Retinal blood vessel segmentation

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Introduction

Retinal blood vessel segmentation is a complicated task because of the varying widths of the vessels, low contrast, and the presence of the optic disk. Modern cutting edge technologies use deep networks to learn how to extract the vessels, and they work incredibly well. (Samuel and Veeramalai, 2021) In this project, I implement a Hessian-based multi-scale filter combined with hysteresis thresholding, to extract the vascular tree.
In this short document, I will present my solution with which I achieved a 71% average DICE score on the DRIVE dataset.

Preprocessing and FOV masking

To start with, we have the retina image and a manually drawn vessel mask serving as ground truth.

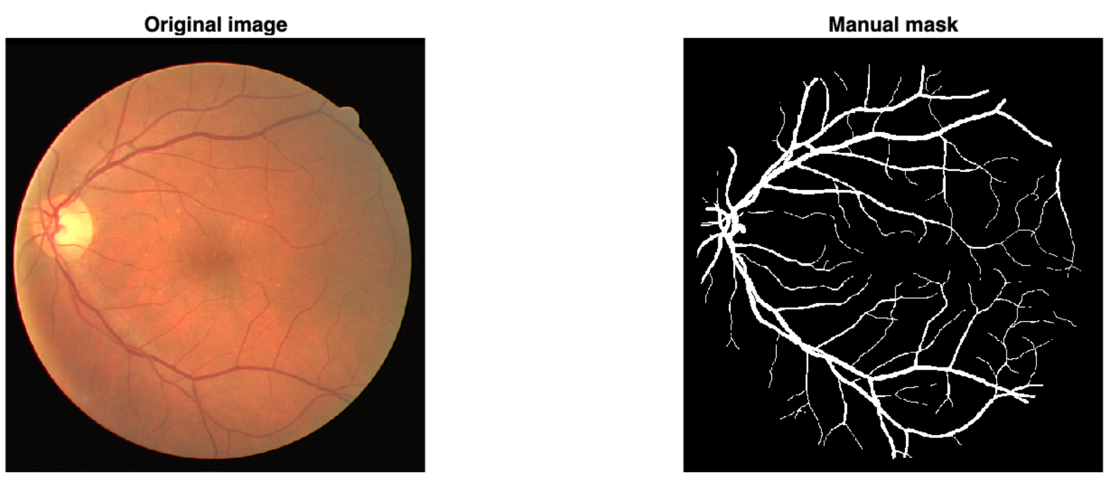

Figure 1: Original image and mask

Before we can make any mathematical calculations to determine the correct way of segmentation we have to preprocess the image.

First we extract the green channel of the image and work with that from now on. The green channel is the best for this, because blood vessels absorb green light more than red or blue, as you can see on the figure. This creates the highest contrast between the vessels and the rest of the eye.

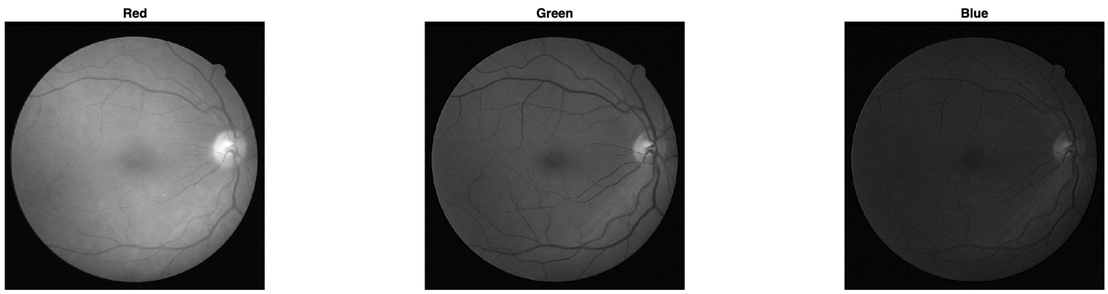

Figure 2: Red Green and Black channels

Next, we have to create a FOV mask around the eye on the image, so that the sudden change from the black background and the eyeball itself is not recognized falsely as a vessel. A FOV mask is created by the following steps: First a simple thresholding, the background is black, the rest is brighter, so it is easy to find the contour. And then it is followed by a small, 5px eroding so that we exclude the boundary from the analysis.

