

Supplemental Material: VC-Net: Deep Volume-Composition Networks for Segmentation and Visualization of Highly Sparse and Noisy Image Data

1 SUPPLEMENTAL FIGURES

Supplemental figures are included for demonstrating additional qualitative results from TubeTK and MICRO-MRI datasets in Fig. 1, and different modalities of input image examples from TubeTK MRA and MICRO-MRI datasets in our VC-Net method in Fig. 2.

2 ADDITIONAL QUANTITATIVE PERFORMANCE EVALUATION

In order to further demonstrate the effectiveness of our VC-Net (especially 3D-to-2D projection in dual-stream and 2D-to-3D unprojection for joint embedding in our proposed architecture), Tab. 1 shows the numerical analyses on some simple combinations of the final results from 3D U-Net and 2D U-Net through average and max operations on the probabilities.

Table 1: Quantitative performance evaluation between different combinations of 3D U-Net and 2D U-Net and our method on TubeTK dataset.

Methods / Metrics	Dice (%) ↑
2D U-Net	65.10
3D U-Net	71.01
Average Fusion	65.15
Max Fusion	69.41
Ours	71.81

From Tab. 1, we can see our VC-Net overall outperforms both combination methods of the final results of 3D U-Net and 2D U-Net. As shown in Sec. 4.1 of the paper, 2D U-Net performs much worse than a standalone 3D U-Net on each metric. Unlike the 2D composited MIP stream in VC-Net, 2D U-Net itself essentially does not involve any complementary or enhancement information, and the reception field of 2D U-Net is restricted to an isolated 2D slice patch every time and thus lack of the contextual information from the third dimension, which is fatal to the sparse 3D vessel segmentation. Without comprehensive 3D spacing neighborhood, 2D U-Net is more prone to strong noise perturbation (high-intensity true negative) and insensitive to weak vessel signal (low-intensity true positive), as a result, 2D U-Net performs unsatisfactorily even when equipped with more feature embedding channels. Consequently, it may not be an ideal idea to fuse the results from 3D U-Net and 2D U-Net through the simple combinations.

Here, Dice Similarity is provided since it is the most comprehensive and effective indicator / metric to justify the segmentation performance. It measures the intersection over union between the prediction and the ground truth, which comprehensively takes into account all true positive (TP), false negative (FN), as well as false positive (FP). This is also why we (as well as many other research works) select Dice Similarity as the loss function in our VC-Net.

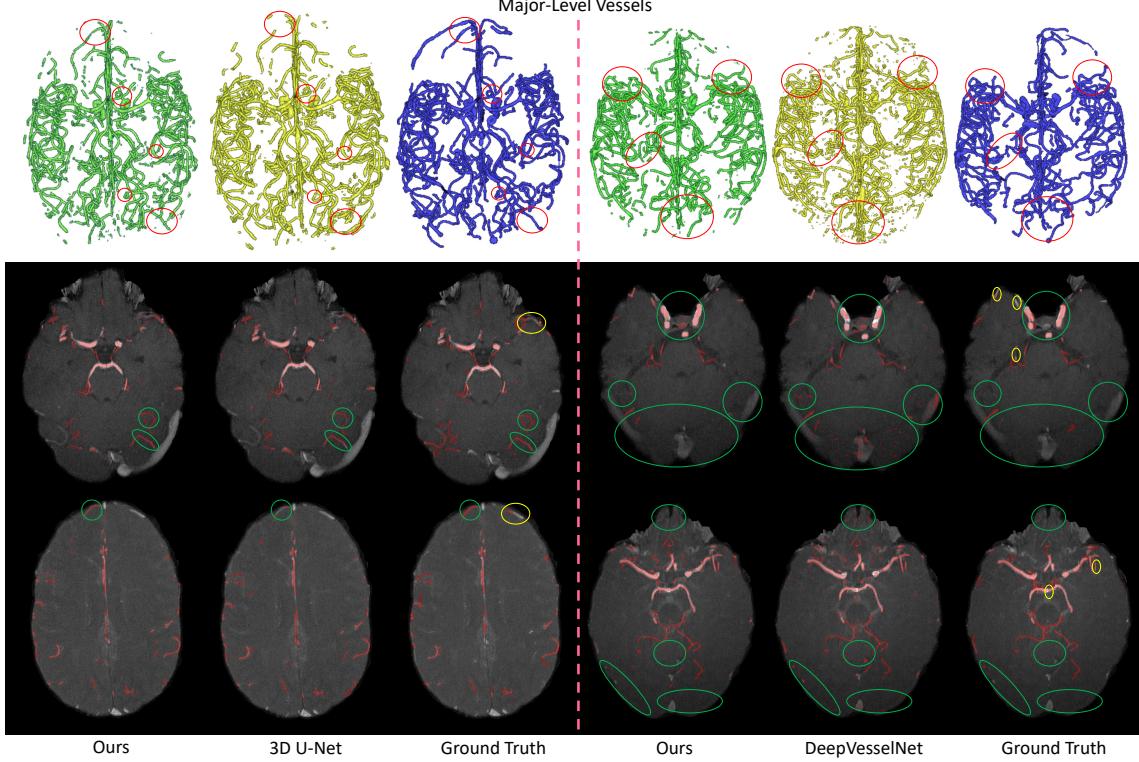
3 LABELING REFINEMENT AND VISUALIZATION TOOL

