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CARDIOVASCULAR SEGMENTATION WITH CONVOLUTIONAL NEURAL NETWORKS

Gabriel D. Maher (1), Jameson M. Merkow (2), Alison L. Marsden (3)

(1) Institute for Computational and Mathematical Engineering,
Stanford University
Palo Alto, CA, USA

(2) Electrical and Computer Engineering,
University of California San Diego,
San Diego, CA, USA

(3) Bioengineering, Pediatrics,
Stanford University
Palo Alto, CA, USA

INTRODUCTION

In recent years, numerical simulations of cardiovascular ~~biomechanics~~ have ~~been shown to have a range of useful applications, such as aiding in~~ understanding cardiovascular biomechanics ~~and~~ clinical applications such as ~~analysis of~~ atherosclerosis [1] and coronary artery disease [2]. However, cardiovascular ~~biomechanics~~ simulations require accurate three dimensional ~~digital~~ models of the cardiovascular anatomy ~~of the subject under consideration. The process of digital anatomical model construction for a particular subject is known as patient-specific modeling~~ [3]. ~~During model construction, typically volumetric medical images, such~~ as magnetic resonance (MR) or computed tomography (CT) scans, ~~are used~~.

SimVascular is an open-source software package with which users can perform patient-specific blood flow simulations [4] [5]. SimVascular contains functionality to visualize and segment medical images, construct meshes for numerical simulations and perform cardiovascular fluid dynamics and fluid-structure interaction simulations. At present, to segment medical images with SimVascular, users ~~may~~ perform manual segmentation or use ~~a number of~~ classical image processing methods such as thresholding [5] or active contours [6][7].

~~Manual segmentation produces accurate segmentations, however it requires significant time, effort and expertise from the user. Classical image processing methods can also be used to produce high quality segmentations but typically require significant time investments to tune method specific parameters which are sensitive to individual image quality, anatomical region and vessel size. As such it is difficult to use manual segmentation and classical image processing methods on large numbers of medical images, containing varying anatomical regions.~~ Medical image segmentation is thus a significant bottleneck in performing numerical cardiovascular biomechanics simulations, both for users of SimVascular and for patient-specific modeling in general. It is therefore desirable to find, or develop, cardiovascular medical image segmentation methods that can be used without significant user intervention across a wide range of medical images.

Convolutional Neural Networks (CNNs) are a class of machine learning models tailored towards processing visual data. Recently (CNNs) have been used to develop accurate medical image processing methods. Example applications include, among others, pancreas segmentation [8], brain lesion detection [9], brain tumor segmentation [10], kidney segmentation [11] and cardiovascular edge detection [12]. Segmentation methods developed with CNNs are typically parameter-free making them a promising approach for improving the patient-specific modeling process. Furthermore the Vascular Model Repository [14] is a repository that contains over 100 medical images and cardiovascular models segmented by users of SimVascular, and is a suitable source of data with which to train machine learning models for cardiovascular segmentation.

~~However, it is not evident how to use segmentations produced by CNNs to construct patient-specific models that can be used for cardiovascular biomechanics simulations. Therefore~~ in this work we propose a method with which CNN-based segmentations of medical images can be used to construct accurate 3D cardiovascular models that can then be used for numerical blood flow simulations. The method consists of (1) using CNNs to segment image patches extracted from medical images with user-annotated vessel centerlines, (2) extracting vessel boundaries from the produced segmentations, and (3) combining the extracted boundaries to form a solid model. We demonstrate that a CNN-based approach outperforms an active contour method when compared to vessel boundaries produced by users with manual segmentation.

METHODS

The proposed method for cardiovascular model construction in this work is based on the current model construction process available ~~through~~ SimVascular ~~that is described in~~ [5][7]. An outline of the model construction process is shown in Figure 1. In the first step users load a 3D medical image and annotate vessel centerlines by selecting (x,y,z) coordinates in the image. ~~For~~ the second step, segmentations ~~can be~~ produced along individual vessels, using an intensity probe that displays the image intensity along the vessel. ~~During~~ the third step solid models for each vessel are constructed by lofting the segmentations from step 2. Finally a single solid model is made by combining the individual vessel models.

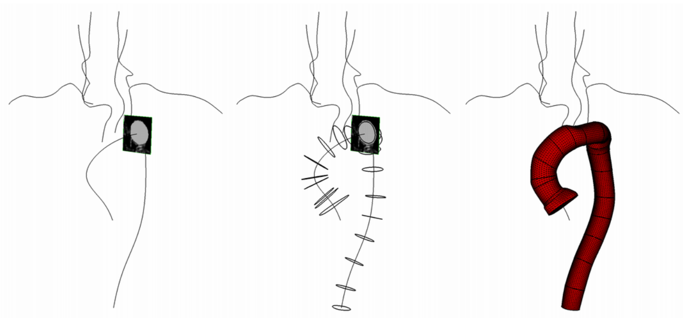

Figure 1: Outline of cardiovascular model construction process in Simvascular (taken from [3]). Left: User-annotated vessel centerlines and medical image intensity probe, Middle: Vessel centerlines with user constructed vessel boundaries, Right: Solid model constructed by lofting vessel boundaries.

Centerline ~~annotation~~ and vessel segmentation are the most time consuming parts of the model construction process. The proposed method in this work is aimed at improving the vessel segmentation step. ~~Currently segmentations can be produced by either manually segmenting the image patch displayed by the intensity probe or by applying classical image processing methods on the image patch. For the new~~ proposed method, the image patch of the intensity probe is given as input to a CNN that has been trained to output a binary image. The pixels of the binary image are classified by the CNN as being inside or outside of a blood vessel, where outside or inside are denoted by pixels values of 0 and 1 respectively. Vessel boundaries are then extracted from the segmentation with the marching squares algorithm.

