VSMOD: A Vessel Segmentation and MODelization plugin for 3D Slicer

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Summary

The volumetric annotation of vessels in medical images is a challenging and time-consuming task that typically requires extensive expert manual work. *VSMOD* is a free, user-friendly plugin for 3D Slicer (Fedorov et al., 2012) designed to simplify and streamline the vascular annotation process. *VSMOD* offers a semi-automatic two-step segmentation approach, that combines RANSAC-based centerline detection (Yureidini et al., 2012) and a region growing approach with automatic seed selection to accelerate vessel annotation. Users can interactively generate vessel centerlines by placing two points – one marking the vessel's starting location, and the other indicating its initial direction thereby defining a branch. Additional branches are created by tracking a new branch near existing ones. From these centerlines, a vascular tree graph is automatically constructed and can be exported as a NetworkX graph (Hagberg et al., 2008), facilitating efficient data storage and external manipulation. Finally, a region growing segmentation is applied using seeds automatically derived from the centerlines.

Initially designed for pulmonary artery annotation, *VSMOD*'s methodology is adaptable to various vascular structures across different organs (e.g., brain, liver). This plugin significantly reduces the time required to obtain complete volumetric vessel segmentation. Moreover, it generates fully connected vascular trees with precise topology, which is nearly impossible to achieve with conventional annotation tools.

VSMOD enables users to create accurate and topologically consistent vascular network annotations, facilitating large-scale supervised machine-learning dataset generation for vascular segmentation. Future developments will focus on improving the segmentation step using deep learning-based approaches and further assessing the framework's generalizability across diverse vascular segmentation tasks. The plugin is available at this Github Repo.

Statement of need

Accurate annotation of vascular networks in medical imaging remains a critical challenge and is essential to develop accurate deep learning-based segmentation models. Current segmentation models still struggle with preserving the connectivity of complex vascular networks (Carneiro-Esteves et al., 2025; Keshwani et al., 2020; Rougé et al., 2024) which is crucial for downstream tasks such as flow dynamic simulations. Improving the quality and precision of annotated datasets is crucial for training more effective models. However, traditional manual annotation methods are extremely time-consuming and subject to inter-observer variability creating important concept shifts in the annotation, ultimately leading to lower model performance (Rougé et al., 2025).

Existing vessel annotation tools have notable limitations. Traditional paint and brush tools in image analysis software such as *3D Slicer*[1] ([Pinter et al., 2019](#)) or *ImageJ*[2] required slice-by-slice pixel-level annotation, making the process extremely laborious and often resulting in disconnected segmentations. Tubular shape prior tools have been proposed, such as the *Draw Tube* tool from the SlicerSegmentEditorExtraEffects extension[3]. However, this method requires manually drawing each vessel separately, and its fixed tubular shape is poorly suited for real vessels, which exhibit tortuosity and variable radii. Additionally, constructing a fully connected vascular tree remains particularly challenging.

Recently, Lamy *et al.* proposed the *RVXLiverSegmentation* plugin ([Lamy et al., 2022](#)) for 3D Slicer to segment vascular networks of the liver. This tool enables fast and accurate vascular segmentation by requiring users to place predetermined points at branching nodes. However, it is designed specifically for the vasculature of the liver and is not applicable to other organs. *VSMOD* is designed to overcome these limitations by providing a user-friendly plugin for efficiently generating accurate and topologically correct vascular segmentations.

