Three-Dimensional Reconstruction of Ribs Based on Point Cloud Adaptive Smoothing Denoising

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Abstract

The traditional methods for 3D reconstruction mainly involve using image processing techniques or deep learning segmentation models for rib extraction. After post-processing, voxel-based rib reconstruction is achieved. However, these methods suffer from limited reconstruction accuracy and low computational efficiency. To overcome these limitations, this paper proposes a rib 3D reconstruction method based on point cloud adaptive smoothing and denoising. We convert the voxel data from the CT images to multi-attribute point cloud data. Then, we apply point cloud adaptive smoothing and denoising methods to eliminate noise and non-rib points in the point cloud. Additionally, efficient 3D reconstruction and post-processing techniques are employed to achieve high-accuracy and comprehensive rib 3D reconstruction results. Experimental calculations demonstrate that compared to voxel-based rib 3D reconstruction methods, the rib 3D models generated by the proposed method achieve a 40% improvement in reconstruction accuracy and are twice as efficient as the former.

II. INTRODUCTION

Rib 3D reconstruction technology can help doctors diagnose and treat related diseases such as rib fractures, and is of great significance to clinical medicine. Rib fractures are a common finding after chest trauma [1], usually caused by chest trauma, blunt force, medical conditions such as cancer and obesity [2], among which chest trauma accounts for 10–15% of all trauma cases [3]. Due to inadequate pain control, respiratory complications caused by rib fractures often occur, such as post-traumatic pneumonia [4]. The structure and morphology of the ribs are a stable reference for various analysis and quantification tasks, such as lung capacity estimation and skeletal abnormality quantification [5]. The number and types of rib fractures can serve as the basis for further treatment strategies [6], so accurate detection of rib fractures in CT scans can help with appropriate patient care [7]. Rib 3D reconstruction technology can improve the diagnostic rate of diseases such as rib fractures, and this research and its application are of great significance.

Before the rise of deep learning, rib 3D reconstruction mainly relied on traditional image processing, computer vision, and geometry methods. Firstly, the CT image was preprocessed to remove noise and improve contrast through methods such as Gaussian filtering, median filtering, and histogram equalization, thereby highlighting the rib structure. Secondly, methods such as threshold segmentation, region growing, and edge detection were used to separate and process the ribs from the CT scan, thus determining the rib region. Finally, the rib region segmented by skeletonization using distance transformation, erosion, and thinning methods was used to obtain the centerline of the rib. Finally, surface-based or voxel-based 3D reconstruction methods were used to achieve rib 3D reconstruction.

Although the above research methods have made some progress in rib 3D reconstruction, their effectiveness is limited. Firstly, traditional methods are greatly affected by complex backgrounds, noise interference, and incomplete data, resulting in poorer reconstruction accuracy compared to deep learning methods. Secondly, traditional methods often require manual adjustment of parameters to achieve better
results, which can lead to unstable results and the need for parameter re-adjustment for different datasets. Finally, traditional methods often separate the segmentation and reconstruction processes, leading to error accumulation and information loss.

With the rise of deep learning, neural network segmentation models have been used for rib voxel segmentation, which can significantly improve the accuracy of rib segmentation. Many rib 3D reconstruction tasks have achieved significant performance improvements. However, voxel data contains information such as position, size, and attributes, resulting in high spatial complexity and computational complexity, greatly increasing reconstruction inference time. At the same time, voxel segmentation is based on a discrete network structure, leading to geometric distortion on the object surface and reducing the accuracy of rib 3D reconstruction.