The interface and basic functions of our specifically-designed cerebrovascular labeling and visualization tool are shown in Fig. 3. Our tool enables slice-wise refinement based on the pre-computed vessel labels by MRAG_{nls}, MRVG_{avg}, and SWI_{ATRG} methods, instead of labeling from scratch manually. The interactive vessel editing is conducted in the current image slice window, e.g., manually labeling / erasing brush, automatically labeling connected components by flood-fill method as shown in Fig. 3 (a). The slice under editing is simultaneously visualized in solid red for a clearer examination in Fig. 3 (d). Unlike the operation in most of the general-purpose labeling / segmentation softwares in which the current labeling (2D) slice is usually isolated from its (3D) context and thus lacks the crucial reference, the vessel labeling in our developed tool is comprehensively assisted and guided by the following specifically-desired functions: (1) simultaneously updated 3D vasculature system from the beginning to the current slices with several interactions, such as rotation and zooming in / out, to check the cross-plane 3D vessel connectivity (Fig. 3 b); (2) synchronized brain vessel volume rendering to trace the overall segmented vasculature system (Fig. 3 c); (3) adaptive MIP labeling display (with user-defined number of projection slices) that enables users to evaluate the contextual slices to strengthen the vessel connectivity and rule out noise (Fig. 3 e). Our tool can greatly facilitate the continuous slice-wise labeling and reduce the labeling ambiguity in some challenging areas of the micro-cerebrovascular structure, which have been extensively tested and evaluated by our collaborative domain experts. Supplemental Video is included to demonstrate the dynamic visualization and interaction in detail.

4 SUPPLEMENTAL VIDEO

Supplemental video is included to demonstrate the joint 3D visualization of the major-level and micro-level vessels in the midbrain and the whole brain on MICRO-MRI dataset; as well as the dynamic visualization and interaction of our developed cerebrovascular labeling and visualization tool.

