Multicenter Aortic Vessel Tree Extraction using Deep Learning

SPIE.

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INTRODUCTION

Over the last years, new medical imaging modalities were developed to help detect, diagnose and monitor different illnesses. Historically, the interpretation and analysis of the images obtained with these methods was conducted by trained radiologists or physicians, but, in recent years, with the development of more and more sophisticated computational image analysis methods and machine learning techniques, computer-aided medical image analysis finds its way into the clinical practice [1]. To highlight anatomical structures or pathological changes in images and therefore make the diagnostic process easier, more accurate and more efficient, segmentation is the method to go with [2]. In the last 10 years, the number of papers describing automatic heart and vessel segmentation in medical images has greatly increased, showing that with the improvement over classical methods and the significant increase in computational capabilities, the popularity of automated cardiovascular image analysis has also increased [3,4]. Since pathologies of the cardiovascular system, like dissections and aneurysms, can be life-threatening and require prompt attention, automatic segmentation can be a helpful tool to promptly identify an abnormal anatomy. To simplify this process, we developed a 3D deep neural network that consists of an encoder-decoder network together with a self-attention block and evaluated the role of the attention block.

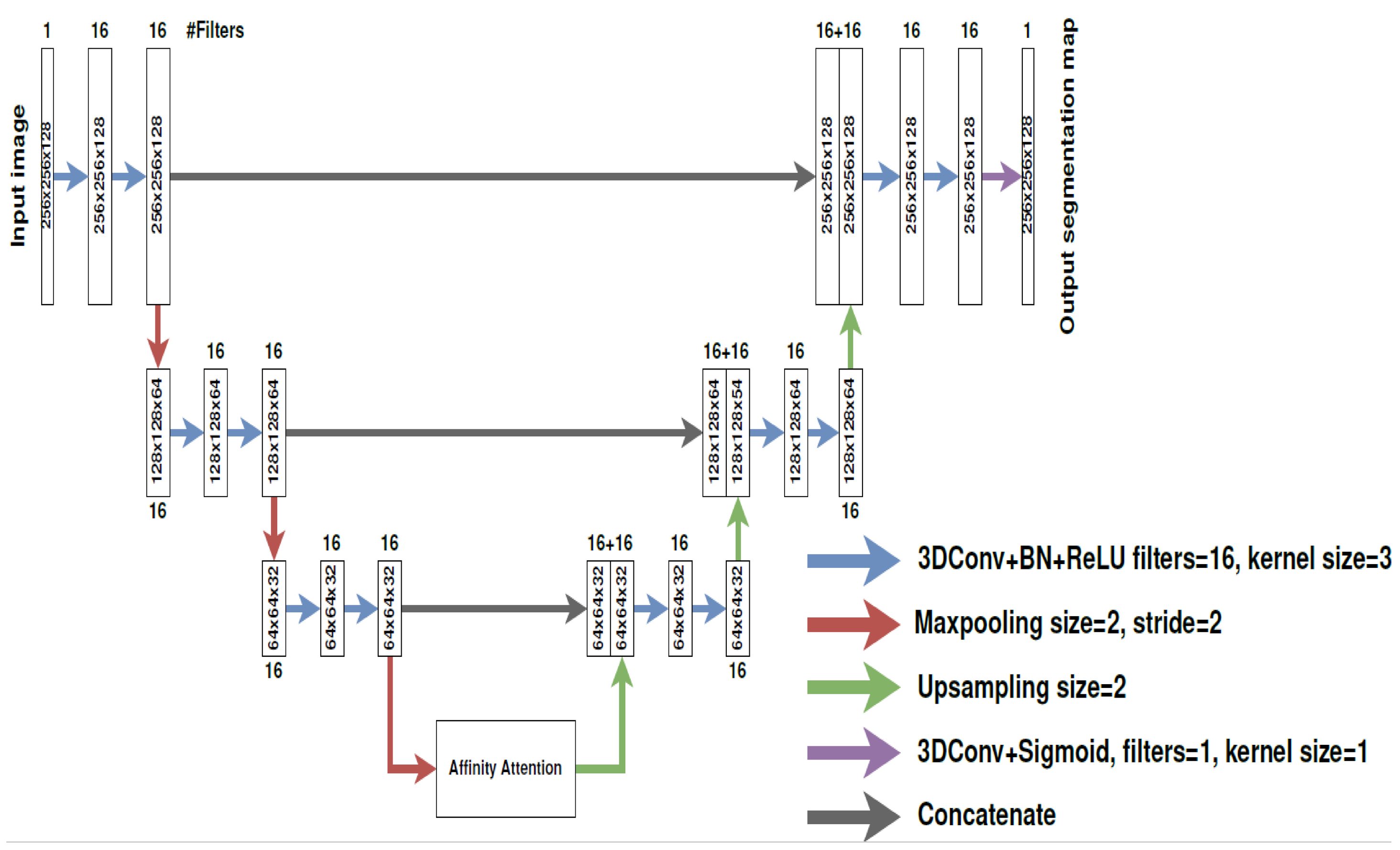