For CNN architectures we build a simple fully-convolutional CNN with both convolutional and fully-connected layers. Our CNN architecture has been designed to localize vessels close to the centerline, hence we denote it as Region-Selection Network (RSN). ~~As a further step~~ we apply the object-boundary guided segmantic segmentation method of [14] to RSN and call the CNN obtained in this way Object-Boundary Guided RSN (OBG_RSN). We additionally retrain the Holistically-Nested edge-detection (HED) [15] and I2INet [12] architectures as these are state of the art for edge-detection and cardiovascular edge-detection respectively. The training, validation and test datasets consist of 17331, 3036 and 1831 image patches respectively, with dimensions of 64x64 pixels. The data is split so that image patches from the same medical image are always in the same set. As a baseline classical image processing method we use the level set method available in SimVascular [7], with a fixed set of parameters tuned to produce accurate segmentations on a reference aorta model. To assess the quality of vessel boundaries produced by each method we computed the Jaccard distance error metric [16] (equation 1) with respect to vessel boundaries produced by users of SimVascular. A and B denote sets and $|A|$ denotes the cardinality of set A. $J(A,B)$ is 0 if A and B are non-overlapping and 1 if A and B are the same, as such the Jaccard distance allows the similarity between vessel boundaries to be quantified.

$$J(A,B)=\frac{|A\cap B|}{|A\cup B|} \quad (1)$$

RESULTS

~~In this section~~ example vessel boundaries and error metric results ~~are presented~~ for each method we considered~~.~~ Figure 2 ~~shows vessel boundaries produced by each method on~~ example image patches. When the vessel is large and clearly visible all methods produce a vessel boundary that resembles that segmented by the user. When the vessels are small, or ambiguous the level set method is unable to produce the desired boundary. All CNN architectures are able to segment small vessels and infer reasonable boundaries in the ambiguous fourth image patch.

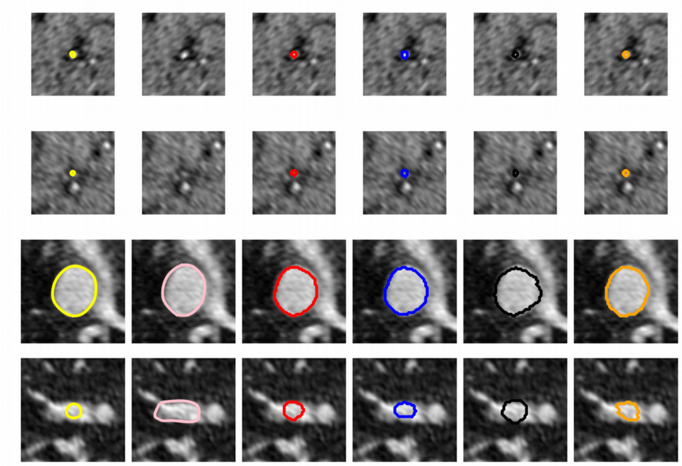

Figure 2: Example image patches and corresponding vessel boundaries produced by all methods. Yellow: Manual segmentation, Pink: Level set, Red: RSN, Blue: OBG_RSN, Black: HED, Orange: I2INet

To quantify the performance of each method, we define the cumulative error distribution $F(x)$ (equation 2), where N is the total number of image patches. For a given method, $F(x)$ denotes the fraction of vessel boundaries with a Jaccard distance error below x. Figure 3 shows the cumulative error distribution for each method being considered. In figure 3 a larger area under a curve approximately indicates a better performing method. From figure 3 it is evident that all CNN-based methods have similar performance and improve on the level set method. The level set primarily underperforms due to failing to produce a vessel boundary on approximately 60% of image patches when used with one set of fixed method parameters.

$$F(x)=\frac{|\{J_i : J_i \le x\}|}{N} \quad (2)$$

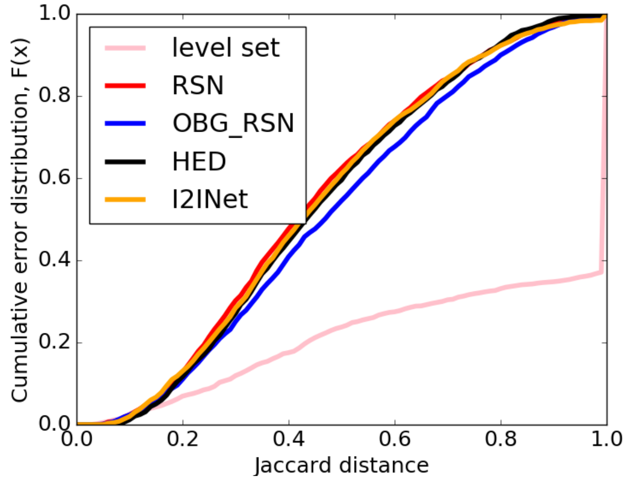

Figure 3: Cumulative error distribution for each CNN and the level set method.

DISCUSSION

~~The results shown in this work~~ provide evidence that CNN-based segmentation methods can be used to improve the patient-specific modeling process for cardiovascular models. However, the CNN-based method is conditional on the availability of medical images with accurate annotated vessel centerlines. The fact that all CNN-based methods performed similarly indicates that the precise CNN architecture is not crucial, as long as the CNN has enough capacity to model the data.

The underperformance of the level set method in this case is most likely due to the fact that only one set of level set parameters was used for all images and not due to the level set method itself. The performance of the level set could be improved by using different level set parameters for different images. However, this precisely illustrates why the level set requires significant user intervention to be used across many different images. Once the CNNs have been trained, the CNN-based method is parameter free and therefore requires significantly less user intervention.

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