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Artery and Vein Segmentation of the Cerebral Vasculature in 4D CT using a 3D Fully Convolutional Neural Network

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ABSTRACT

Segmentation of the arteries and veins of the cerebral vasculature is important for improved visualization and for the detection of vascular related pathologies including arteriovenous malformations. We propose a 3D fully convolutional neural network (CNN) using a time-to-signal image as input and the distance to the center of gravity of the brain as spatial feature integrated in the final layers of the CNN. The method was trained and validated on 6 and tested on 4 4D CT patient imaging data. The reference standard was acquired by manual annotations by an experienced observer. Quantitative evaluation showed a mean Dice similarity coefficient of 0.94 ± 0.03 and 0.97 ± 0.01, a mean absolute volume difference of 4.36 ± 5.47 % and 1.79 ± 2.26 % for artery and vein respectively and an overall accuracy of 0.96 ± 0.02. The average calculation time per volume on the test set was approximately one minute. Our method shows promising results and enables fast and accurate segmentation of arteries and veins in full 4D CT imaging data.

Keywords: 4D CT, Artery, Vein, Cerebral vasculature, Deep learning, Convolutional neural network

1. INTRODUCTION

The cerebral vasculature only constitutes a small percentage of the total intracranial space but is present in the whole intracranial space and may have complex morphological configurations. Segmentation of arteries and veins aids the visual assessment of the cerebral vasculature and is important for the detection of vascular related pathology such as arteriovenous malformations. Four dimensional (4D) Computed Tomography (CT) allows for better improved discrimination between artery and vein as it captures both the arterial and venous phase during scan time, opposed to CT Angiography (CTA) where only the arterial phase is captured. Varying configurations of the cerebral vasculature make atlas based methods[1] less appropriate for the segmentation of arteries and veins as there are multiple complex morphological variations in the cerebral vasculature. Furthermore, the cardiovascular condition of the patient and the injection rate of the contrast agent may influence the arrival time of the contrast agent, making global thresholds[2] inadequate for automatic segmentation of arteries and veins.

Convolutional neural networks (CNN)[3] have shown good results in visual recognition, image segmentation and other machine learning tasks. Most of these networks use 2D slices or 2D slices from multiple orientations to solve 3D segmentations tasks.[4] Yet, with new hardware improvements 3D fully convolutional architectures are now available. This allows for fast and complete segmentation of large 3D volumes. However, most networks only use contextual information and use no spatial information. In this paper, we propose a 3D fully CNN with integration of spatial features at the final convolutional layers of the network for the automatic segmentation of arteries and veins in the cerebral vasculature.

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2. METHOD

2.1 Data

This study was approved by our institutional review board and informed consent was waived. In total, 10 subjects who underwent 4D CT for clinical suspicion of acute cerebral ischemic stroke were included in this study. Patients were admitted to the emergency department of our hospital between February 1st 2015 and May 31st 2015.

Image acquisition was done on a 320-row Toshiba Aquilion ONE CT scanner with 16 cm coverage (Toshiba Medical Systems Corporation, Japan). The 4D CT protocol consisted of 19 volumetric acquisitions starting with a high dose acquisition at 200 mAs 5 seconds after contrast injection, followed by 13 scans every 2 seconds at 100 mAs, followed by 5 scans every 5 seconds at 75 mAs. Each volumetric acquisition was made at 80 kV at 0.5 seconds rotation time with injection of 50 mL Iomeron contrast agent. Image reconstruction was done with a smooth reconstruction kernel (FC41) resulting in image sizes of 512x512x320 voxels with voxel sizes of 0.43x0.43x0.5 mm. All temporal volumes were rigidly registered to the first time point to resolve potential head movement during acquisition.[5]

The artery and vein segmentations were annotated by a trained observer, as shown in Figure 1. To facilitate this process, the complete cerebral vasculature was pre-segmented using the method of Meijs et al.[6] and utilized to suppress tissues other than the cerebral vasculature. The annotations were supervised by an experienced neuroradiologist. Four subjects were used to train the network and two subjects were used as a validation set to prevent over-fitting. Four subjects of a separate dataset were used as a test set for quantitative evaluation.