Fig. 1: Structure of the proposed neural network model.

METHODS

The overall dataset consists of 56 CTA-scans from three different public sources with ground truth segmentations and includes aortas with abdominal aortic aneurysms and aortic dissections [5]. We first re-sampled the images to a uniform voxel size, cropped the images around the center of the image and subsequently windowing was applied to remove unnecessary information. After that, the images were normalized and patches were extracted. The suggested network models are based on the U-Net architecture [6] and incorporate the Channel and Spatial Attention Module (CSAM) proposed by Mou et al. [7] that is inspired by the Dual Attention Network (DANet). As bottom block, either a convolution block was used, or a spatial and a channel attention module (CSAM). We tested 6 different networks, named after their respective number of filters. As an example, the U-Net16 with the Channel and Spatial Attention Module (CSAM) is visualized in Fig. 1. Six images of the dataset were set aside as test data, and the remaining data, 250 patches, was split into 30% validation data and 70% training data. The network was trained on a PC with a Nvidia GeForce RTX 2070 with 8GB of video memory, using the Adamax-optimizer ($\beta 1 = 0.9$, $\beta 2 = 0.999$ and $\varepsilon = 0.01$) and a modified Dice-loss, where the loss is multiplied by a large negative number to improve the learning process. The initial learning rate was set to 0.001 and was reduced by a factor of 0.1 after 10 epochs without validation loss improvement. The training was stopped early after 20 epochs without validation loss improvement.

