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DEEP CORTICAL VESSEL SEGMENTATION DRIVEN BY DATA AUGMENTATION WITH NEURAL IMAGE ANALOGY

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ABSTRACT

During a craniotomy, a bone flap is temporarily removed from the skull to reveal the brain for surgery. The cortical vessels located at the surface of the brain are considered strong features to guide surgeons during the procedure, since they appear in both preoperative and intraoperative images and are an indication of how the brain may have shifted. We propose a method utilizing a deep neural network to perform cortical vessel segmentation in craniotomy images captured through the surgical microscope. Following a U-Net architecture, our solution classifies each pixel of a craniotomy image as vessel, parenchyma, or surrounding tissue and background. We use neural image analogy to build a diverse training set of unique images mirroring cortical anatomy generated from a limited amount of manually labeled data. The synthesized images enhance generalization of our model to various types of cortical surface appearances and geometries. Experiments on real data from human patients show that intraoperative cortical vessel segmentation can be performed accurately.

Index Terms— Vessel segmentation, Deep neural network, Craniotomy, Neural image analogy

1. INTRODUCTION AND RELATED WORK

A craniotomy is the surgical removal of part of the bone from the skull to expose the brain, commonly performed to provide access for tumor resection or other surgical operations. Surgeons often use image-guidance systems to assist these procedures, where a patient’s head is registered with a preoperative MRI scan to plan the location and size of the craniotomy prior to surgery, as well as to identify relevant brain features [1].

The utility of image-guidance systems that rely on preoperative imaging is reduced by the deformations of the brain following a craniotomy due to gravity, tissue manipulation, loss of cerebrospinal fluid, and other factors. This phenomenon, called brain shift, can impact surgical outcomes because it leads to changes in the location of structures used as landmarks from their locations in preoperative imaging [2]. Following craniotomy, however, the cortical surface, and particularly the vessels, can act as an additional resource to inform image-guidance systems. Therefore, there is a need

for robust, automated cortical vessel segmentation techniques to extract the information provided by the cortical surface.

Because the detection and analysis of blood vessels play important roles in medical diagnosis, several blood vessel segmentation methods have been proposed in a variety of contexts, including intraabdominal endoscopy [3], fetoscopy [4], colonoscopy [5] and retinal surgery [6]. In neurosurgery, Filipe *et al.* [7] estimated brain displacement by manually labeling vessel centerlines and then using the coherent point drift method to register to preoperative MRI scans. Then, using the thin-plate spline method, a new MRI volume was generated to reflect the deformation. Luo *et al.* [8] manually identified cortical vessel features using an optically tracked stylus; brain shift was then estimated and corrected for after dural opening based on these features using a model-based workflow. Jiang *et al.* [9] relied on phase-shifted 3D measurement to capture the texture of the cortical surface, then used the Frangi filter to extract cortical features used for modeling surface deformation. Haouchine *et al.* [10] used cortical vessels to drive a biomechanical model to compute the brain deformation. The vessels were selected manually by an operator and the centerlines were used for registration with the preoperative MRI. The approach was later improved in [11] by the use of deep learning. However, limited by the scarcity of real data available, small image patches were used instead of the whole images. Using vesselness filtering enhancement followed by edge detection, Ding *et al.* [12] were able to extract centerlines from craniotomy images and build a binary map. This method was later used as input for vessel tracking [13] with the purpose of estimating cortical displacement directly from microscopic videos. However, this method cannot be generalized due to the high variability of craniotomy shapes, sizes, and locations.

In this paper, we propose a fully automated method using a convolutional neural network (CNN) for the segmentation of cortical vessels in craniotomy images acquired through the surgical microscope. Our main contribution is a style-enforced neural image analogy model used to generate realistic analog images to enlarge the training dataset. Our approach demonstrated good segmentation performance on synthesized and real patient data evaluated retrospectively.