Deep learning-based rib 3D reconstruction methods usually outperform traditional rib reconstruction algorithms in rib reconstruction accuracy, but there is still room for improvement in performance and efficiency, which cannot meet the current level of medical diagnosis and treatment. Therefore, designing a rib 3D reconstruction method that can obtain stable rib 3D reconstruction results and meet the current medical diagnosis and treatment level in terms of reconstruction inference time and accuracy can greatly improve the quality and effectiveness of medical treatment in rib-related fields. Our main contributions are summarized as follows: (1) proposing a rib 3D reconstruction method based on point cloud adaptive smoothing and denoising, effectively solving the limitations of traditional methods in terms of reconstruction quality and computational efficiency; (2) designing a new point cloud denoising algorithm that can effectively eliminate noise generated during data acquisition and conversion, improving the quality and reconstruction accuracy of rib point cloud data; (3) proposing an innovative post-processing method for 3D reconstruction that can further optimize rib 3D reconstruction results, improve reconstruction accuracy, comprehensiveness, and obtain higher quality rib 3D reconstruction visualization results for medical applications.

RELATED WORK

Previous research on 3D reconstruction of skeletal tissues can be classified into three main categories: traditional image processing methods, deep learning methods, and point cloud reconstruction methods.

Early research on 3D reconstruction of skeletal tissues relied mainly on traditional image processing techniques such as threshold segmentation, region growing, and edge detection. These methods preprocess the original CT images to separate the skeletal tissue structures and use 3D surface reconstruction techniques to complete the 3D reconstruction of skeletal tissues. Chen et al. [8] used sagittal and coronal multiplanar reconstruction (MPR), maximum density projection (MIP), and surface shading imaging (SSD) to reconstruct the bone structures around the ankle joint and carefully observe the 3D morphology of the ankle joint through maximum density projection. Although this method can achieve good results, it requires parameter adjustment, which makes the reconstruction process complex. Maken et al. [9] performed 3D reconstruction of patient anatomical structures by calibrating, contour
extraction, 2D image correspondence, and registration of X-ray images in sequence. Although this method can achieve the reconstruction goal, the steps are cumbersome, require manual intervention, and are time-consuming, making it difficult to obtain stable 3D visualization results. Liu et al. [10] used multiplanar reconstruction CT to calculate pelvic tilt. Although this method simplifies the steps of CT reconstruction, it is susceptible to noise limitations, resulting in lower accuracy in calculating pelvic tilt. Effatparvar et al. [11] proposed an ultrasound-based 3D modeling algorithm to reconstruct the lumbar spine. Although the reconstruction process of this method is relatively simple, the quality of the reconstruction is highly susceptible to the quality of the image. Gajny et al. [12] proposed a new manual input strategy and used statistical inference, image analysis techniques, and fast manual rigid registration to calculate the parameter model of the spine and obtain a 3D reconstruction model of the spine. Although this method does not require manual intervention, it has many steps and is susceptible to cumulative errors, which affects the accuracy of the final reconstruction model. In addition, there are also some methods based on MRI images [13], which can provide richer information on soft tissues and aid in the diagnosis and evaluation of spinal diseases. However, these methods are susceptible to resolution and noise limitations, resulting in lower reconstruction accuracy, making it difficult to handle complex morphologies and structures.

With the development of deep learning, especially convolutional neural networks (CNNs), which have shown superior performance in image processing [14, 15], image segmentation [16, 17], pattern recognition [18,19], and computer vision [14] tasks, many studies have begun to explore the use of deep learning methods for 3D reconstruction of skeletal tissues. Deep learning methods have strong feature learning capabilities and can automatically learn effective feature representations from data, thereby improving the accuracy of 3D reconstruction of skeletal tissues. Fang et al. [20] proposed a method for spinal segmentation by improving the FCN neural network, which achieved 3D reconstruction of the vertebral body. This method achieved the automation of the 3D reconstruction process of the vertebral column through deep learning, but the complex network structure required significant computing resources. Aubert et al. [21] proposed a new, fast, and automated method for 3D spinal reconstruction, using a convolutional neural network (CNN) to fit the real statistical shape model of the spine to the image. This method has low computational resource requirements, but the accuracy of the obtained spinal reconstruction is limited, with significant room for improvement. In addition, Forsberg et al. [22] proposed a method for segmenting spinal MRI images using deep convolutional neural networks, thereby achieving 3D reconstruction of the spine. Although this method has stable 3D reconstruction results and improved reconstruction accuracy compared to traditional reconstruction methods, the efficiency of voxel data compression and storage is low, and voxel reconstruction requires significant amounts of data processing, resulting in unnecessary calculations and overlapping regions at voxel edges, limiting reconstruction efficiency.

