Novel Algorithm for Accurate Brain Vessel Segmentation in MRI Scans Using Variance Wells

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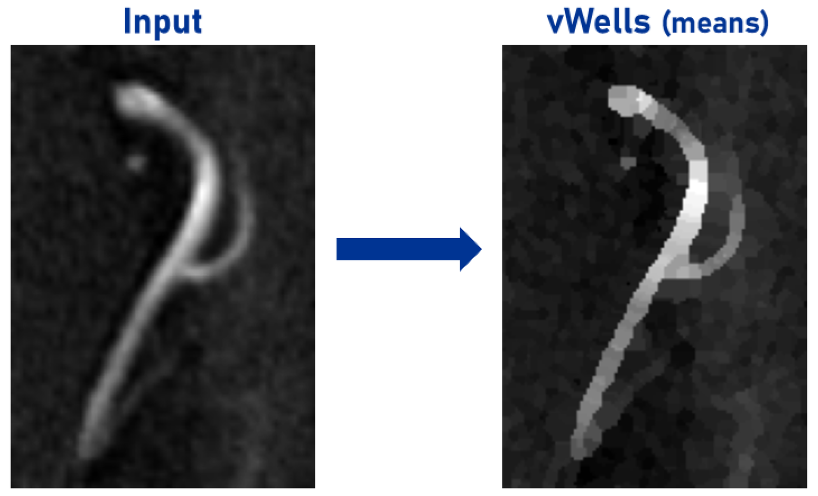
INTRODUCTION

It is believed that conditions such as late-life depression and Alzheimer's have etiological roots in brain vasculature. As a result, methods to study the morphology of brain vessels are warranted. Current methods allow for viewing 3D MRI brain scans to examine patient vasculature, but segmentation of the vessels is often a tedious manual process or an unreliable automated one. We present a novel image analysis algorithm designed to accurately segment the vessels of the brain from 3D MRI images for further analysis.

FORMING VWELLS

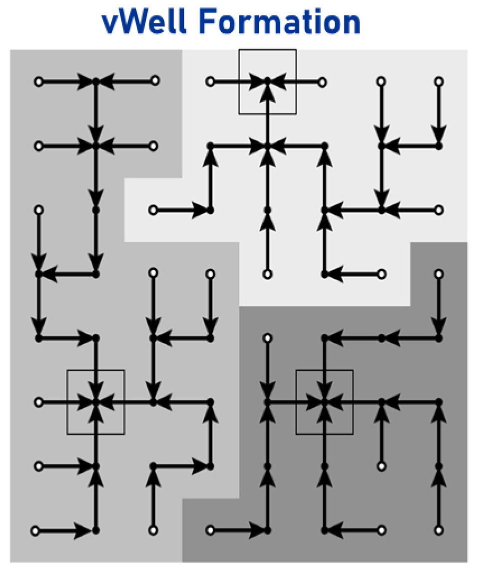
Our algorithm begins by preprocessing the image into small, relatively homogeneous regions we refer to as 'variance wells' or 'vWells.'



We first iterate through each pixel, computing the local variance of a small kernel around it to generate a variance image.

The variance image shows high (bright) values at boundaries between regions, and low (dark) values in relatively homogenous areas.

From this image, we construct a directed graph structure where nodes are pixels and edges connect orthogonally neighboring pixels, pointing to the neighbor with the lowest variance [1].



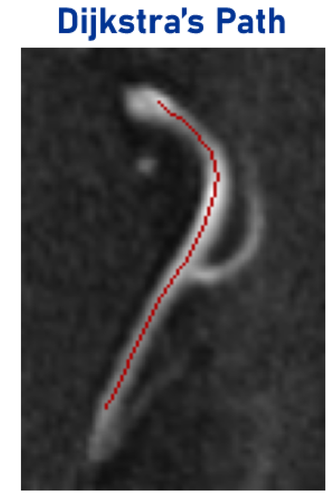
As a result, disjoint tree-like structures are formed where the roots are local minima in variance. These trees are traced backward to form vWells.

SEGMENTING WITH VWELLS

Each vWell represents a localized 'well' of variance. They are relatively uniform regions that maintain clear boundaries between adjacent objects. While vWells don't typically represent whole anatomical structures, they can be combined with adjacent vWells to segment complete structures such as vessels from brain images.