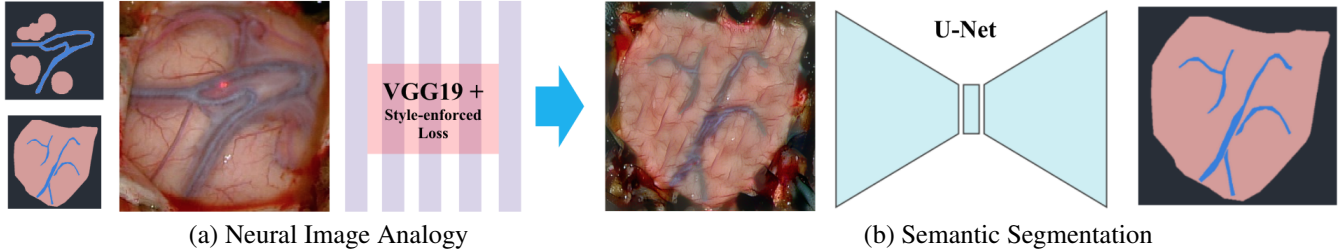


Fig. 1: Our pipeline for segmenting craniotomy images: (a) shows the image generation using style-enforced neural image analogy. (b) describes the vessel segmentation model, which takes an image as input, and outputs a class label for each pixel. The model is built using a deep learning approach with U-Net architecture trained on the images generated in (a).

2. METHODS

2.1. Dataset

Our preliminary dataset was composed of 71 craniotomy images obtained from video recorded through the surgical microscope. These images were manually segmented into three classes: vessel, parenchyma (functional tissue of the brain), and background.

2.2. Style-enforced Neural Image Analogy

In order to train a vessel segmentation model that generalizes well to new data, we needed to increase the amount of available training data through data augmentation. We used style-enforced neural image analogy, which can be used to generate an arbitrarily large and variable dataset of artificial images resembling real craniotomy images.

Image analogy models can learn a transformation from an image \mathcal{A} to a filtered image \mathcal{A}' and apply this transformation to another image. For instance, a new target image \mathcal{B} can be filtered to generate \mathcal{B}' which relates to \mathcal{B} analogously to how \mathcal{A}' relates to \mathcal{A} [14]. Neural image analogy extends this concept to complicated transformations utilizing image information available at various layers in CNNs. It can be used to combine the style and texture of a source image with the high-level content representations of a target image [15]. Style-enforced neural image analogy places emphasis on replicating the style of the source image over other features. Using this idea, we sought to artificially generate many unique images that replicate the style of craniotomy images, which can then be used to train the vessel segmentation model.

Specifically, our implementation generates a target image \mathcal{I} by applying the style of a source image \mathcal{J} to an annotated input image $\mathcal{I}_{\text{label}}$ while retaining the high-level content of $\mathcal{I}_{\text{label}}$, as illustrated in Figure 2. A distinct style representation is created for each region of \mathcal{J} specified in $\mathcal{J}_{\text{label}}$, and is applied to the corresponding region of $\mathcal{I}_{\text{label}}$. Based on this principle, we generated new images that applied the style of craniotomy images to artificially generated masks that represent cortical geometry. These masks allow the specification of distinct styles for background, parenchyma, and vessel.

We use neural image analogy based on a CNN, using layers from the pre-trained VGG-19 model and L-BFGS optimizer to minimize the following loss function:

$$\mathbf{L}(\mathcal{J}, \mathcal{I}) = \sum_l \sum_c \sum_{ij} \left(\mathbf{w}_{\mathcal{J}_{\text{label}}}^{l,c} \mathbf{G}_{ij}^l(\mathcal{J}) - \mathbf{w}_{\mathcal{I}_{\text{label}}}^{l,c} \mathbf{G}_{ij}^l(\mathcal{I}) \right) \quad (1)$$

where $\mathbf{G}_{ij}^l(\mathcal{J})$ is the Gram matrix of image \mathcal{J} at l -th convolutional layer, and $\mathbf{w}_{\mathcal{J}_{\text{label}}}^{l,c}$ are the weight factors to normalize each Gram matrix by the number of pixels in a label class c of $\mathcal{J}_{\text{label}}$. This allows for quantification of the difference between the style of the source image \mathcal{J} and the style of the target image \mathcal{I} as it is being generated. Importantly, computing the inner-most sum over each label class c allows for style comparison within each region specified in $\mathcal{J}_{\text{label}}, \mathcal{I}_{\text{label}}$.