In recent years, point cloud 3D reconstruction has received widespread attention in the fields of computer vision and graphics. This type of method involves point cloud pre-processing, point cloud segmentation, and point cloud 3D reconstruction. Point cloud pre-processing aims to generate a point cloud model or generate high-quality point clouds for subsequent steps. Typically, this step includes four sub-steps:
registration, noise filtering, outlier removal, and downsampling [23]. The purpose of point cloud segmentation is to segment the point cloud and obtain the points that meet the mathematical model of the object of interest. With the introduction of PointNet [24] and PointConv [25] into point cloud segmentation, the performance of point cloud segmentation has been further improved. The purpose of point cloud 3D reconstruction is to generate a geometric model of the object of interest through the point cloud fragments obtained in the previous steps, effectively generating a dense point cloud shape of the object. There have been studies that have applied point cloud 3D reconstruction to medical imaging. Yang et al. [26] proposed an automatic liver segmentation method based on adversarial image-to-image networks, which extracts point cloud data from medical images and performs 3D reconstruction. This method can directly process 3D data with high spatial resolution and efficiency, but there may be noise introduced and details lost in the process of obtaining point cloud data, reducing the reconstruction accuracy of the liver. Dixit et al. [27] used machine learning methods to extract features such as color, size, and depth from 2D X-ray images of the femur, and created a mesh point cloud based on this information. They then converted the image into an STL representation and used CNN to create a 3D femur model. This method obtained point cloud data with rich information and avoided information loss during the conversion process, but lacks effective post-processing methods, resulting in limited reconstruction accuracy.

In summary, traditional image processing methods in the field of 3D reconstruction of skeletal tissues have the disadvantages of cumbersome steps and unstable visualization results, while deep learning methods have the disadvantages of long processing time and limited accuracy. The 3D reconstruction results obtained by both methods are difficult to meet the requirements of the medical field. Point cloud 3D reconstruction avoids the cumbersome steps by relying on the advantages of not requiring manual segmentation, and point cloud data can provide detailed surface information of objects and have high efficiency, which helps to quickly generate high-precision 3D models. Therefore, this study uses point cloud data with high computational efficiency and strong expressive ability to replace voxel data used in previous research methods, and relies on an accurate and automated reconstruction process to achieve 3D reconstruction of ribs.

## 8. METHOD

To overcome the limitations of existing methods for 3D reconstruction of ribs, including low accuracy and inefficiency, this paper proposes a novel method for rib 3D reconstruction based on adaptive smoothing and denoising of point clouds. As shown in Fig. 1, the overall framework of this method consists of three parts. The first part is the multi-attribute point cloud data acquisition module, which obtains point cloud data that captures the shape and structure of the object, rather than just pixel intensity information. Specifically, the voxel grid in the CT image is filtered based on Hounsfield unit (HU) values to obtain rib voxel grid data, which is then converted to point cloud data represented by spatial coordinates. The normal vectors of the rib surface are also obtained to enrich the local information of the point cloud data. The second part is the point cloud adaptive smoothing and denoising module, which uses noise removal algorithms to eliminate noise generated during data conversion. The point cloud data is also segmented
using a semantic segmentation model to obtain accurate and stable rib point cloud data. The third part is the 3D reconstruction and post-processing module, which uses 3D reconstruction techniques to obtain a 3D model of the rib and performs post-processing operations such as outlier removal, point cloud data smoothing, and label smoothing to further improve the quality and accuracy of the reconstruction results.