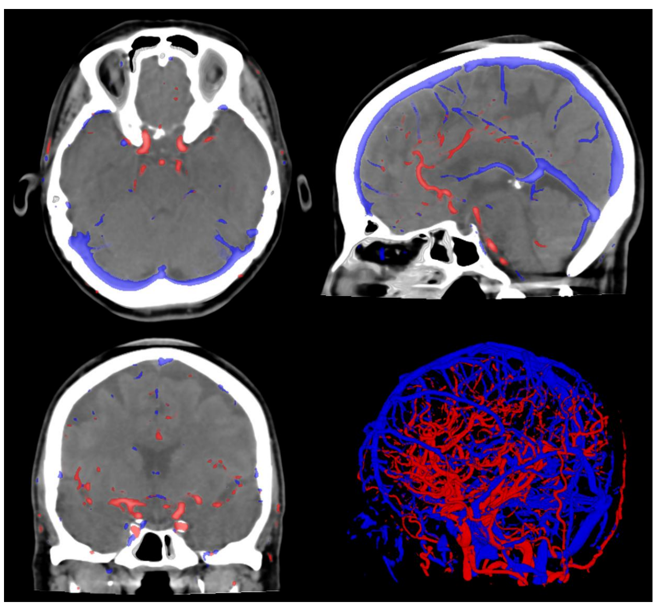

Figure 1. Clockwise from bottom left: Coronal, axial and sagittal view of the labeled annotation as an overlay on a 4D CT slice averaged over time and a 3D rendering of the labeled annotation.

2.2 Input Data and Spatial Features

A Time-to-Signal (TTS) image was used as input image and was defined as the time to reach 95% of the maximum intensity in each voxels along the temporal dimension of the 4D CT image. These arrival times may still have a high inter-patient variability as the arrival time is influenced by injection time and cardiovascular condition. Therefore, the TTS images were normalized around a flow-window, which was calculated from the histogram of the TTS image. The start of the flow-window was defined at the first bin to account for at least 5% of the total cerebral volume. The end of the flow-window was defined at the last bin to account for at least 5% of the total cerebral volumes, as shown in Figure 2.

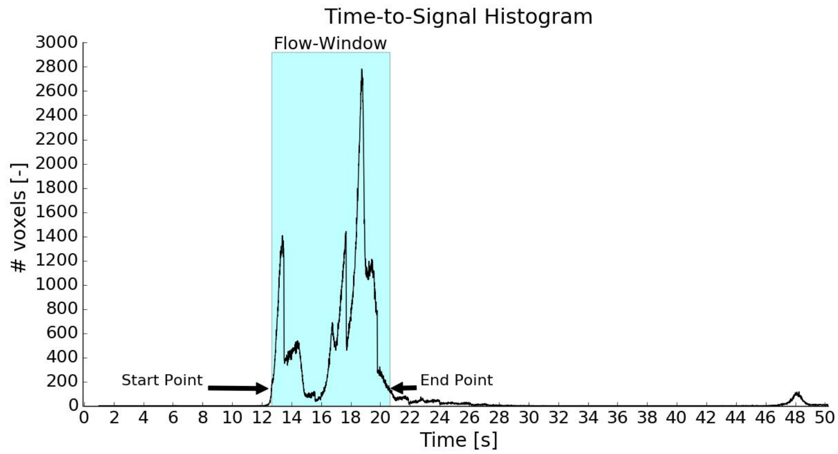

Figure 2. Histogram of the Time-to-Signal (TTS). The arrival times and the amount of voxels per bin are shown on the x-axis and y-axis, respectively. The flow-window is depicted in blue from 12.7 to 20.6 seconds.

The TTS images were then normalized with the formula as given in Equation 1,

$$I_N = \frac{I - FlowWindow_{min}}{FlowWindow_{max} - FlowWindow_{min}} \tag{1}$$

where I and I_N are the original and normalized Time-to-Signal values, respectively.

As spatial feature the distance from each voxel to the center of gravity of the brainmask in mm was used. The brainmask was calculated using the method of Patel et al.[7] The distance was decomposed into x, y and z components. The distances were positive for voxels left, anterior and below the center of gravity and negative for voxels right, posterior and above the center of gravity. The spatial features were normalized between -1 and 1.

2.3 Network Architecture

A 3D fully CNN[3] was implemented using the Theano and Lasagne libraries.[8,9] Inspired by the work of Mohsen et al.[10] the network was modified with integration of the spatial features in the final convolutional layers. The network utilized context information on multiple scales together with spatial features to classify the cerebral vasculature in artery or vein. The network architecture is shown in Figure 3.

