

Creating 3D Heart Models of Children with Congenital Heart Disease using Magnetic Resonance Imaging

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Purpose: Whole-heart magnetic resonance angiography is appealing for planning interventions in children and adults with congenital heart disease [1]. A free-breathing 3D electrocardiogram and respiratory navigator-gated steady-state free precession sequence (3D SSFP) is commonly used to acquire high-resolution images of the heart and evaluate intra-cardiac and vascular abnormalities [2]. However, visualizing the 3D image data remains challenging. Clinicians typically slice through 2D images of the 3D SSFP image, and must mentally integrate these 2D images to form their impression of the 3D heart geometry and interpret spatial relationships. 3D surface heart models have potential for improving procedural planning by enabling simultaneous viewing of the ventricles, great vessels and anatomical defects in three dimensions. Creating surface models requires image segmentation to delineate the blood pool and epicardial surfaces (including the great vessel walls) [3]. This is typically done manually, necessitated by the intensity inhomogeneities, low contrast and thin walls in 3D SSFP cardiac images. Manual segmentation can require ~8 hours per image. Our goal is to develop a robust semi-automatic segmentation algorithm to reduce the interaction time to less than 1 hour, allowing patient-specific heart models to be created in clinical practice (Fig. 1).

Methods: 3D SSFP datasets were acquired from 4 children with complex congenital heart disease as a clinical routine on a 1.5T MR scanner (Philips Achieva) with a 32 element coil and the following imaging parameters: voxel size reconstructed to ~1 mm³, TR/TE/ α 3.4/1.7/60° and SENSE factor 2. Scan time was 5-15 minutes. Cardiac motion was minimized by confining the acquisition to a short rest period of the heart in each cardiac cycle (50-100 ms). The respiratory-induced heart motion was compensated for by only accepting data acquired within a narrow acceptance window around end expiration (3-5 mm). The 3D SSFP datasets were reconstructed online and analyzed retrospectively for segmentation. The 3D SSFP datasets were manually segmented to serve as a gold standard. In our proposed semi-automatic segmentation algorithm, only 10-15 short-axis "reference" slices (out of 100-200) are manually segmented, which can be done in less than 1 hour of interaction time. The blood pool and epicardium labels are automatically propagated through the remaining dataset using a patch-based segmentation algorithm [4]. For each image patch within a new slice to be segmented, the ten most similar patches within the two closest reference slices are found. The similarity between two patches is a function of their intensities, intensity gradients, and physical locations in the image. The segmentations of the ten most similar reference patches vote for their labels to determine the labeling of the new patch. Finally, we used open-source visualization toolkits (3D Slicer and Paraview) to create heart surface models from the resulting segmentations. The accuracy of the proposed semi-automatic segmentation algorithm was quantified by comparing it to manual segmentation. In this study, the reference slices were extracted from the 3D manual segmentation. The accuracy metrics were (1) absolute surface-to-surface distances between surface models and (2) volume overlap of the blood pool and epicardium label maps (1 indicates perfect agreement).

Results: Fig. 2 compares the proposed patch-based segmentation algorithm with manual segmentation. The accuracy metrics comparing the proposed semi-automatic algorithm to manual segmentation in 4 patients are shown in Table 1. The percentages of surface model vertices within 0.5/1.0/2.0 mm of the gold standard were 74/87/94% for the blood pool and 70/84/92% for the epicardium. Fig. 3 shows a 3D surface heart model of a child with complex congenital heart disease (double outlet right ventricle), which is cut into two pieces to better visualize the intra-cardiac anatomy including the atria, ventricles, aorta, pulmonary arteries and ventricular septal defect. This visualization promises to be more intuitive for planning interventions compared to viewing multiple 2D slices as in Fig. 2.

Conclusions: We developed a procedure to create 3D heart models from 3D SSFP images to aid planning interventions for children with complex congenital heart disease. We reduced the segmentation time from ~8 hours to less than 1 hour of interaction time using a semi-automatic segmentation algorithm, while maintaining high accuracy.

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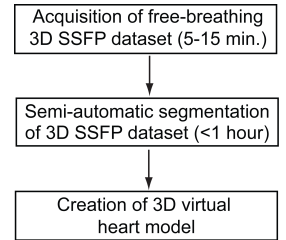


Fig. 1: Pipeline to create virtual 3D heart models.

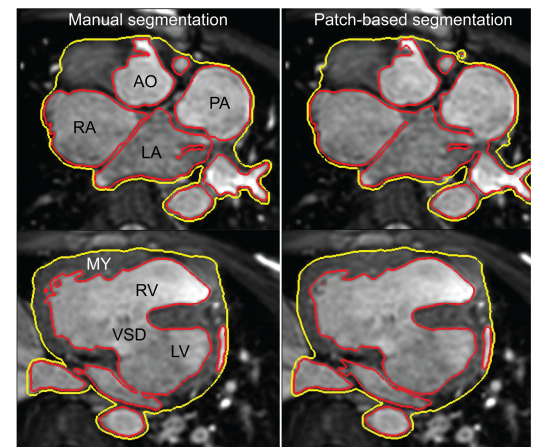


Fig. 2: Example slices of a 3D SSFP image, illustrating good agreement between segmentations done manually and using the proposed semi-automatic algorithm. Red and yellow contours show the blood pool and epicardial borders, respectively. AO = aorta; PA = pulmonary artery; LA/RA = left/right atrium; LV/RV = left/right ventricle; VSD = ventricular septal defect; and MY = myocardium.

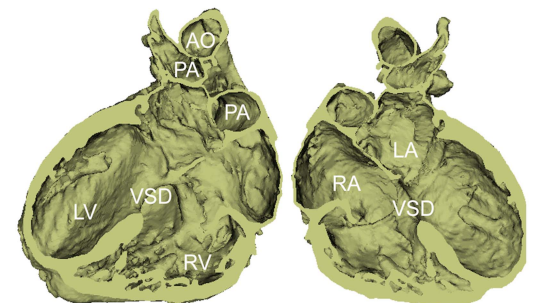


Fig. 3: Graphical display of a 3D heart surface model of a patient with double outlet right ventricle, created with the proposed semi-automatic algorithm.

Accuracy metric	Mean \pm Standard Deviation	
	Blood-pool	Epicardium
Surface-to-surface distance (mm)	0.51 \pm 0.90	0.60 \pm 0.99
Volume overlap (maximum is 1.0)	0.95 \pm 0.01	0.89 \pm 0.01

Table 1: Accuracy metrics show good performance of the proposed semi-automatic segmentation algorithm compared to the gold standard manual segmentation, in 4 patients.