A. Acquisition of Multi-attribute Point Cloud Data

Currently, there are no publicly available point cloud datasets for human tissue reconstruction. In this study, we analyzed the distribution of Hounsfeld Unit (HU) values in human rib tissue and used a HU threshold range of [200, 1000] to select voxel data containing ribs, which was then used to generate a voxel grid containing rib voxels. We used a topology-based point cloud generation algorithm to process rib data with complex geometric shapes and obtain point cloud data with high accuracy and completeness, as shown in Fig. 2. The generated point cloud data includes spatial coordinate and normal vector attribute information in the format (x, y, z, nx, ny, nz) compared to point cloud data with only spatial coordinate attribute information in the format (x, y, z). This not only reduces the loss of information from voxel-to-point cloud conversion to enhance the local geometric representation of point cloud data, but also helps to display clearer rib contours during 3D reconstruction. After generating the point cloud data, we matched the mask data with the point cloud data point-by-point and saved it as point cloud labels, providing useful supervised information for subsequent point cloud segmentation model training. Additionally, we converted the rib mask into point cloud data as standard rib point cloud data for subsequent experimental evaluation.

Through the above process, we successfully converted human voxel data into multi-attribute point cloud data and performed corresponding preprocessing work, laying the foundation for subsequent point cloud adaptive smoothing and denoising, 3D reconstruction, and post-processing operations. In the following sections, we will describe these processing methods in detail to achieve high-precision and comprehensive 3D reconstruction results for ribs.

B. Point Cloud Adaptive Smoothing Denoising

In the process of 3D reconstruction of ribs, the point cloud data obtained from CT scans often comes with noise and errors. In order to improve the accuracy, visualization, and analysis efficiency of subsequent rib modeling, this study adopted an outlier removal method to process the rib point cloud data, specifically using a combination of outlier removal and PointTransformer model segmentation to obtain high-quality rib point cloud data.

By using Formula (1), we obtain $n$ point cloud data that needs to be denoised. Using the KNN method, we adaptively select neighboring points for each point, and use Formula (2) to obtain $K$ neighboring points for each point.

\[
p = \{p_1, p_2, p_3, \ldots, p_n\} \tag{1}
\]

\[
p_i = \{p_{i1}, p_{i2}, p_{i3}, \ldots, p_{ik}\} \tag{2}
\]
Using Formula (3), we can calculate the number of neighboring points to obtain the point density $c_i$ for each point. Then, using Formula (4), we can calculate the average distance $d_i$ between each point and its neighboring points.

$$c_i = k, i = 1,2, \ldots, n \quad (3)$$

$$d_i = \frac{1}{k} \sum_{j=1}^{k} ||p_i - p_{ij}||, i = 1,2, \ldots, n \quad (4)$$

By setting thresholds for point density and average distance, we can use Formula (5) to determine whether each point satisfies the following conditions: the point density $c_i$ is greater than the point density threshold $c_{th}$, and the average distance $d_i$ is smaller than the average distance threshold $d_{th}$. For points that do not meet these conditions, we consider them as noise points and remove them.

$$c_i > c_{th} \text{ and } d_i < d_{th} \quad (5)$$

After removing the noise points, we use the Gaussian kernel smoothing method to smooth the point cloud data, and use Formula (6) to obtain the optimized point cloud data.

$$p_i'' = \frac{\sum p_j' \in N(p_i') e^{\frac{-||p_j' - p_i'||^2}{2\sigma^2}}}{\sum p_j' \in N(p_i') e^{\frac{-||p_j' - p_i'||^2}{2\sigma^2}}}, i = 1,2, \ldots, n \quad (6)$$

Where $p_i''$ is the coordinate of the point cloud after Gaussian kernel smoothing, $N(p_i')$ is the set of neighboring points of the point $p_i'$, $p_j'$ is one of the neighboring points, $\sigma$ is the width of the Gaussian kernel, and $||p_i' - p_j'||$ is the distance between points $p_i'$ and $p_j'$. Additionally, in this study, we used the Point Transformer point cloud semantic segmentation model [28] to extract the rib region from the point cloud data after the above process, removing residual noise points and non-rib point clouds to obtain accurate and high-quality rib point cloud data.