A 64x64x64 tile voxels was used as input for the CNN. The left pathway of the network consisted of two convolutions of 3x3x3, each followed by a rectified linear unit (ReLu) and a 2x2x2 max pooling operation with stride 2 for downsampling. In the right pathway similar 3x3x3 convolutions were applied followed by a ReLu and a 2x2x2 upscaling with a stride of 2 in each dimension. This was concatenated with the output of the left pathway of the network before the next convolutional layer. At the end of the right pathway, the feature maps were concatenated with a 3x24x24x24 tile containing the 3 coordinates from spatial feature. After this concatenation two 1x1x1 convolutions were applied followed by a ReLu. The numbers of filters per convolutional layer are shown in Figure 3. Finally, a softmax function was calculated over the volume to obtain the segmentation class probabilities.

2.4 Training of the Architecture

Artery and vein samples were randomly sampled from the manual annotations. The sampling was done in a way that the prevalence of artery and vein voxels was balanced. The sampled voxels were used as center point to extract tiles of 64x64x64 voxels from the input images and 24x24x24 from the annotation. Only voxels present in the vessel segmentation were considered for the calculation of the cross-entropy loss function. Adaptive Moment Estimation (ADAM)[11] was used to minimize the loss with a learning rate of 10^{-3}. L1-regularization of 10^{-6}, L2-regularization of 10^{-4} and two dropout layers of 50% before the convolutions in the deepest layers were used

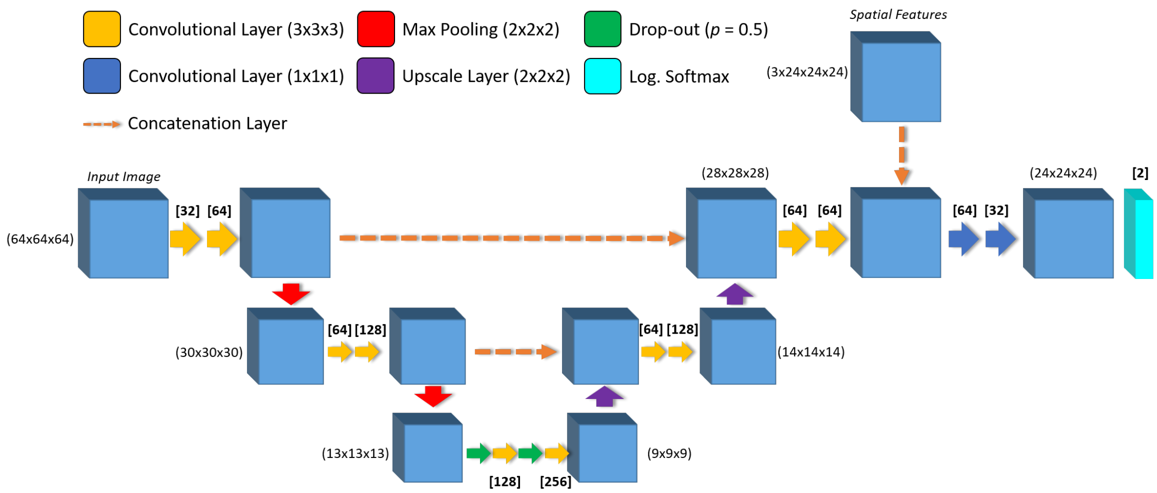

Figure 3. Architecture of 3D fully CNN (U-Net). Boxes represent feature maps. Yellow and blue arrows represent the 3x3x3 and 1x1x1 convolutional layers followed by a rectified linear unit (ReLu), respectively. Bold numbers in square brackets represent the number of filters used. Red and purple arrows represent the 2x2x2 max pooling and upscaling layer, respectively. Green arrays represent the drop-out layer.

for regularization. The network was trained for a total of 1500 iterations, with a batch-size of 5 patches and 50 patches per iteration, on an NVIDIA TitanX GPU.

3. RESULTS

Figure 4 and 5 show qualitative results of the network for two cases. Red and green indicate correct and incorrect segmented arteries, respectively. Blue and yellow indicate correct and incorrect segmented veins, respectively.