This implementation can be extended to efficiently apply the style of a source image \mathcal{J} to arbitrarily many annotated images to generate a large set of images resembling \mathcal{J} in texture with unique high-level content, making this method an attractive candidate for data augmentation.

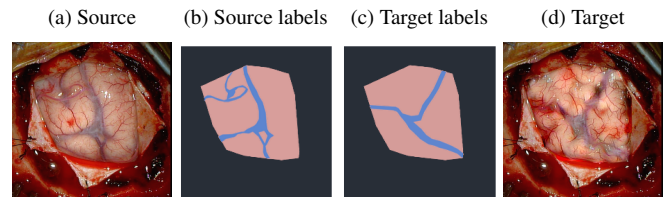


Fig. 2: Neural image analogy: given a source image \mathcal{J} (a) and its annotated images $\mathcal{J}_{\text{label}}$ (b), we synthesize a target image \mathcal{I} (d) following its annotation image $\mathcal{I}_{\text{label}}$ (c). Dark gray, pink, and blue represent background, parenchyma, and vessel, respectively.

Images from the original dataset were selected to be used as style sources for neural image analogy on the basis of high quality, lack of obstructions, and representative anatomy. The image annotations resulting from the manual labeling of the original dataset were utilized as input images $\mathcal{I}_{\text{label}}$ to preserve realistic geometry in generated images. We empirically

found that sparse labeling of source images as demonstrated in the top-left corner of Figure 1-a sometimes led to higher quality results than whole-image labeling, possibly due to the generation of style representations with less variability and noise. We therefore used a combination of sparse labeling and whole-image labeling in our style sources.

2.3. Model Architecture

We relied on a deep CNN following a typical U-Net architecture to extract the vessels from the cortical surface visible during a craniotomy. U-Net architecture was chosen due to its strong performance in pixel-wise classification even with few labeled training images, making it an ideal model for biomedical image processing. Ronneberger *et al.* provide a detailed explanation of the architecture here [16].

The input is one RGB image of size $256 \times 256 \times 3$ and the final layer is a Softmax classifier that assigns a class label $\{0, 1, 2\}$ to each pixel corresponding to background, parenchyma, and vessel, respectively. We empirically found that a categorical cross-entropy loss results in improved accuracy with our data compared to Dice loss widely used for medical image segmentation. The output image is represented as an image of size $256 \times 256 \times 3$.

3. RESULTS

We generated 618 images using neural image analogy from 10 craniotomy style source images and 71 annotated inputs. These images were randomly split, with 464 images used in the training set and the remaining 154 images left for the validation set. The training set was augmented using horizontal and vertical flips to expand the training set to 1856 images. The model was trained over 94 epochs using mini-batches of size 8 with Adam optimizer and a learning rate of 0.001. We used the Tensorflow framework (www.tensorflow.org) on an NVidia GeForce GTX 1070.

The original annotated inputs to the neural image analogy algorithm accurately mapped vessel geometry in the synthesized images, so annotated inputs served as data labels for the corresponding images when preparing the data for training. Availability of labeled data is a common bottleneck to training deep learning models, so the ability to use our pre-generated annotations as labels was an additional benefit of neural image analogy for data augmentation. The model achieved high accuracy on the validation set as measured by IoU 0.71 and Dice 0.82.

Table 1: Five-fold cross-validation of our model

	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Overall
IoU	0.713	0.711	0.705	0.716	0.701	0.709
Dice	0.825	0.823	0.820	0.827	0.816	0.822

To verify the accuracy of the model we also performed five-fold cross-validation, shown in Table 1. The results show consistently high accuracy across folds which shows the model achieves good vessel segmentation with images generated from neural image analogy.