As shown in Fig. 3, during the inference stage, a single test sample CT image was converted to point cloud data and processed with point cloud adaptive smoothing and denoising. Specifically, after removing noise points to obtain the point cloud data to be segmented, we sampled the point set in batches of 50K points and shuffled the point sets to comply with the unordered principle of point clouds. The shuffled point sets were then fed into the PointTransformer loaded with the best weights to obtain the predicted rib point cloud. The predicted results of each point set were visualized using partial point cloud labels. Finally, all the partial point cloud predictions were merged to obtain the complete rib point cloud prediction. Multiple predictions were made using majority voting to improve prediction accuracy. After obtaining the complete point cloud prediction, 3D reconstruction and post-processing operations were performed to obtain the 3D reconstruction results of the ribs.

C. 3D Reconstruction and Post-processing
During the reconstruction process, we used a point-based surface reconstruction algorithm, which can generate accurate and smooth 3D models of ribs. After reconstruction, we post-processed the generated 3D models to eliminate any errors introduced during the reconstruction process and obtain high-precision and comprehensive 3D reconstruction results for ribs.

Firstly, for each point, we used formulas (7) and (8) to calculate the average distance $u_i$ and standard deviation $\sigma_i$ of its K nearest neighbors, and used formula (9) to determine whether each point was an outlier by comparing its distance with the sum of the average and a certain multiple of the standard deviation. All data judged to be outliers were removed from the predicted point cloud.

$$u_i = \frac{1}{k} \sum_{p_j \in N(p_i)} \| p_i - p_j \| \quad (7)$$

$$\sigma_i = \sqrt{\frac{1}{k} \sum_{p_j \in N(p_i)} (\| p_i - p_j \| - \mu_i)^2} \quad (8)$$

$$\| p_i - \mu_i \| > t * \sigma_i$$

Secondly, we converted the predicted point cloud data and corresponding labels to 3D matrices with the same size as the original CT image, determined the number of connected regions in the matrix, and removed smaller connected regions to eliminate non-rib structures. We used morphological closing operations (dilation followed by erosion) to smooth the segmented rib point cloud data. Finally, we set a filter window size, counted the number of occurrences of predicted point cloud labels within the window, and selected the label value with the highest occurrence as the mode of the window to smooth misclassified points in the rib point cloud prediction labels.

V. EXPERIMENTS

To validate the effectiveness of the proposed rib 3D reconstruction method based on point cloud adaptive smoothing and denoising, we designed a series of experiments to evaluate its performance. The experiments mainly consisted of the following parts:

A. Dataset

In this study, we used the publicly available CT rib datasets RibFrac [29] and RibSeg [30], which contain CT images of patients with different ages, genders, and disease states. The mask files in RibSeg were labeled with a uniform voxel value of 1 for ribs. However, to distinguish between different ribs during 3D reconstruction, we needed to label ribs with different voxel values. Therefore, we uniformly labeled each rib in the mask file. Firstly, we analyzed the connected domains in the CT images to obtain their centroid coordinates and identified whether they were left or right ribs based on the X component of the centroid coordinates. Secondly, we determined the order of the ribs based on the Y and Z components of the
centroid coordinates, and labeled each rib with a unique voxel value (1–12 and 13–24) in the order of the ribs. Finally, we visually inspected the labeled voxels for each rib and corrected any labeling errors to ensure accurate annotation.

As shown in Fig. 4, we obtained a mask file with 24 ribs labeled with different voxel values based on the above labeling method. We preprocessed these images, including HU value filtering, to generate point cloud data suitable for this experiment. As shown in Table 1, the dataset was divided into training, validation, and testing sets, with a reasonable distribution of 8:1:1 for the three sets to evaluate the performance of the model.