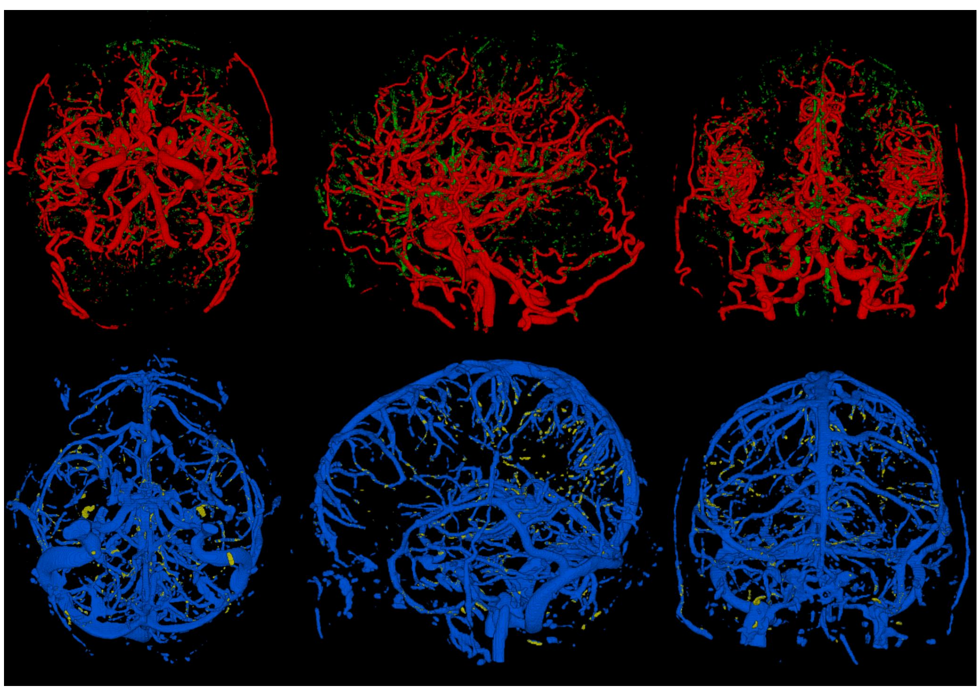

Figure 4. Qualitative result of the network. Red indicates correctly classified arteries, green incorrect. Blue indicates correctly classified veins, yellow, incorrect.

The Dice similarity coefficient (DSC),[12] absolute volume difference (AVD) and accuracy were used as quantitative measures to evaluate the performance of the network. The result of the test set are shown in Table 1.

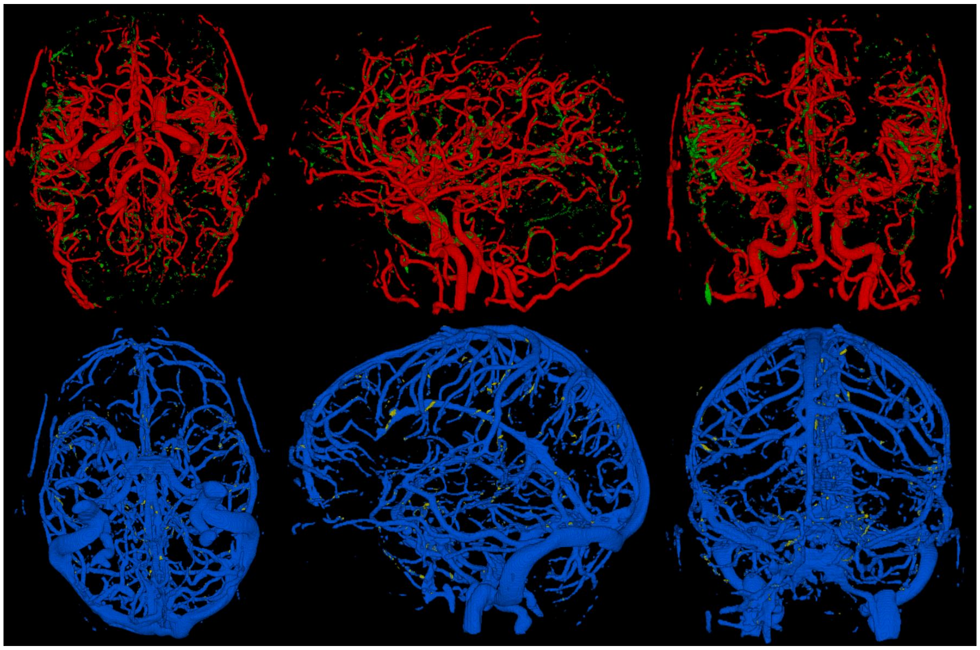

Figure 5. Qualitative result of the network. Red indicates correctly classified arteries, green incorrect. Blue indicates correctly classified veins, yellow, incorrect.

Table 1. Quantitative evaluation results in comparison to the reference standard.