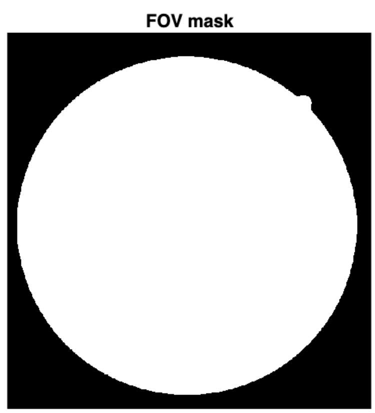

Figure 3: FOV mask

Now that we have a filter we only need a few more steps to perfect the preprocessing. By inverting the image we convert the ”valleys” (dark vessels) into ”ridges” (bright vessels). This will satisfy the input requirements of our Hessian-based ridge detector.
And then the CLAHE(Contrast Limited Adaptive Histogram Equalization) (Zuiderveld, 1994). solves the problem of uneven illumination, which occures mostly because of the optic disc’s brightness. CLAHE operates on local tiles (8×8) to enhance local contrast, and then we use a limit, to stop the equalization to create noise by running through homogeneous parts of the image.

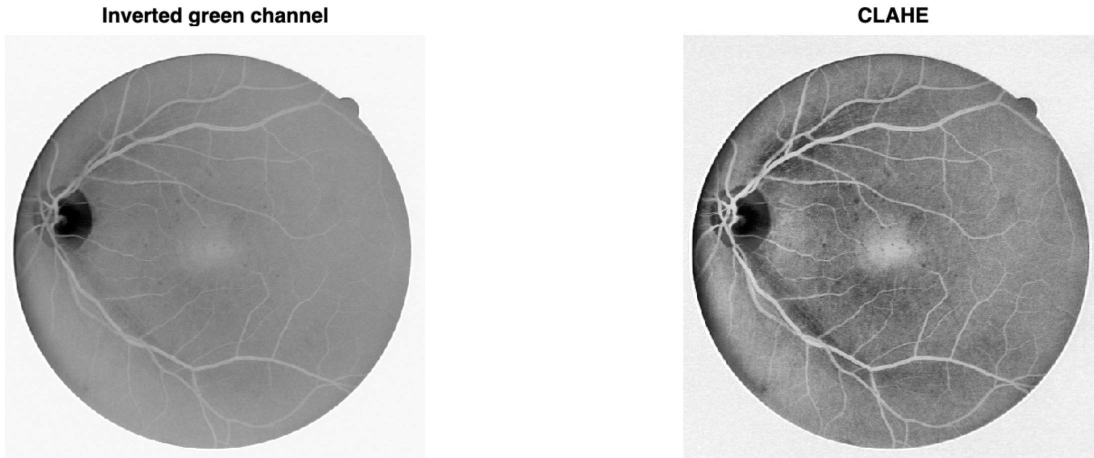

Figure 4: Inversion and CLAHE

The Frangi Vesselness Filter

The Math (Hessian Matrix)

After preprocessing the image, we just have to figure out where the vessels are. In our image, the vessels are the bright spots. But how do we distinguish a vessel's brightness from a random noise spot? We look for curvature. We can imagine the whole image as a terrain map where bright spots are hills and dark spots are valleys. In this case, a bright noise spot is just a cone, from which every way leads down into a valley. But if we stand on a vessel, the ground only slopes down from the right and left sides; in front of us and behind us, it is relatively flat. (Frangi et al., 1998)

To measure a shape mathematically, we use the Hessian matrix. This matrix describes the 2nd-order derivatives (curvature) of the image intensity I at scale σ:

$$H = \begin{bmatrix} I_{xx} & I_{xy} \\ I_{yx} & I_{yy} \end{bmatrix} \tag{1}$$

Detecting the shape: Eigenvalues

By calculating the Eigenvalues (λ_1, λ_2) of this matrix, we determine the shape of the structure at that pixel, invariant to rotation:

- $\boldsymbol{\lambda_1}$ **(Small):** Represents the curvature *along* the vessel. For a tube, this should be near 0 (flat).
- $\boldsymbol{\lambda_2}$ **(Large):** Represents the curvature *across* the vessel. For a tube, this should be high (steep drop-off).

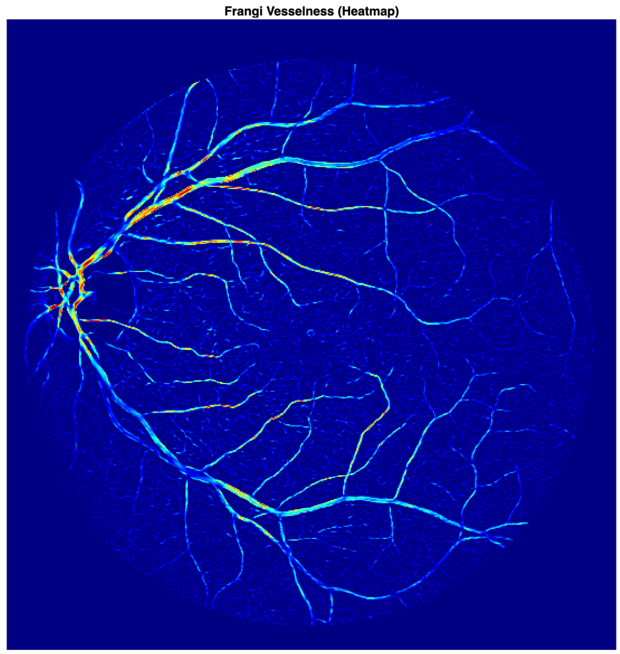

Figure 5: The Frangi Vesselness Map. Warmer colors indicate a higher probability of a vessel.