Overview of VSMOD

VSMOD integrates two complementary modules (cf. Fig. 1). First, the **centerline module** uses a RANSAC centerline tracking algorithm to create a graph model of the vascular network, ensuring that parent-child relationships between vessels are preserved, and providing precise geometry and radius estimation. Then, the **segmentation module** automatically generates seeds to initialize a region growing segmentation yielding a completely connected vascular segmentation.
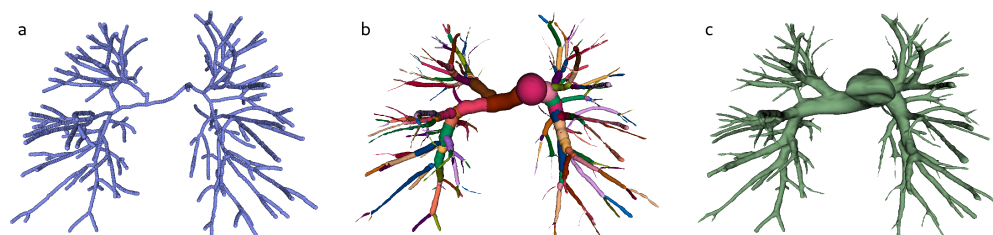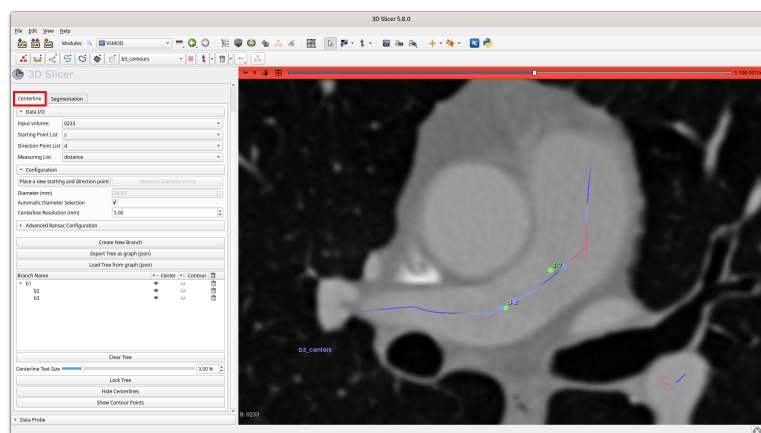

Figure 1: Example of the annotation process on pulmonary arteries. From left to right: a) Centerlines detected using the RANSAC-based algorithm. b) 3D visualization of automatically placed seeds for region-growing. c) The final vessel segmentation.

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[1] https://www.slicer.org/
[2] https://imagej.net/ij/
[3] https://github.com/lassoan/SlicerSegmentEditorExtraEffects

Centerline Module

Figure 2: Example of the centerline module interface. Green dots represent user-selected points, while blue and pink lines indicate centerlines detected by the RANSAC algorithm. The bottom-left panel displays the vascular graph, where the b1 branch splits into b2 and b3.

The first module of *VSMOD* extracts vessel centerlines (cf. Fig. 2). Users begin by placing starting and directional points to define the initial vessel path. Then, the RANSAC algorithm (Yureidini et al., 2012) iteratively tracks points along the vessel centerline. At vessel intersections, the algorithm randomly selects a branch and continues tracking until it reaches the end of the vessel. To annotate additional vessels, the user selects two new points near an existing centerline. The algorithm then automatically detects the new branch and connects it to the previously identified centerlines. An estimate of the diameter of the vessel at the beginning of the vessel has to be set when launching the algorithm for the first time. This is the only parameter that is required. The other RANSAC algorithm parameters can be set manually by the user for a fine user control, but good default values are provided.

Additionally, this module enables users to export and load a vascular network as a NetworkX graph (Hagberg et al., 2008) in JSON format. This feature allows for pausing and resuming the annotation process while preserving the vessel hierarchy and structural relationships for further computational analysis.

Segmentation Module
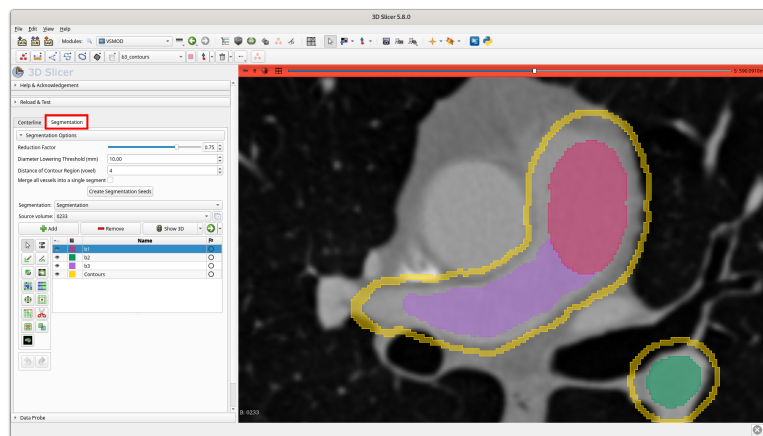
Figure 3: Example of the segmentation module interface with automatically generated seed points on a patient's axial view. The automatic seeds are displayed in different colors inside the vessels (pink, purple and green) and surrounded by the yellow border to constrain the region growing process.