	DSC [-]		AVD [%]		Accuracy [-]
	Artery	Vein	Artery	Vein	Overall
Case 1	0.91	0.96	0.53	0.25	0.94
Case 2	0.96	0.98	1.21	0.54	0.98
Case 3	0.91	0.97	13.80	5.70	0.98
Case 4	0.97	0.99	1.90	0.69	0.95
Mean	0.94 ± 0.03	0.97 ± 0.01	4.36 ± 5.47	1.79 ± 2.26	0.96 ± 0.02

4. DISCUSSION

We present a state-of-the-art method using a 3D fully CNN with integrated spatial features for automatic segmentation of arteries and veins of the cerebral vasculature in 4D CT images. The architecture provides both speed and accuracy for large input size images. We demonstrate that the described CNN architecture shows promising results despite a limited amount of training data.

5. CONCLUSION

The proposed method has shown good results in comparison to the reference standard obtained by manual annotation. Artery and vein separation is important for improved visualization and for the detection of vascular related pathologies. Furthermore, the presented architecture forms a valuable step in the development of methods for CAD systems in vascular pathologies.

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REFERENCES

[1] Robben, D., Türetken, E., Sunaert, S., Thijs, V., Wilms, G., Fua, P., Maes, F., and Suetens, P., "Simultaneous segmentation and anatomical labeling of the cerebral vasculature," in [*International Conference on Medical Image Computing and Computer-Assisted Intervention*], 307–314, Springer (2014).

[2] Mendrik, A., Vonken, E.-J., van Ginneken, B., Smit, E., Waaijer, A., Bertolini, G., Viergever, M. A., and Prokop, M., "Automatic segmentation of intracranial arteries and veins in four-dimensional cerebral CT perfusion scans," *Medical physics* **37**(6), 2956–2966 (2010).

[3] Çiçek, Ö., Abdulkadir, A., Lienkamp, S. S., Brox, T., and Ronneberger, O., "3D U-Net: learning dense volumetric segmentation from sparse annotation," in [*International Conference on Medical Image Computing and Computer-Assisted Intervention*], 424–432, Springer (2016).

[4] Prasoon, A., Petersen, K., Igel, C., Lauze, F., Dam, E., and Nielsen, M., "Deep feature learning for knee cartilage segmentation using a triplanar convolutional neural network," in [*International conference on medical image computing and computer-assisted intervention*], 246–253, Springer (2013).

[5] Manniesing, R., Oei, M. T., Oostveen, L. J., Melendez, J., Smit, E. J., Platel, B., Sánchez, C. I., Meijer, F. J., Prokop, M., and van Ginneken, B., "White matter and gray matter segmentation in 4D computed tomography," *Nature Scientific Reports* **7** (2017).

[6] Meijs, M., Patel, A., van de Leemput, S., Prokop, M., van Dijk, E. J., de Leeuw, F.-E., Meijer, F. J. A., van Ginneken, B., and Manniesing, R., "Robust segmentation of the full cerebral vasculature in 4D CT images of suspected stroke patients," **7** (2017).

[7] Patel, A., van Ginneken, B., Meijer, F. J. A., van Dijk, E. J., Prokop, M., and Manniesing, R., "Robust cranial cavity segmentation in CT and CT perfusion images of trauma and suspected stroke patients," *Medical Image Analysis* **36**, 216–228 (feb 2017).

[8] The Theano Development Team, Al-Rfou, R., Alain, G., Almahairi, A., Angermueller, C., Bahdanau, D., Ballas, N., Bastien, F., Bayer, J., Belikov, A., et al., "Theano: A Python framework for fast computation of mathematical expressions," *arXiv preprint arXiv:1605.02688* (2016).

[9] Dieleman, S., Schlter, J., Raffel, C., Olson, E., Snderby, S. K., Nouri, D., Maturana, D., Thoma, M., Battenberg, E., Kelly, J., Fauw, J. D., Heilman, M., de Almeida, D. M., McFee, B., Weideman, H., Takcs, G., de Rivaz, P., Crall, J., Sanders, G., Rasul, K., Liu, C., French, G., and Degrave, J., "Lasagne: First release.," (Aug. 2015).

[10] Ghafoorian, M., Karssemeijer, N., Heskes, T., van Uden, I. W., Sanchez, C. I., Litjens, G., de Leeuw, F.-E., van Ginneken, B., Marchiori, E., and Platel, B., "Location sensitive deep convolutional neural networks for segmentation of white matter hyperintensities," *Scientific Reports* **7** (2017).

[11] Kingma, D. and Ba, J., "Adam: A method for stochastic optimization," *arXiv preprint arXiv:1412.6980* (2014).

[12] Dice, L. R., "Measures of the amount of ecologic association between species," *Ecology* **26**, 297–302 (1945).