SB³C2024
Summer Biomechanics, Bioengineering and Biotransport Conference
June 11-14, Lake Geneva, WI, USA

ADVANCING 3D ORGAN GEOMETRIC RECONSTRUCTION FROM MRI: A HYBIRD FRAMEWORK WITH DEEP LEARNING AND ITERATIVE OPTIMIZATION

Hui Wang (1)(2), Xiaowei Li (3), Chenxin Zhang (1)(2), Jianwei Zuo (1)(2), Xiuli Sun (3), Jianliu Wang (3), Jiajia Luo (1)(2)

(1) Institute of Medical Technology, Peking University Health Science Center, Beijing, China
(2) Biomedical Engineering Department, Peking University, Beijing, China
(3) Department of Obstetrics and Gynecology, Peking University People's Hospital, Beijing, China

INTRODUCTION

Reconstructing 3D organ geometric models from magnetic resonance imaging (MRI) is essential in numerous fields, such as patient-specific solid biomechanical numerical simulations [1], computer-aided diagnosis, treatment and prognosis, and virtual surgical planning. Using high-quality 3D geometric models precisely depicts organ spatial architecture, crucial for finite element analysis. Typically, conventional methods involve either manual or automatic segmentation of 2D MRI slices, followed by several post-processing steps such as reconstructing 3D geometric models, repairing complex geometries, and manually partitioning meshes [2]. The shapes of many organs are complex and diverse, often requiring a significant amount of effort to create high-quality 3D geometric models. The reconstruction process is complicated, tedious, and time-consuming, taking several hours or even days. Furthermore, the consistency of reconstruction results varies with different technicians, limiting its practicality for large-scale analysis.

As an alternative to traditional reconstruction methods, deep learning approaches exhibit great potential in reconstructing 3D geometric models, demonstrating fast execution time and desirable geometric quality. These techniques are categorized into implicit and explicit methods. Implicit methods achieve indirect reconstruction of 3D models by predicting the implicit surface using the signed distance function (SDF) [3], but still necessitate laborious post-processing steps like iso-surface extraction and mesh correction. Explicit methods, which include direct shape prediction and deformable shape modeling, tackle various challenges. The first approach, dependent on loss functions for quality control [4], struggles with training and is limited to simpler geometries. The second, focusing on template geometry deformation to fit the target [5], solves some of these difficulties. However, it presents challenges in designing adaptable templates for different organs and ensuring uniform application across diverse organ reconstructions.

In this work, our aim was to develop a unique hybrid framework for deformable shape modeling. This framework integrates deep learning with iterative optimization to streamline the reconstruction of high-quality 3D organ models from 3D MRI, enabling a flexible tradeoff between reconstruction time and model quality.

METHODS

Figure 1 illustrates our framework's architecture, showcasing inputs and outputs. For instance, 3D MRIs are processed to predict the organ model. Initially, the MRIs undergo segmentation, either manually or automatically. The resulting segmentations are converted into point clouds, which represent the organ boundaries. These points are then normalized within a -1 to 1 range. The deep learning module then processes these point clouds, predicting displacements for spherical template deformation. These displacements serve as initial inputs for the

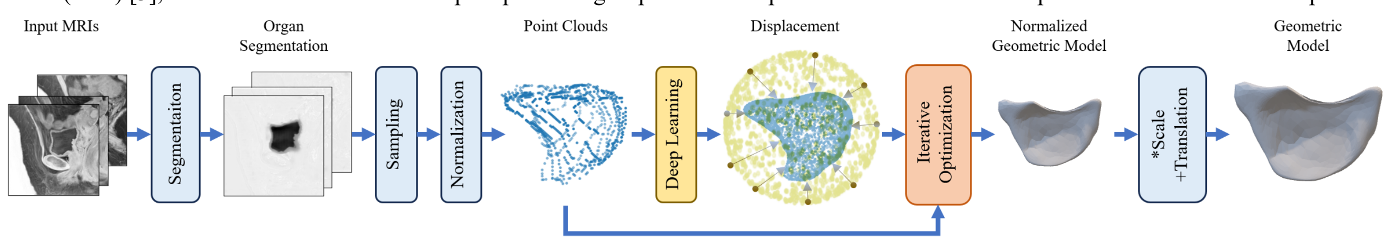

Figure 1: Our framework's architecture

iterative optimization module, refining the organ models. Finally, the resulting model is scaled and positioned by reversing normalization process to form the final 3D organ geometric model.