Table  Dataset Partition Table

<table>
<thead>
<tr>
<th>Set partition</th>
<th>Number of CT scans (count)</th>
<th>Number of point clouds (count)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Train set</td>
<td>290</td>
<td>72508 0000</td>
</tr>
<tr>
<td>Validation set</td>
<td>37</td>
<td>8884 0000</td>
</tr>
<tr>
<td>Test set</td>
<td>37</td>
<td>9621 0000</td>
</tr>
</tbody>
</table>

B. Experimental Setup

In terms of the training settings for rib segmentation, we balanced the dependence on hardware resources between input size and batch size. We set the number of downsampled point clouds per training iteration to 10K, used the AdamW optimizer, trained for 300 epochs, and set the batch size to 8. The learning rate was updated using a warm-up cosine annealing method, with a warm-up period of 15 epochs, a maximum learning rate of 0.1, and a minimum learning rate of 0.00001. Point cloud data was normalized to the point cloud center and augmented with random rotation, random perturbation, and scaling. The cross-entropy loss was used as the loss function to optimize the model parameters.

C. Evaluation Metrics

To evaluate the proposed method in this study, we compared it with the traditional voxel-based rib 3D reconstruction method. The inference testing was conducted on a machine with a Linux operating system and four GeForce 3090Ti GPUs using PyTorch 1.11.0 and Python 3.9. In the experiment, we focused on the following evaluation metrics: reconstruction accuracy and reconstruction time. To measure the difference between the reconstructed ribs and the true ribs, we calculated the root-mean-square error (RMSE) between the reconstructed ribs and the true ribs to evaluate the reconstruction accuracy of a single test sample:

\[
RMSE = \sqrt{\frac{1}{N} \sum (P_i - Q_i)^2}
\]
where $P_i$ and $Q_i$ represent the coordinates of the i-th point on the reconstructed ribs and true ribs, respectively, and $N$ is the total number of paired points. A smaller RMSE value indicates higher reconstruction accuracy.

To measure the time required for rib reconstruction, we calculated the time required for the complete execution of the reconstruction method to evaluate the reconstruction time of a single test sample (Time).

**D. Experimental Results**

To validate the effectiveness of the proposed point cloud adaptive smoothing and denoising method and compare the effect of different parameters on point cloud adaptive smoothing and denoising, we took the original point cloud data as the experimental object. By setting different point density thresholds ($c_{th}$) and average distance thresholds ($d_{th}$), and setting a random seed during the use of the semantic segmentation model to ensure segmentation prediction invariance, we finally obtained the denoised rib point cloud. The denoising effect was evaluated by calculating the mean root-mean-square error (Mean RMSE) between the denoised rib point cloud and the standard rib point cloud for all test samples. As shown in Table 2, this experiment tested the mean RMSE obtained with three different sets of average distance thresholds (4, 5, and 6) corresponding to point density thresholds of 0.25, 0.15, and 0.05, respectively. The mean RMSE obtained with a point density threshold of 0.15 was generally lower than that obtained with point density thresholds of 0.25 and 0.05. In addition, with a fixed point density threshold, the average distance threshold of 5 was found to be the best based on the mean RMSE values obtained with the three different sets of average distance thresholds.

Table  Metrics Table for Point Cloud Adaptive Smoothing Denoising Algorithm
As shown in Fig. 5(a), one of the test samples was selected for visualization to observe the human body point cloud model before denoising. Then, the outlier removal step in our point cloud adaptive smoothing and denoising algorithm was used to process the noisy points, with the three sets of point density thresholds and the corresponding best average distance thresholds as described above. As shown in Fig. 5(b), when the point density threshold and average distance threshold were set to 0.25 and 5, respectively, bone tissue fracture occurred, as indicated by the red circle, indicating an over-denoising state. As shown in Fig. 5(c), when the point density threshold and average distance threshold were set to 0.05 and 5, respectively, noise point attachment occurred, as indicated by the red circle, indicating an under-denoising state. As shown in Fig. 5(d), when the point density threshold and average distance threshold were set to 0.15 and 5, respectively, the bone structure was clear and complete, and the best denoising effect was obtained.