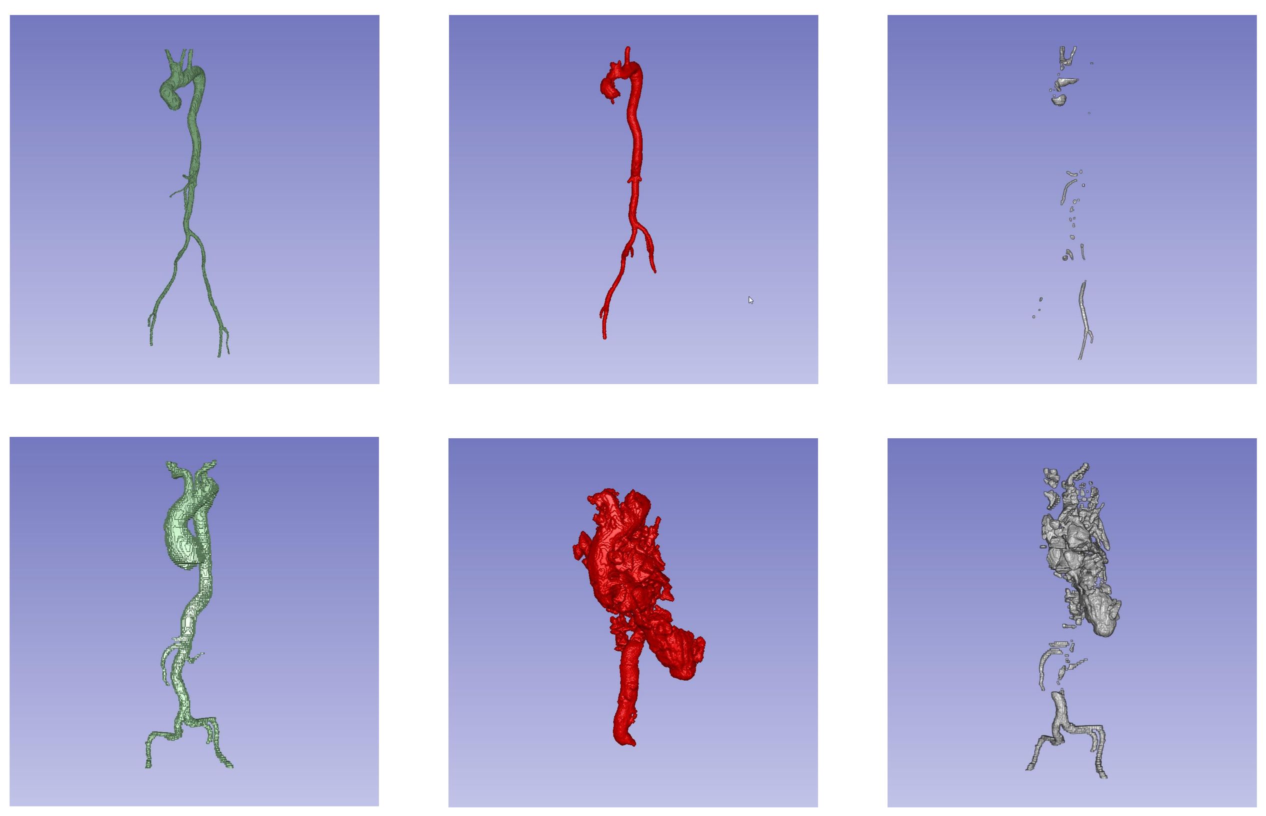

Fig. 2: The images show from left to right the ground truth, the segmentation results and the difference between segmentation and ground truth of images R3 and D3 as exemplary results of the network U-Net16+CSAM.

RESULTS

The training of the networks was done in 38 to 66 epochs in a time of 3-8 hours. Only the weights of the model at minimal validation loss were saved and used for predictions. The proposed methods yielded the results described in Table 1 for the test dataset. Fig. 2 shows exemplary segmentation results.

Network	Image	D1	D3	R1	R3	K1	K3
U-Net 16	Dice	**0.889**	0.189	0.607	0.794	0.840	0.589
	HD	10.06	55.25	43.04	6.59	4.47	20.05
U-Net 16 + CSAM	Dice	0.856	**0.541**	0.613	0.830	0.828	0.485
	HD	5.68	17.3	9.59	5.72	5.06	47.34
U-Net 176	Dice	0.883	0.369	**0.897**	**0.883**	0.847	**0.836**
	HD	9.95	41.94	11.94	1.62	2.93	17.16
U-Net 176 + CSAM	Dice	0.877	0.318	0.585	0.779	0.803	0.749
	HD	9.48	33.35	12.48	6.97	5.12	19.04
U-Net 352	Dice	0.843	0.043	0.715	0.867	**0.882**	0.821
	HD	10.37	68.99	13.73	3.72	2.63	17.39

Table 1: Segmentation results.

CONCLUSIONS

Generally, the classical U-Nets preformed better without the Spatial and Channel Attention Module, suggesting that this attention mechanism might not work well for AVT segmentation. All the networks delivered good segmentations in at least three of six cases, although in some cases the networks delivered poor results, possibly because of differing image parameters like image intensity at the aorta. These models were developed with low computational requirements, therefore the model could be tested with increased patch size, network width and depth and higher number of filters in the future. A challenge was the small amount of available data, therefore a massive dataset of similarly acquired CTA scans might improve performance.

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