Algorithm 1: Training

Input: $Pointcloud_{train}, Mesh_{sphere}$
$Displacement_{train} = 0\ (Zero\ Matrix)$
for $iter = 1 \rightarrow T$ **do**
  $Mesh_{train} = Mesh_{sphere} + Displacement_{train}$
  $Displacement^{*}_{train} = \underset{Displacement_{train}}{\operatorname{argmin}} [Loss_{CD}(Pointcloud_{train}, Mesh_{train}) + Loss_{ENL}(Mesh_{train})]$
end for
$\theta_{train} = \theta_0$
repeat
  $Displacement_{train} = NN_{\theta_{train}}(Pointcloud_{train}, Mesh_{sphere})$
  $\theta^{*}_{train} = \underset{\theta_{train}}{\operatorname{argmin}} [\mathbb{E}_{training\_set}[Loss_{MSE}(Displacement^{*}_{train}, Displacement_{train})]]$
until converged
Output: θ^{*}_{train}

Algorithm 2: Inference

Input: $Pointcloud_{infer}, Mesh_{sphere}, \theta^{*}_{train}$
$\theta_{infer} = \theta^{*}_{train}$
$Displacement_{infer} = NN_{\theta_{infer}}(Pointcloud_{infer}, Mesh_{sphere})$
for $iter = 1 \rightarrow T$ **do**
  $Mesh_{infer} = Mesh_{sphere} + Displacement_{infer}$
  $Displacement^{*}_{infer} = \underset{Displacement_{infer}}{\operatorname{argmin}} [Loss_{CD}(Pointcloud_{infer}, Mesh_{infer}) + Loss_{ENL}(Mesh_{infer})]$
end for
$Mesh_{infer} = Mesh_{sphere} + Displacement^{*}_{infer}$
Output: $Mesh_{infer}$

NN represents the deep learning network. The symbol θ denotes the network's parameters. The minimum value of the variable post-iteration is identified with an asterisk (*). $\mathbb{E}_{training\_set}[]$ signifies the expected outcome of the enclosed expression within the training set.

Figure 2: The algorithm of the training and inference pipeline.

Figure 2 depicts the algorithm of the deep learning and the iterative optimization modules for both training and inference. In training, the iterative optimization module searches for optimal displacement, aiming to minimize the Chamfer Distance (CD) between deformed geometry and input point clouds, augmented with loss function ENL (Edge Loss, Normal Loss, and Laplacian Loss [1]) for geometric model quality. These optimal values are the ground-truth for deep learning training. During inference, the trained deep learning model predicts displacement, initializing the optimization module's further refinement, resulting in the final organ geometric model.

Figure 3 shows the deep learning module's structure. Initially, EdgeConv [6] extracts features from the input point clouds and spherical template individually. These features are combined using a multi-head cross-attention module, followed by spatial feature transformation through EdgeConv. An alternating structure of convolutional neural network (CNN) and self-attention modules is then used for encoding and decoding. Ultimately, EdgeConv is used to perform spatial transformation on the output features, yielding the final displacement values.

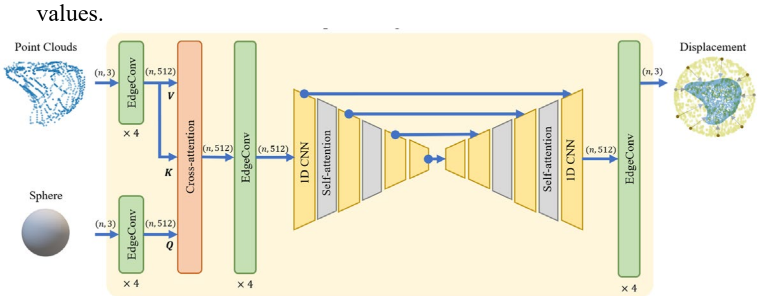

Figure 3: The structure of the deep learning module.

