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SCROLLING 2D U-NET FOR THE 3D SEGMENTATION OF THE INTERNAL CAROTID ARTERY

Arya YAZDAN PANAHA, Guanghui FU, Didier DORMONT, Bruno STANKOFF, Olivier COLLIOT

Sorbonne Université, Institut du Cerveau - Paris Brain Institute
ICM, CNRS, Inria, Inserm, AP-HP, Hôpital de la Pitié Salpêtrière, F-75013, Paris, France

1. INTRODUCTION

There are several challenges attached with segmenting brain vasculature from angiographic images, including small vessels, uneven contrast, sparse structures, and unique anatomy. Precise and connected segmentations are necessary for analyzing cerebral vasculature and guiding the treatment of cerebral aneurysms. The main challenge is to cover all vessels branching from the main feeding artery in each image.

2. METHODS

2.1. Dataset & pre-processing

The dataset contained 35 rotational angiographies from subjects with intracranial aneurysms captured in Tours, France using a GE INNOVA 3D machine. The images have a resolution of $0.227 \times 0.227 \times 0.227 \text{mm}^3$ and include the cranium bone without subtraction. Radiopaque contrast dye highlights relevant vessel structures. Two experts in neurovascular anatomy and X-ray imaging delineated cerebral arteries branching from the Internal Carotid Artery (ICA). Images are re-scaled to $[-1, 1]$, padded/cropped to $(512, 512, 510)$, and reoriented to the canonical (RAS+) voxel orientation.

2.2. Model architecture

The segmentation model uses a modified 2D U-Net [1] with group normalization instead of batch-norm, "Leaky ReLU" instead of "ReLU", and up-sampling instead of up-convolutions. The model has 16 filters at the first convolution block output and performs three downsampling steps using average pooling. It takes 10 channels as input.

2.3. Training procedure

The dataset was divided into 22, 6, and 7 subjects for training, validation, and testing, respectively. The model was trained for 800 epochs using a batch size of 32, an Adam optimizer, and an initial learning rate of 0.001. The loss used is an average of the Dice loss and the binary cross Entropy (BCE). The training procedure is outlined under Algorithm 1. We have trained the model by sliding it along the inferior-superior direction (IS) and extracting a stack of $N_{channels} = 10$ slices of the image.

2.4. Inference

Images are processed through the model in all $N_{dirs} = 6$ anatomical directions: anterior-posterior, posterior-anterior, left-right, right-left, superior-inferior, and inferior-superior.

Algorithm 1 Training during 1 epoch, on IS direction

```
 $X \leftarrow \text{pad}_N(\text{Batch}_{image}) \triangleright (B, 1, 512, 512, 510 + 2N)$   
 $Y \leftarrow \text{pad}_N(\text{Batch}_{mask})$   
 $C \leftarrow (\text{DiceLoss}() + \text{BCE}())/2$   
for  $i = [N : 510 + N]$  do  
     $x \leftarrow \text{reshape}(X[\dots, i : i + N]) \triangleright (B, N, 512, 512)$   
     $y_{gth} \leftarrow \text{reshape}(Y[\dots, i : i + N])$   
     $y_{pred} \leftarrow \text{model}(x)$   
     $L \leftarrow C(y_{gth}, y_{pred})/510 \triangleright$  gradient accumulation  
    Backpropagate  $L$   
end for  
Step the optimizer
```

All model outputs are summed and normalized by a factor $N_{channels} \times N_{dirs}$. After visual inspection, we decided on a threshold of 0.3 to consider a voxel as correctly detected. Meaning it was detected at least through scrolling in one direction. The largest connected component (CC) is retained, resulting in output segmentations with only one CC.

3. RESULTS

Dice	Jaccard	MI	CIDice	AvgHausD
0.94 ± 0.01	0.88 ± 0.01	0.02 ± 0.00	0.91 ± 0.02	0.82 ± 0.21
Recall	Precision	VER	AVER	CC_{gth}
0.94 ± 0.01	0.93 ± 0.02	-0.01 ± 0.03	0.04 ± 0.02	1.71 ± 0.36

Table 1. Performance of the proposed method.

Table 1 summarizes results for our test dataset. Results are reported as mean \pm standard error of the mean.

4. CONCLUSIONS

A scrolling 2D U-Net is able to perform remarkably well in 3D segmentation tasks, with minor postprocessing cleanup.

5. REFERENCES

- [1] Olaf Ronneberger, Philipp Fischer, and Thomas Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," *arXiv:1505.04597 [cs]*, May 2015, arXiv: 1505.04597.