Additional Results on TubeTK Dataset



Additional Results on MICRO-MRI Dataset

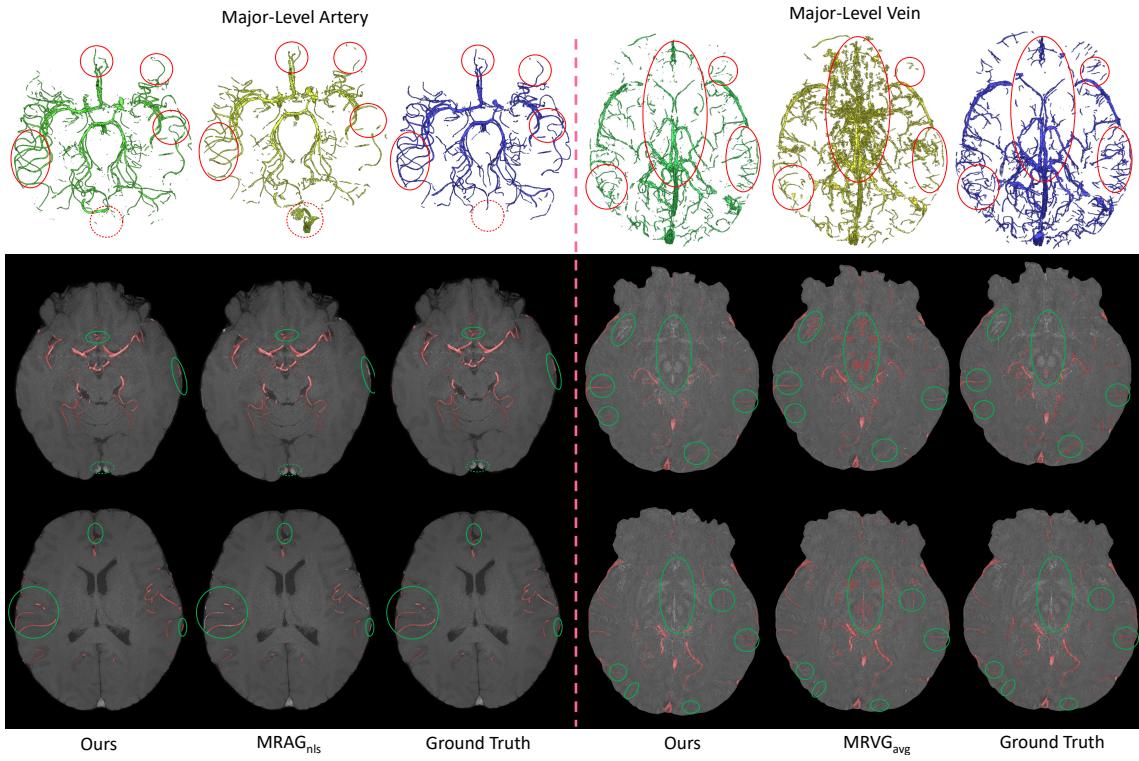


Fig. 1: Additional qualitative results from two datasets (top: TubeTK dataset, bottom: MICRO-MRI major-level vessel dataset): The 3D global vessel segmentations are shown from superior direction. The MIP segmentations are visualized by 5-sliced MRA / MICRO-MRI images, and the corresponding vessel masks in MIPs are marked in semi-transparent red. The highlighted comparison areas are marked in circles. The 3D MRAG / MRVG images from MICRO-MRI dataset only focus on midbrain area and thus have less vessels compared with TubeTK dataset. It is noted that in TubeTK dataset even the ground truth vessel label does not perfectly cover certain vessel continuity, which can be clearly traced on MIPs (such as some yellow circles in the ground truth MIPs), in the corresponding MRA slices. We will further refine the ground truth vessel labels of TubeTK dataset by using our developed labeling tool under the domain experts' guidance in our future work.