We utilized the Mean Squared Error (MSE) loss function for predicting deep learning displacement. Both CD and Hausdorff Distance (HD) are used as the evaluation metrics.

For training, we adopted the Adam optimizer with a learning rate $1e^{-4}$ and a batch size of 1 across all experiments. The network was implemented using Python 3.8.8, and Pytorch 1.12.0, and executed on an Nvidia Titan RTX graphic card with 24GB of computational memory.

We constructed a 3D MRI dataset of 100 subjects from Peking University People's Hospital. Specifically, the T2 3D sagittal MR data of each subject at rest were used. The MR images had a 2 mm spacing and slice thickness. The dataset was randomly divided into training, validation, and testing sets at a 6:2:2 ratio by subject. During training, we ran 10,000 iterations to ensure optimal reconstruction for each organ. To prove the effectiveness of our approach, we compared it with three other advanced 3D organ reconstruction deep learning methods, including Voxel2mesh [5], MR-net [1], and MeshDeform-Net [7]. To address the significant size discrepancies among individuals and their organs, we adopted a normalized geometric model for quantitative assessments.

RESULTS

Table 1: 3D reconstruction performance on the testing set.

	Bladder		Uterus		Rectum		Levator	
Methods	CD$_{(mm)}$	HD$_{(mm)}$	CD$_{(mm)}$	HD$_{(mm)}$	CD$_{(mm)}$	HD$_{(mm)}$	CD$_{(mm)}$	HD$_{(mm)}$
Voxel2mesh	0.0574	0.7469	0.0887	0.8462	0.0356	0.6227	0.0281	0.5936
MR-net	0.0535	0.7609	0.0875	0.8580	0.0383	0.6052	0.0226	0.5869
MeshDeformNet	0.0467	**0.6647**	0.0732	0.8949	0.0348	0.7189	0.0235	0.5364
Ours	**0.0399**	0.7005	**0.0705**	**0.8287**	**0.0263**	**0.5210**	**0.0190**	**0.5036**

The testing results of the 3D reconstruction, along with comparative analysis, are summarized in Table 1, where smaller metrics indicate better results. Additionally, Figure 4 displays the 3D reconstruction and runtime results for four organs (bladder, uterus, rectum, and levator) of a subject from the testing set. These results suggest that our 3D reconstruction closely matches the ground-truth, and the iterative optimization module improves reconstruction quality without the lengthy runtime typical of traditional methods.

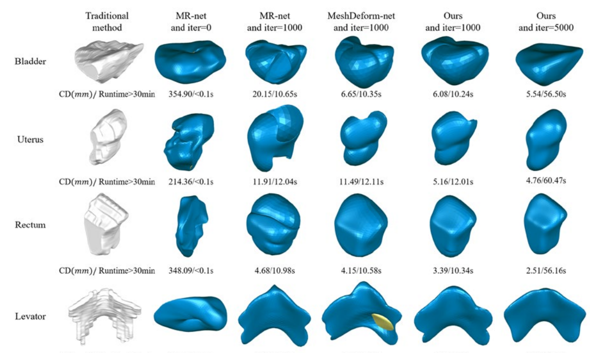

Figure 4: A visual comparison of 3D reconstruction results. The yellow area in the result signifies the bad self-intersection issue.

DISCUSSION

This study introduces a unique hybrid framework for deformable shape modeling, combining deep learning with an iterative optimization module to streamline the reconstruction of high-quality 3D organ models from 3D MRI. The experimental results demonstrate that our framework effectively balances reconstruction speed and quality, proving versatile for various complex organs. Looking ahead, expanding the training dataset is anticipated to further enhance the reconstruction process.

ACKNOWLEDGEMENTS

National Key R&D Program of China 2023YFC2411201, NSFC Grant 31870942, Peking University Clinical Medicine Plus X-Young Scholars Project PKU2020LCXQ017 and PKU2021LCXQ028, PKU-Baidu Fund 2020BD039.

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