SB³C2022
Summer Biomechanics, Bioengineering and Biotransport Conference
June 20-23, Eastern Shore, MD, USA

LEARNING WHOLE HEART MESH GENERATION FROM PATIENT IMAGES FOR COMPUTATIONAL SIMULATIONS

Fanwei Kong and Shawn C. Shadden

Department of Mechanical Engineering
University of California, Berkeley
Berkeley, California, USA

INTRODUCTION

Patient-specific cardiac modeling combines geometries of the heart derived from medical images and biophysical simulations to simulate various aspects of cardiac function. It can provide useful physiological information non-invasively to facilitate understanding, diagnosis and treatment planning of cardiac diseases for individual patients [1]. However, generating simulation-suitable meshes of the heart from patient image data often requires complicated procedures and significant human efforts, limiting clinical translations. We are thus motivated to develop fast and automated methods to construct simulation-ready meshes of the heart from medical images.

Deep learning methods can train neural networks from existing data to automatically process medical images and generate whole heart reconstructions. While most prior deep learning methods have focused on image segmentation, our recent approaches directly reconstructed surface meshes from patient image data [2-3]. By deforming a surface mesh template, our previous methods eliminate the intermediate segmentation step that sometimes introduce extraneous regions containing topological anomalies that are unphysical and unintelligible for simulation-based analyses [2]. We have also combined free-form deformation (FFD) with deep learning to predict the displacement of a control point grid to deform the space enclosing a simulation-ready whole heart template, thus enabling direct reconstruction of simulation-ready meshes from image data [3].

However, since FFD has limited capability for complex shape deformation, our prior method requires a dense control point grid including thousands of control point to achieve acceptable whole heart reconstruction accuracy [3]. Here we propose a new deep-learning approach that leverage biharmonic coordinates to deform the whole heart template to fit the target image data with higher accuracy and using far less control points. We also introduce a few effective learning biases as objective functions to produce meshes that better satisfy the modeling requirements for computational simulation of cardiac flow.

METHODS

Dataset: We trained our method with 87 contrast-enhanced CT images and 41 MR images that cover the whole heart [3]. 15 CT images and 6 MR images were used for validation. The final performance of our model was evaluated on the MMWHS held-out test dataset that contains 40 CT and 40 MR images [4], as well as time-series CT images.

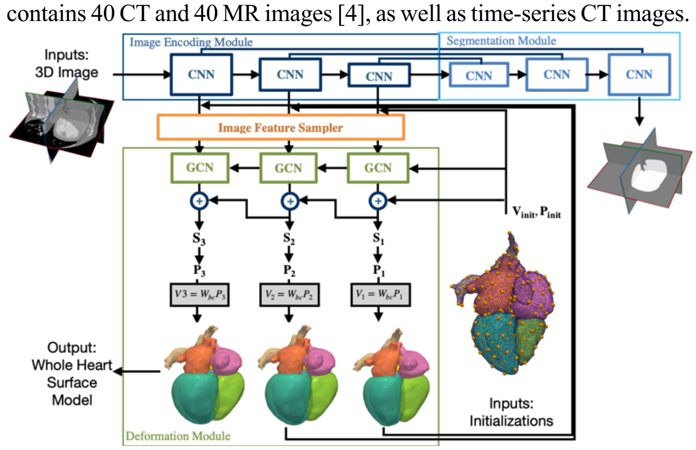

Figure 1: Proposed automatic whole heart reconstruction approach

Shape Deformation Using Biharmonic Coordinates: Our approach constructs whole heart meshes by deforming a pre-defined whole heart mesh template. We parameterize the deformations with the translations of a small set of deformation handles uniformly sampled from the mesh template. Given a set of mesh vertices $V \in R^{n\times 3}$ and a set of control points $P \in R^{c\times 3}$, we compute the biharmonic coordinates $W \in R^{n\times c}$, which is a linear map, $V = WP$. W is pre-computed by minimizing a quadratic deformation energy function while satisfying the handle constraints with linear precision [5].

Neural Network Architecture: As shown in Fig 1, our framework first uses an image encoding module that extracts and encodes image features. These features are used as inputs to graph convolutional layers to predict the displacements of mesh vertices ($S \in R^{n\times 3}$) from their previous locations. We then select control handles ($P \in R^{c\times 3}$) from the updated mesh vertex locations to deform the template. The shape deformation module consists of three deformation blocks that progressively deform mesh templates, using increasing number of control handles (75, 150 and 600, respectively). We also use a segmentation module that predict a binary segmentation map to enable additional supervision using ground truth annotations.

Neural Network Optimization: 3D ground truth meshes of the whole heart extracted from manual segmentations were used to supervise the training of the neural network model. We used point and normal consistency losses to supervise the geometric consistency between the prediction and the ground truth. In contrast to [2], which uses edge length and Laplacian regularization losses, the smoothness of the mesh prediction is naturally constrained by the biharmonic coordinates used to deform the template. For CFD simulation of cardiac flow, the inlet and outlet vessel geometries need to be trimmed to have planar faces orthogonal to the vessel walls. We thus applied a co-planar loss on the cap that penalizes the L2 differences of surface normal vectors among mesh vertices on the caps. For mesh vertices that are on the vessel walls near the caps, we minimize the absolute value of the dot products between their surface normal vectors and the surface normal vector of the caps to encourage orthogonality. As geometries of inlet vessels are important to the accuracy of CFD results, we applied a higher weight of the geometric consistency loss on mesh vertices that are located on vessel walls near the inlets.