Performance on artificially generated images is a good indicator that the model is working as expected, but the more important result is performance on real data as we hope to deploy the model to real cases. Therefore, we tested our model’s performance on real craniotomy images from 4 patients, and found that the model accurately mapped vessels based on visual inspection. We also compared the performance against a baseline U-Net using conventional data augmentation techniques [11] as well as the Frangi vesselness filter used in the final step of the automated cortical vessel segmentation method proposed by Ding *et al.* [12] (Figure 3). Segmentation using the vesselness filter appeared to be much noisier and less specific for the larger vessels compared to our method. The baseline U-Net did not achieve consistent segmentation over all the images, particularly noted in the right-most column of Figure 3. Our model achieved the highest IoU and Dice values across these images.

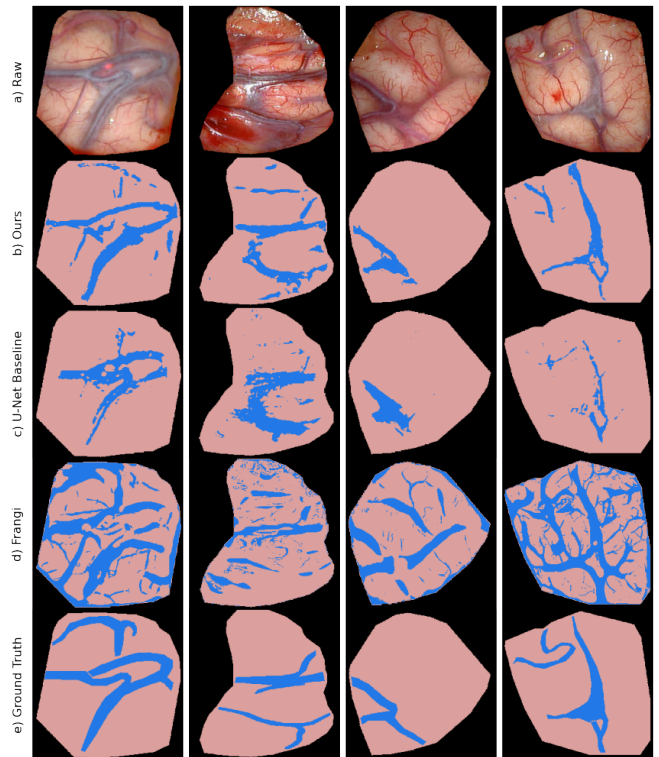


Fig. 3: Comparison of (b) our approach using U-Net with neural image analogy against (c) baseline U-Net using traditional data augmentation techniques and (d) Frangi vesselness filter for cortical vessel segmentation. IoU and Dice values for the respective models were (b) 0.79, 0.86 (c) 0.76, 0.844, and (d) 0.66, 0.75.

4. CONCLUSION

In this paper, we demonstrated a deep learning approach to cortical vessel segmentation in craniotomy images. This approach holds great promise in the field of image-guided neurosurgery as it provides an automated, accurate method for extracting the information from the cortical surface during craniotomy, which can be utilized to drive image-guided neuro-navigation systems. Notably, we have shown that a model trained fully with data generated artificially with neural image analogy performs well when evaluated on real patient data. The usage of this artificially generated data circumvents a common problem encountered in deep learning contexts—scarcity of real labeled data.

Future work will consist of enhancing our neural image analogy approach by experimenting with different labeling techniques with the aim of generating more realistic images. In doing so, we hope to assemble a larger data repository which can be used to train a more robust model.

5. COMPLIANCE WITH ETHICAL STANDARDS

This work was conducted on retrospective data in line with the principles of the Declaration of Helsinki. Approval for use of this data was granted by the Internal Review Board (IRB) at Brigham and Women’s Hospital, Boston, MA.

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