PATHFINDING ALGORITHM

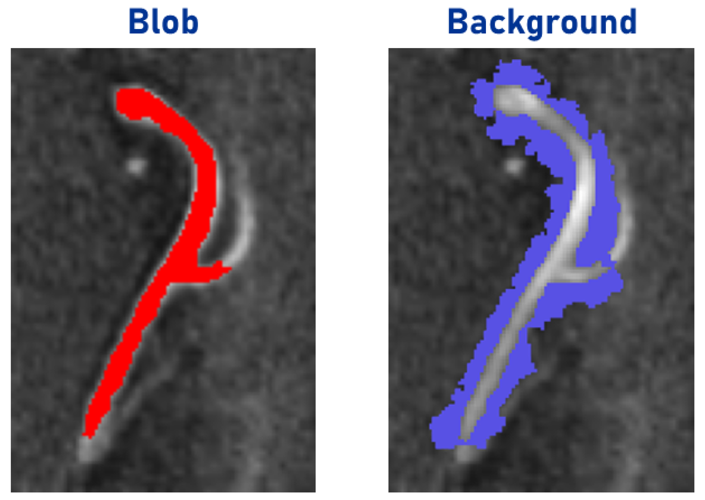
The algorithm finds a path through a vessel by connecting manually placed guide points using a modified Dijkstra's and A-star algorithm. Similar to how GPS programs find the best path between locations, it uses t-tests between adjacent vWells to identify the most similar vWells, ensuring the best path along the vessel.



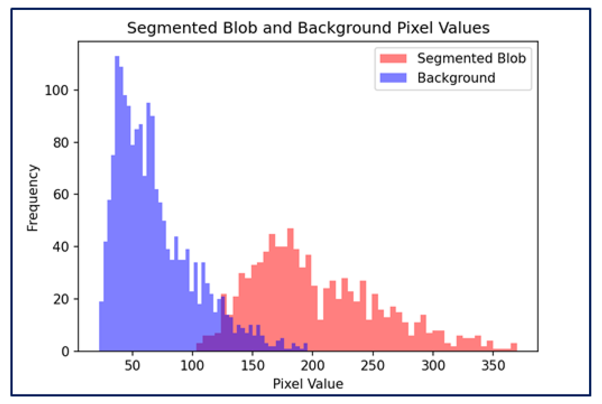
Using the t-test adds robustness and versatility to our algorithm, as it focuses solely on statistical similarity between vWells, making it applicable to a wide range of structures.

REGION GROWING ALGORITHM

From the path found by the pathfinding process, the algorithm grows outward until the vessel is fully segmented. Initially, a "blob" consisting of the path within the vessel and the 'background' of surrounding vWells are compared using t-tests. VWells are then iteratively moved from the background to the blob, enlisting new neighboring vWells into the background. This process continues until the t-value no longer increases, indicating the blob and background are as distinct as possible.



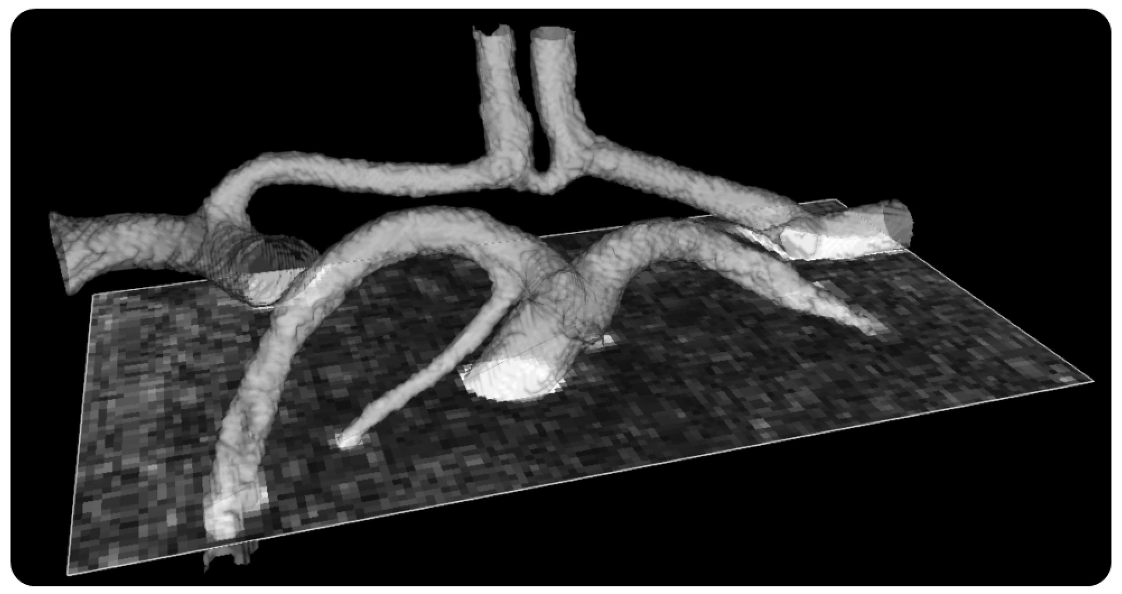
The blob represents the fully segmented vessel.



