

SEQSEG: AUTOMATIC IMAGE-BASED VASCULAR MODEL CONSTRUCTION USING SEQUENTIAL SEGMENTATIONS

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INTRODUCTION

Image-based computer modeling of vasculature has become an important aspect of patient care and cardiovascular research [1]. These modeling approaches use medical images to construct an anatomically accurate geometry of patient's blood vessels to be used for simulation-based modeling. Despite its wide range of applications, constructing anatomically correct geometries of blood vessels from medical images remains challenging and involves multiple steps and a combination of approaches, including ones reliant on labour intensive manual inputs.

Segmenting blood vessels from other nearby tissue is challenging because of limited resolution, unclear boundaries and image artifacts. To simplify the task, a "centerline" path is often constructed along vessels of interest, which is then traversed to perform 2D segmentations of the vessel lumen at discrete steps along the path. These 2D segmentations can then be lofted using spline interpolations to form a unified 3D surface representing the blood vessel domain[2]. Until now, these two steps (centerline generation and lumen segmentations) have been viewed as separate, resulting in methods to either accurately construct centerlines [3] or accurately determine lumen boundaries around centerlines [4]. We present a novel method to do both at once automatically, utilizing local deep-learning based segmentation with a tracing algorithm to construct a global vascular segmentation piece-wise while taking steps.

METHODS

Our approach tackles blood vessel segmentation by operating locally around a particular blood vessel segment. Local 3D segmentations are processed to determine vessel direction and size in order to take steps.

Algorithm. Figure 1 shows an overview of the algorithm steps. The algorithm is initialized using a given seed point and radius estimate, which is used to extract the first subvolume. The subvolume is segmented using a 3D U-Net neural network, where pixels are classified in a binary manner; either belonging to blood vessel or not. The segmentation is converted into surface mesh representation using the marching cubes algorithm, and a centerline is extracted using the open-source Vascular Modeling Tool Kit library. The resulting centerline is then post processed to estimate the size

of the vessel and choose the next point to move to. If the centerline includes two or more branches, the largest branch is chosen for immediate stepping and the others are stored in a bifurcation queue for subsequent tracing. During step-taking, we save the local segmentations and assemble them in a single global model as the final output.

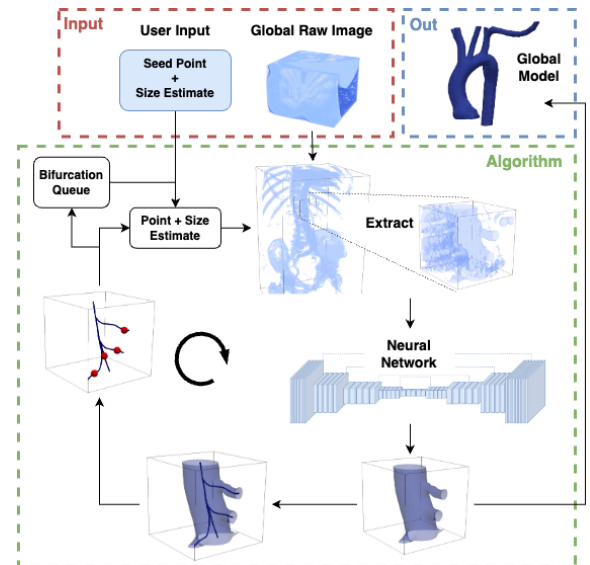


Figure 1: The different steps in the SeqSeg algorithm from initialization with inputs of seed point, radius estimate and global raw image, to subvolume extraction, 3D U-Net segmentation, surface and centerline calculation and stepping. Bifurcation points are saved in queue for subsequent tracing.

Datasets and Sampling. The datasets used are aortic and aortofemoral models from CT, and MR image data, see Table 1, acquired from the open and free Vascular Model Repository, accessible at vascularmodel.com[5].

Each case in a dataset has a medical image scan (CT/MR) with corresponding segmentation and centerline, see inputs in Figure 2. For neural network training, the global 3D medical image volume is sampled along the centerline of its corresponding vasculature model, see Fig. 2 for reference. Two subvolumes are extracted at each instance: 1) raw medical image data, and 2) binary segmentation of blood vessel. The samples vary in centering and size; some centered along the centerline while others shifted perpendicular to its tangent, and sizes vary from barely capturing the vessel lumen, to others including more nearby tissue. This variance is purposefully added to represent the variance that the tracing algorithm encounters in practice and is intended to increase the neural network’s robustness. Approximately 15% of subvolumes are used for validation and 20% of cases are kept aside for testing, see further details in Table 1.