The second module of *VSMOD* transforms the extracted centerline data into a volumic vessel segmentation (cf. Fig. 3). This process leverages the "Grow from seeds" region growing segmentation tools from 3D Slicer (Zhu et al., 2014) to refine and expand the segmentation. The process begins with the automatic generation of seed points along the detected centerline. The seed size is determined by the radius estimations obtained from the previous step. These seeds serve as anchor points, guiding the segmentation along the vessel path. The background seeds are produced by applying dilation and subtraction operations, to create a raw boundary outside the vessels. This ensures that the region-growing process remains confined within the vascular structure and does not extend into surrounding tissues. The distance between the edge of the vessel and the outside boundary is a parameter that can be adjusted by the user.

Results

Reduction of the annotation time

In this section we compare the time to annotate a complete pulmonary vascular network from a computed tomography pulmonary angiography (CTPA).

Ten CTPA images were extensively annotated with the *VSMOD* plugin by an expert who reported an average time of 3 hours and 35 minutes per image to annotate the complete vascular network (269 vessels on average per image).

Most of this time was spent in the centerline module, where users manually place vessel start and directional points. Additional time was dedicated to refining seed placement around embolized regions, which required extra attention due to their complexity.

Extensive manual annotation of the vascular network using traditional tools was impractical due to the significant time required. Instead, two experts annotated several individual vessels representative of the network's complexity using the available tools in 3D Slicer. The annotation process took an average of four minutes and 46 sec per vessel, which would equate to approximately 21 hours 22 minutes per image for a complete vascular network. *VSMOD* reduces annotation time by 80% (cf. Table 1).

Beyond efficiency gains, *VSMOD* offers additional advantages by automatically generating a hierarchical vessel tree, providing centerline data, radius estimations, and graph connectivity

information – critical components for downstream vascular analysis.

Table 1: Comparison of average segmentation times per patient calculated on data with an average of 269 vessels

Annotation method	Time per vessel	Total time per patient
Manual	4m46s	21h22m52s
VSMOD	48s	3h35min12s

Plugin usage on different vascular networks

VSMOD is not restricted to the vascular network of a specific organ. Its algorithms are generic and rely solely on the assumption of vessel geometry-tube-like structures with curvature. Extensive testing was conducted on the pulmonary vascular network, as discussed in the previous section. Additionally, the plugin was tested on the brain vascular network using magnetic resonance angiography (MRA). Despite the significant geometric differences between pulmonary and cerebral vessels, *VSMOD* was also able to segment these vessels, as illustrated in Fig. 4.
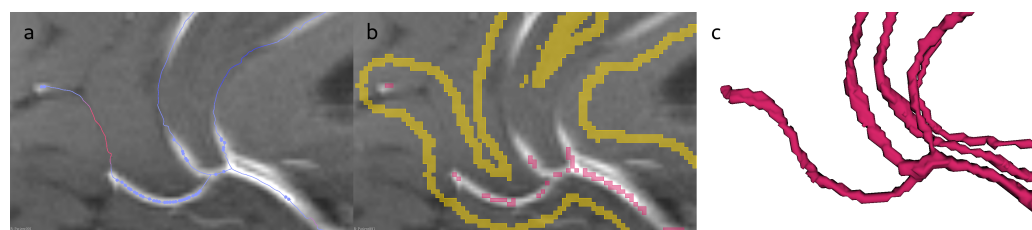
Figure 4: Example of the annotation process on brain vessels. From left to right: a) Centerlines detected using the RANSAC-based algorithm. b) 3D visualization of automatically placed seeds for region-growing. c) The final vessel segmentation.

In conclusion, *VSMOD* provides a user-friendly framework for generating vascular network segmentation annotations. By automating the most labor-intensive aspects of vascular segmentation, this module significantly reduces manual effort while still allowing users to fine-tune the results as needed.

Future work will focus on optimizing RANSAC parameters by introducing anatomy-specific default settings for different types of vessels. This would minimize the need for manual fine-tuning, improving usability and adaptability. Additionally, integrating deep learning models could further enhance segmentation accuracy and reduce manual intervention, particularly in the segmentation module.

Acknowledgements

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