A histogram illustrating the separation of pixel values of the blob and background.

APPLICATIONS IN 3D

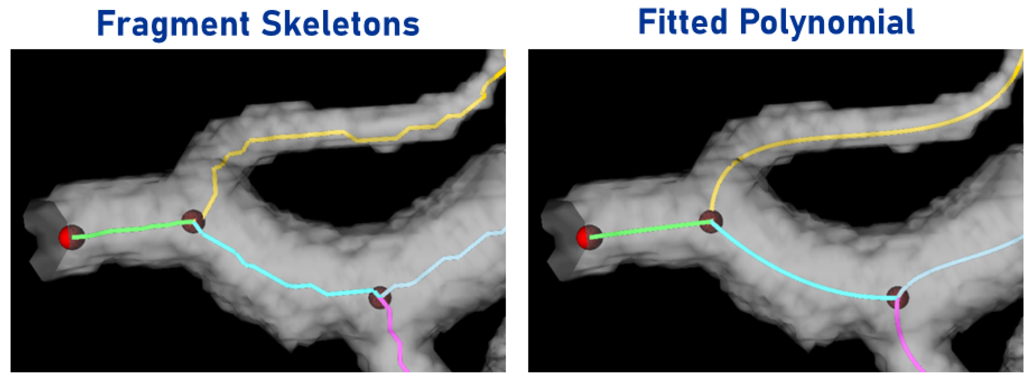
Final analysis of the brain's vessels must be conducted on 3D MRI scans, as the vessels navigate various directions throughout the brain. Our segmentations appear to provide an accurate representation of the brain's vessels, further enabling analysis to get precise measurements of curvature, radius, length, and more.



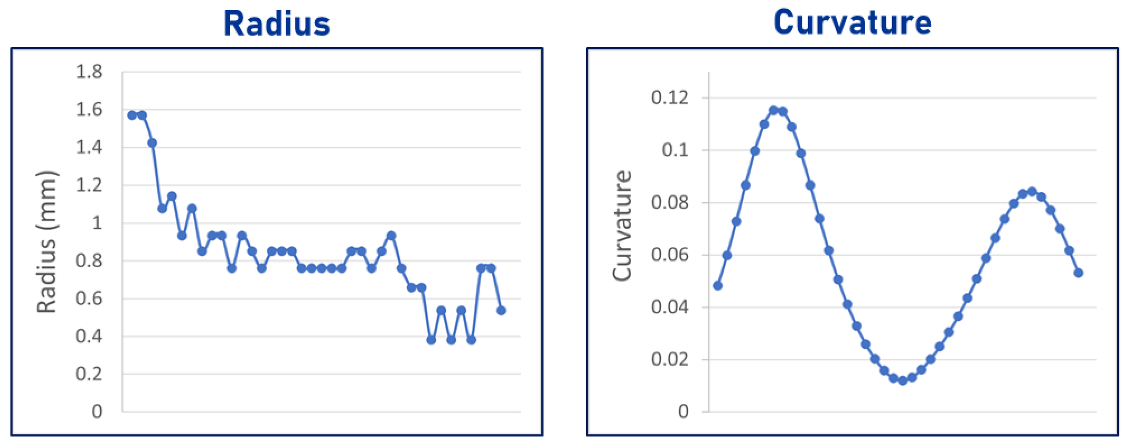
The user places points along the vessels in 3D, as the algorithm performs real-time segmentation accurately lining up with the MRI scan.