RESULTS

We compare the performance of whole-heart reconstructions from our method against two mesh reconstruction methods, HeartFFDNet [3] that learns FFD to deform mesh template of the heart, MeshDeformNet [2] that learns to predict displacements from sphere mesh templates, as well as two segmentation methods, 2D UNet [6] and a modified 3D UNet [7].

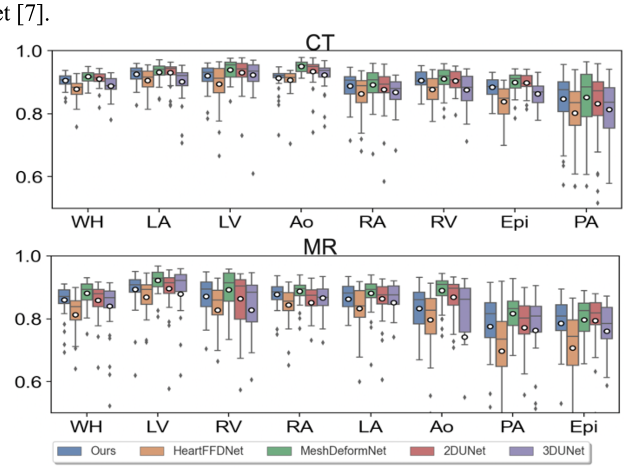

Figure 2: Dice scores of different methods on MMWHS test set

Figure 1 shows the average Dice score (a similarity index) of the reconstruction results of both the whole heart and individual cardiac structures for the MMWHS test dataset. For both CT and MR data, our method consistently outperformed HeartFFDNet and 3D UNet and achieved comparable performance with MeshDeformNet and 2D UNet. Figure 3 compares the reconstructed whole heart geometries from different methods for time-series CT images. From end-diastole to end-systole, mesh-based methods produced more anatomically and temporally consistent geometries than segmentation-based methods (the UNets). MeshDeformNet is prone to gaps between adjacent cardiac structures since it deforms uncoupled spheres to represent separate structures. Our method avoids this issue by deforming a realistic whole heart template. Compared with HeartFFDNet, we used far less control points (600 vs 4096) and achieved better accuracy.

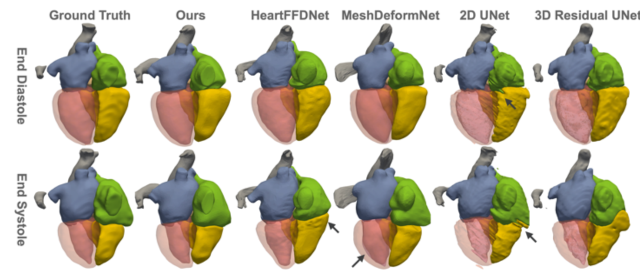

Figure 3: Qualitative comparisons for time-series CT images

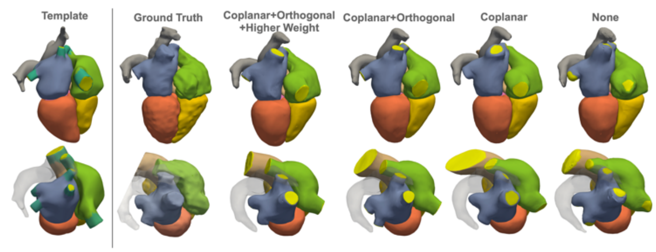

Figure 4: Contribution of different loss components on vessel inlet geometries. 1st column shows the template mesh with caps tagged in yellow and walls tagged in turquoise.

Figure 4 demonstrates the effect of adding individual loss components on the predicted inlet and outlet geometries (pulmonary veins, vena cava, and aorta). The coplanar loss and the orthogonal loss succeeded in producing planar cap geometries that are orthogonal to vessel walls. Applying a higher weight on the inlet mesh vertices in the geometric consistency loss improved the accuracy of inlet geometries.

DISCUSSION

Automated image-based reconstruction of cardiac meshes is important for computational simulation of cardiac physiology. We have demonstrated a novel approach for automated image-based cardiac model reconstruction that is generally more geometrically accurate than our prior approach [4] while at the same time better satisfying modeling requirements for cardiac flow simulations. Our approach can automatically construct whole heart meshes within seconds on modern desktop computers. Once being trained on the whole heart template, the network can deform alternative template meshes that represent a subset of the geometries in the template to accommodate different modeling requirements, by interpolating the biharmonic coordinates onto new template meshes. Future work will focus on validating the reconstructed meshes for CFD simulation of cardiac flow.

ACKNOWLEDGEMENTS

This work was supported by the NSF, Award #1663671.

REFERENCES

[1] Prakosa et al., *Nature Biomed Eng*, 2(10), Oct, pp. 732–740, 2018.
[2] Kong et al., *Medical Image Analysis* 74 (1), 102222, 2021.
[3] Kong et al., *MICCAI*, *Springer* pp. 550-559, 2021
[4] Zhuang et al., *Med Image Analysis*, 58, 101537, 2019.
[5] Wang et al., *ACM Transactions on Graphics* 34(4), 2015.
[6] Ronneberger et al., *MICCAI*, *Springer*, pp 234-241, 2015.
[7] Isensee et al., *MICCAI*, *Springer* pp. 287–297, 2017.