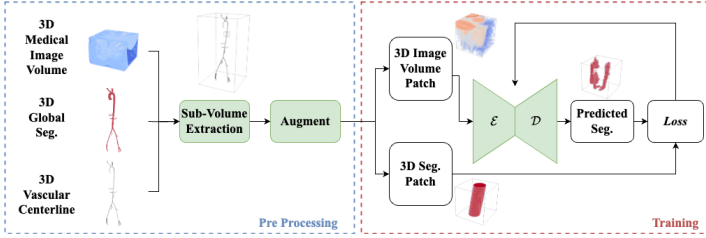


Figure 2: The pre processing of data for neural network training. Samples are extracted along vasculature centerline and augmented, and ground truth segmentations are used for loss calculation.

Table 1: The number of cases used for training and testing.

Dataset	Modality	Train/Val	Test
VMR Aortic / Aortofemoral[5]	CT	33	8
VMR Aortic / Aortofemoral[5]	MR	37	7

Neural Network Architecture and Training. The U-Net architecture is used for the segmentation task, and a 3D-version is chosen. The nnU-Net framework is used for hyperparameter choice and training[6]. The loss function used is a combination of Dice loss and binary cross entropy:

$$l = 1 - \mathcal{D} - \mathcal{CE} \quad (1)$$

where $\mathcal{D}$, $\mathcal{CE}$ are Dice score and binary cross entropy, respectively. Training took place using two GPUs, an NVIDIA k80 dual-GPU, on the Savio High Performance Computing cluster at UC, Berkeley.

Global Assembly. The local segmentations are gathered globally by calculating the mean prediction for each voxel. The final segmentation is then converted to a surface mesh using marching cubes and smoothed to remove voxel artifacts.

RESULTS

We tested our method (SeqSeg) on two different datasets as shown in Table 1, and compare to results from a benchmark model. A global nnU-Net model is chosen as benchmark because of its state-of-the-art performance on medical image segmentation tasks[6]. We compare using Dice score and avg. Hausdorff distance, see Table 2 for the avg. scores across both test datasets. As the results show, SeqSeg, on average, outperforms the benchmark using both metrics. Figure 3 shows a qualitative comparison between the ground truth and predictions from SeqSeg and the benchmark model on six aortic/aortofemoral models, three CT, and three MR. The method, SeqSeg, manages to capture all the branches present in the ground truth model. It also manages to extend the branches further than that was segmented in the ground truth.

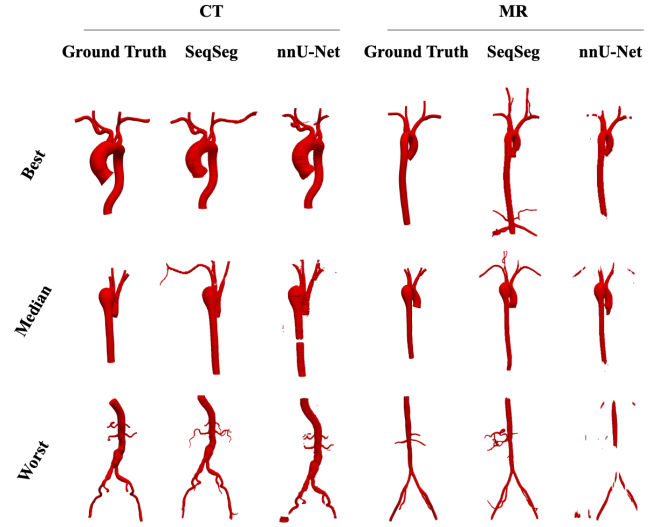


Figure 3: Comparison between ground truth model (left), prediction results from SeqSeg (middle) and nnU-Net benchmark model (right), for CT, and MR data. The cases shown are the best, median, and worst ranking Dice score results for the nnU-Net benchmark model.

Table 2: Avg. Dice score ($\mathcal{D}$) and Avg. Hausdorff distance ($\mathcal{H}$) score results on testing data, comparing SeqSeg (our) and nnU-Net benchmark model.

Dataset	$\mathcal{D} \uparrow$		$\mathcal{H} \downarrow$	
	SeqSeg	nnU-Net	SeqSeg	nnU-Net
CT Aorta VMR	0.927	0.901	0.023	0.071
MR Aorta VMR	0.877	0.844	0.0335	0.114

DISCUSSION

We present a novel model construction method, SeqSeg, based on local step taking, which uses deep learning to predict vascular segments instead of the whole vasculature at once. With only a single seed point, SeqSeg is capable of automatically constructing expansive vasculature. As a result of the neural network training strategy, the machine learning model manages to adequately capture bifurcations and generalize to new vessel branches not present in the training data. The results show the method works both for CT, and MR, image data. Additionally, by assembling vascular models piece-wise, the method ensures connectivity of the final segmentation, a necessity if the final purpose is simulation.

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