FRAGMENT ANALYSIS

From the segmentation, we extract the skeleton, which approximates the medial axis of the segmentation. This skeleton is then used to identify vessel branch points, allowing the connected vessels to be divided into individual "fragments." A smooth 3D polynomial is then fitted to each fragment's skeleton.



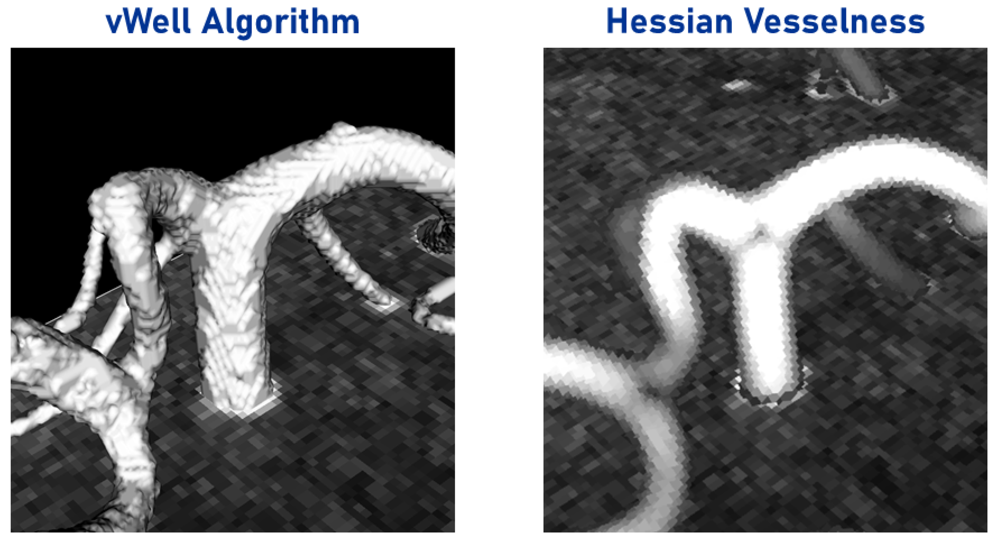
The fragment skeletons and fitted polynomials can be used in various ways to extract data for analysis. In our preliminary tests, we find radius, curvature, and length along fragments.



Radius and curvature data for the vessel highlighted in yellow in the images above. The vessel's total length is 17.75 mm. The radius is calculated using a distance transform to the nearest boundary, while the curvature is derived by applying a curvature equation to the fitted polynomial.

DISCUSSION

Current methods face significant limitations: manual segmentation is highly time-consuming and subjective, while vesselness and thresholding techniques are prone to noise and require extensive post-processing to achieve accurate segmentation. Meanwhile, machine learning algorithms like CNNs rely on large, pre-labeled datasets and computationally intensive models, making them both resource-heavy and complex to implement. In contrast, our approach leverages priors of statistical similarity and vessel connectivity in a targeted region, offering a more robust, intuitive and mathematically grounded solution for brain vessel segmentation.



The vWell algorithm distinguishes clear vessel boundaries from the background, while other techniques like the Hessian vesselness filter tend to produce a less precise segmentation. Additionally, through image resampling, the vWells can detect single-pixel-wide vessels frequently missed by current models.

LIMITATIONS AND FUTURE DIRECTIONS

Challenges of our algorithm include the need for human supervision, and lack of full automation. As with all image processing models, noise in the data leads to errors in vWell formation and segmentation. Future work will focus on reducing these errors and minimizing human involvement to make the process more automated. Even so, preliminary results demonstrate the algorithm's effectiveness, enabling precise, quantifiable comparisons of vessel measurements across diverse 3D MRI scans. Using this model will help advance research into neurological conditions like Alzheimer's disease, where vascular morphology plays a critical role.

REFERENCES AND ACKNOWLEDGEMENTS

[1] G. Stetten, C. Wong, V. Shivaprabhu, A. Zhang, S. Horvath, J. Wang, J. Galeotti, V. Gorantla, and H. Aizenstein, Descending Variance Graphs for Segmenting Neurological Structures, 3rd International IEEE Workshop on Pattern Recognition in Neuroimaging, Philadelphia, PA, June 22-24, 2013.

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