To validate the effectiveness of the proposed research method, we compared and evaluated three different rib 3D reconstruction methods. The first method was a voxel-based rib 3D reconstruction method that used the convolutional neural network nnUnet[31] for rib segmentation, followed by 3D modeling software to generate a more accurate rib 3D model through post-processing operations such as texture mapping. The second method used the commonly used point cloud segmentation model PointNet for rib segmentation, followed by post-processing to achieve rib 3D reconstruction. The third rib 3D reconstruction method was based on the PointTransformer model used in this study for rib segmentation,
followed by post-processing to achieve rib 3D reconstruction, but did not use the outlier removal and post-processing methods in our point cloud adaptive smoothing and denoising algorithm. We generated rib 3D models using all of these methods as well as our proposed rib 3D reconstruction method based on point cloud adaptive smoothing and denoising for all CT scans in the test set, and calculated their corresponding RMSE and TIME metrics to obtain the average root-mean-square error (Mean RMSE) and average reconstruction time (Mean TIME). As shown in Table 3, the voxel-based rib 3D reconstruction method had the highest average RMSE and longest average reconstruction time among the four methods, indicating the limitations of using voxel segmentation for rib 3D reconstruction. The three point cloud-based rib 3D reconstruction methods had roughly half the reconstruction time of the voxel-based method, demonstrating the efficiency of point clouds. The method using the PointNet model had a higher average RMSE and was unable to obtain high-precision rib 3D reconstruction results. However, after using the PointTransformer model, the average RMSE was reduced by 75 percentage points compared to the former, and the reconstruction accuracy was greatly improved. When using our method, the outlier removal step was performed before using the PointTransformer model, and the average RMSE was reduced by 69 percentage points with the help of the innovative 3D reconstruction post-processing method, leading the performance indicators of the other three methods. As shown in Fig. 4.4, the distribution of RMSE and TIME values obtained from the two methods for each CT scan in the test set is shown. As shown in Fig. 6(a), the overall RMSE values obtained by the four methods gradually decreased, and the RMSE values of each CT scan obtained by our proposed method were significantly lower than those of the other methods. As shown in Fig. 6(b), the reconstruction time of each CT scan obtained by the voxel-based method was generally high, while the reconstruction time of our proposed method and the other two point cloud-based methods were roughly the same.

Table  Performance Comparison Table

<table>
<thead>
<tr>
<th>Method</th>
<th>Mean RMSE(mm)</th>
<th>Mean TIME(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voxel-based(nnUnet)</td>
<td>3.86</td>
<td>85.01</td>
</tr>
<tr>
<td>PointCloud-based(PointNet)</td>
<td>3.72</td>
<td>42.36</td>
</tr>
<tr>
<td>PointCloud-based(PointTransformer)</td>
<td>2.97</td>
<td>42.45</td>
</tr>
<tr>
<td>Point cloud denoising(ours)</td>
<td>2.28</td>
<td>42.58</td>
</tr>
</tbody>
</table>

E. Ablation Experiment

To verify the effectiveness of the post-processing method described in this paper, we conducted ablation experiments on the post-processing method. As shown in Table 4, to compare the effects of each stage of the post-processing method on point cloud 3D reconstruction and post-processing, we used the point cloud data before post-processing as the experimental object and obtained the post-processed point clouds at different stages. We calculated the root-mean-square error (RMSE) between the post-processed rib point cloud at each stage and the standard rib point cloud for all samples in the test set, and obtained the average RMSE to evaluate the post-processing effect. Without post-processing, the quality of the
obtained rib point cloud was low, with many outliers, irregular regions, and misclassified points, resulting in a high RMSE. After outlier removal, a large number of outliers were removed, and the quality of the rib point cloud was improved, resulting in a 12 percentage point decrease in RMSE. After point cloud data smoothing, the holes formed by the predicted rib area were filled, and a smooth rib area was obtained, resulting in a 10 percentage point decrease in RMSE. After point cloud label smoothing, many prediction errors in the predicted rib point cloud were smoothed out, and the prediction labels of each independent rib point cloud were greatly improved in correctness, resulting in an 11 percentage point decrease in RMSE.