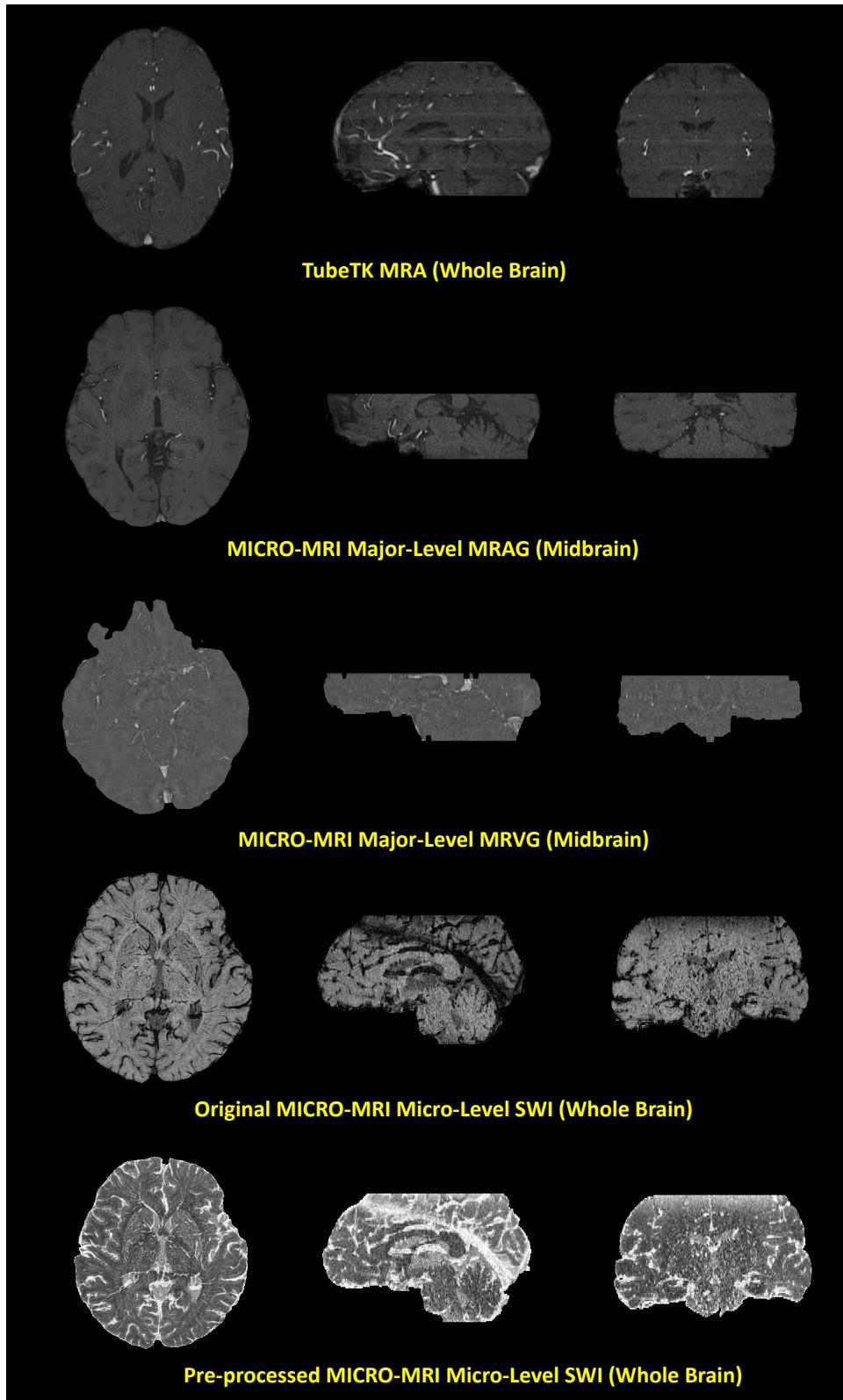


Fig. 2: The different modalities of input image examples from TubeTK MRA and MICRO-MRI datasets in our VC-Net method.

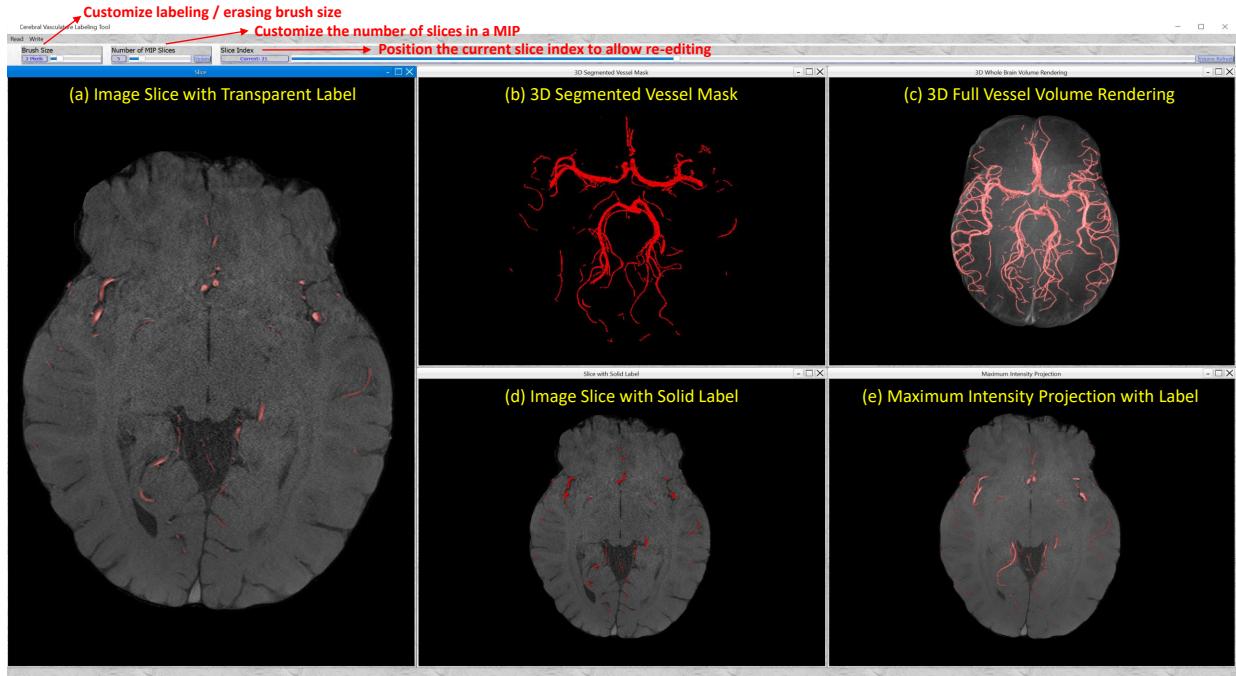


Fig. 3: Our developed cerebrovascular labeling and visualization tool (e.g., an example of major-level arterial vessels from MICRO-MRI).