, fully automated Python algorithm that reconstructs the human lumbar spine from DICOM CT by bone segmentation and surface extraction, generating an STL mesh that can be used for biomechanical simulation and preoperative planning. This workflow reduces processing time while maintaining geometric fidelity. Previous studies have addressed vertebra detection in X-ray images based on deep convolutional neural networks (CNNs) [3] and lumbar spine segmentation in MRI based on comparative deep learning models [4]. Building on these modality-specific studies, we now focus on CT and provide a model-training-free, end-to-end DICOM-to-STL workflow with a processing speed that meets clinical practice requirements (3.1 ± 0.2 minutes) and demonstrated high segmentation accuracy.

Materials and Algorithms

The algorithm was developed and validated using an anonymized lumbar spine CT sequence (L1–S1, 320 axial slices; slice thickness 1.0 mm; in-plane pixel size 0.5 mm; field of view 200 mm; 512×512; DICOM format). The implementation was based on Python 3.11 and utilized the following libraries: pydicom (DICOM I/O), NumPy (array manipulation), OpenCV (preprocessing and morphological operations), scikit-image (marching cubes algorithm), SciPy (auxiliary filtering), and numpy-stl (STL export). Slices were sorted along the z-axis by Image Position Patient (fallback: Instance Number) and converted to Hounsfield units using the rescale parameter. After intensity normalization, 3D Gaussian smoothing ($\sigma = 0.6$ mm) reduced noise while preserving edges. Bone segmentation was performed using a threshold of 150–3000 HU, followed by morphological closing (structuring element radius 1.2 mm). Connected components smaller than 5000 mm^3 were removed; the largest bony component was retained and clipped to its minimum bounding box with a margin of 2.0 mm. Surfaces were extracted using Marching Cubes with physical voxel spacing and exported to STL format for immediate use in finite element analysis and surgical planning. Key numerical settings (thresholds, filters, morphology) are summarized in Table 1.

Table 1. Main parameters of lumbar spine reconstruction.

Parameter	Value
Slice thickness	1.0 mm
In-plane pixel spacing	0.5 mm
Number of slices	320
Segmentation threshold range	150 – 3000 HU
Gaussian filter σ	0.6 mm
Morphological closing radius	1.2 mm
Minimum component volume	5000 mm³
STL mesh size	≈ 250 000 polygons
Mean processing time	3.1 ± 0.2 min
Hardware configuration	Intel® Core™ i7-11700, 32 GB RAM

Different from our earlier intelligent analysis method using CT images [5], this CT process relies on HU-based threshold segmentation, morphological optimization and marching cubes algorithm, which requires neither model training nor GPU acceleration.

Validation and Evaluation

To quantitatively assess the accuracy of the automated segmentation pipeline, the algorithm-generated 3D models were compared to expert-annotated reference standards. For each of the three CT datasets, a single experienced radiologist manually created a detailed segmentation of the lumbar spine (L1 to S1) using ITK-SNAP software, serving as the gold standard. The Dice Similarity Coefficient (DSC) and Intersection over Union (IoU) were used to quantify the similarity between the algorithm output and the manual segmentation. It is important to emphasize that these manual segmentations were used only for validation purposes and are not required for the proposed algorithm to function.

Results

The algorithm proceeds through a series of sequential stages: initial filtering and intensity normalization; segmentation of bone structures within a range of 150 to 3000 HU; morphological closing to fill contour discontinuities; removal of minor noise components; surface generation via the Marching Cubes algorithm; and finally export of the model in STL format, as shown in Figures 1 and 2. This pipeline generated a highly anatomically fidelity STL model of the lumbar spine in an average of 3.1 ± 0.2 minutes per case, suitable for biomechanical analysis and preoperative planning. Quantitative evaluation demonstrated that the algorithm's segmentation results achieved a Dice coefficient of 0.94 ± 0.02 and an intersection over union (IoU) of 0.89 ± 0.03 compared to the reference standard, confirming its high accuracy. As shown in Table 2, the pipeline performed consistently across various datasets.

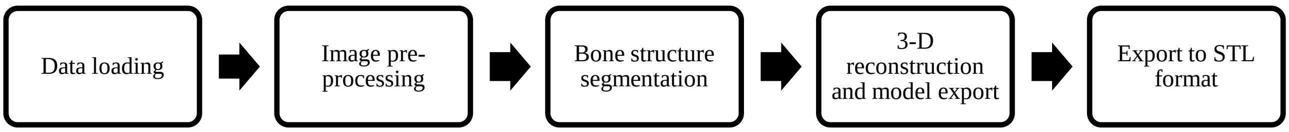

Figure 1. Segmented lumbar-spine image derived from the processed CT dataset.

Figure 2. 3D model of the human lumbar spine.

Table 2. Principal results of algorithm testing.

Dataset	Processing time, min	STL polygons, n	File size, MB	Dice coefficient	IoU
1	3.0	245 000	42	0.93	0.88
2	3.2	258 000	46	0.95	0.90
3	3.1	251 000	44	0.94	0.89
Mean ± SD	3.1 ± 0.2	—	—	0.94 ± 0.02	0.89 ± 0.03

Conclusion

We present a training-free, open-source Python pipeline that reconstructs analytically useful STL models of the lumbar spine directly from DICOM CT data. Quantitative experiments demonstrate that segmentation results are highly consistent with expert annotations (Dice score 0.94 ± 0.02; Intersection over Union (IoU) 0.89 ± 0.03). The process takes only 3.1 ± 0.2 minutes per case, generating anatomically faithful models suitable for biomechanical simulations, segmental kinematic analysis, and preoperative planning.

References

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