Table: Performance Comparison Table of Post-processing Stages

<table>
<thead>
<tr>
<th>Data Removal</th>
<th>Data Smoothing</th>
<th>Label Smoothing</th>
<th>Mean RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>✓</td>
<td></td>
<td>2.61</td>
</tr>
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</tr>
<tr>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>2.28</td>
</tr>
</tbody>
</table>

F. Post-processing Visualization Analysis

As shown in Fig. 7, we visualized the post-processing effect on a test sample that had undergone point cloud adaptive smoothing and denoising. This sample had some misclassified points, which were either non-rib point clouds misclassified as rib point clouds, such as some colored point clouds above the left and right ribs, or a single rib point cloud predicted as another rib point cloud, such as some other colored point clouds on each rib. After the post-processing algorithm, the isolated misclassified points above the ribs were removed, and the predicted labels of the point cloud data on each rib were smoothed out, greatly enhancing the visualization effect of the ribs.

G. Limitations and Future Research Directions

The current research has achieved a certain level of rib cage 3D reconstruction performance, but for certain specific applications, such as precise surgical planning or prediction, further improvement of the accuracy and realism of the reconstruction may be necessary. Therefore, it is necessary to research more accurate reconstruction algorithms or utilize additional data sources (such as MRI, CT, etc.) to improve the 3D reconstruction results of the rib cage.

In addition, the current reconstruction process may have efficiency issues when dealing with large-scale point cloud data. This could become a challenge for real-time or near real-time applications, such as robot control. Therefore, algorithm optimization or parallel computing techniques are needed to improve the speed of point cloud adaptive smoothing denoising and 3D reconstruction to meet the demands of real-time or near real-time applications. These future research directions will help us to have a more
comprehensive and in-depth understanding of the problem of rib cage 3D reconstruction and promote the progress of this field.

V. CONCLUSION

This paper proposes a rib cage 3D reconstruction method based on point cloud adaptive smoothing denoising, which addresses the limitations of voxel-based rib cage 3D reconstruction methods, such as low accuracy and efficiency. This method relies on the advantages of point cloud data over voxel data in terms of data accuracy and processing speed, and uses a suitable point cloud denoising algorithm to effectively remove non-rib cage point clouds. Then, an effective post-processing method for 3D reconstruction is used to obtain a complete and accurate rib cage point cloud, achieving superiority in both reconstruction accuracy and computational efficiency. The experimental results confirm the effectiveness and practicality of this method in the field of rib cage 3D reconstruction, providing a new solution for related fields. In future research, we will continue to optimize the model structure and parameters to further improve reconstruction quality and computational efficiency, while exploring the possibility of applying this method to more medical imaging tasks.

Declarations

Competing interests The authors declare that they have no conflict of competing interests.

Authors contribution statement Guarantors of integrity of entire study, all authors; study concepts/study design, Bishi He, Diao Wang, Darong Zhu; data acquisition, Darong Zhu, Zhe Xu, Yuanjiao Chen; data analysis and interpretation, Bishi He, Diao Wang, Darong Zhu; manuscript drafting or manuscript revision for important intellectual content, Bishi He, Darong Zhu, Diao Wang; approval of final version of submitted manuscript, all authors; agrees to ensure any questions related to the work are appropriately resolved, all authors; experimental studies, all authors.

Ethical and informed consent for data used The datasets analyzed during this study are obtained from public datasets.

RibFrac: https://ribfrac.grand-challenge.org/

RibSeg: https://github.com/M3DV/RibSeg

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References


Figures

Figure 1

Framework of Rib Cage 3D Reconstruction Method Based on Point Cloud Adaptive Smoothing Denoising.
Figure 2

Comparison of Point Cloud Data Attribute Effects.

Figure 3

Schematic Diagram of Point Cloud Inference Stage
Figure 4

Schematic Diagram of Independent Labeling of Ribs
Figure 5

Example Illustration of the Effect of Point Cloud Adaptive Smoothing Denoising Algorithm, where $c_{th}$ represents the point density threshold and $d_{th}$ is the average distance threshold.
Figure 6

Distribution of RMSE and TIME Values for All Samples in the Test Set for Four Experimental Methods

Figure 7

Post-processing Effect of Point Cloud 3D Reconstruction