Multiscale Analysis

Because vessels vary in width, we run this algorithm multiple times with different sigma values ($\sigma \in \{1, 2, 3\}$) and combined the results (max response). This way both the bigger vessels and the small capillaries are discovered.

The Decision: Hysteresis Thresholding

Now that we have the heatmap, we just have to decide which part of the image should be kept as a vessel. A simple cutoff would fail because if the threshold rate is too high, the smaller capillars would disappear and if it were too small a lot of noise would be included.

This is why we need to use Hysteresis thresholding. I defined two parameters:

1. **The Seeds ($T_{high} = 0.12$):** We start with a strict threshold. This finds only the thickest, most obvious vessels.

2. **The Candidates ($T_{low} = 0.06$):** We define a lower, more sensitive threshold. This finds faint vessels, but also noise.

The Connection Rule: We keep a "Candidate" pixel *only* if it is spatially connected to a "Seed" pixel Now the reconstruction strategy works like this: we trust the trunks that pass the high threshold and we only keep a low-threshold vessel if it spatially connects to the already existing vessels. So this method kind of "grows" the vessel tree. Faint vessels are preserved because they connect to the main trunks, while isolated noise spots are rejected. (Canny, 1986)

Results

I evaluated the pipeline using the **Dice Similarity Coefficient**, which measures the pixel-wise overlap between our results and the human expert's annotation.

$$Dice = \frac{2 \times |A \cap B|}{|A| + |B|} \tag{2}$$

- **Final Score:** ≈ 0.71

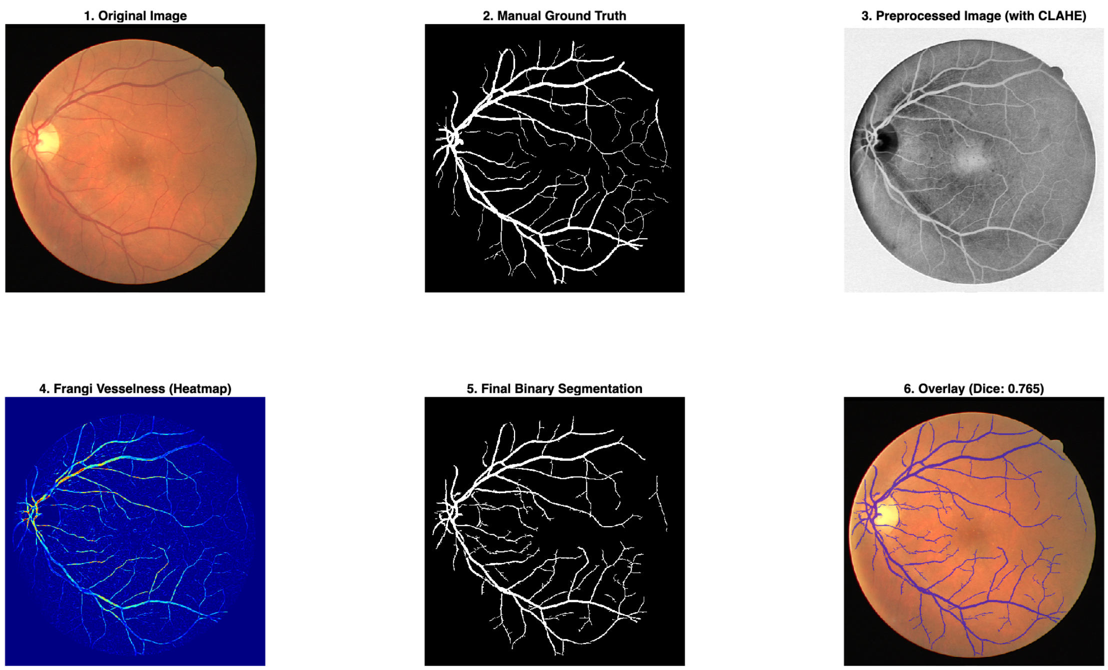

Figure 6: Final Result. The binary mask (blue/color) is overlaid on the original image.

References

Canny, J. (1986). A computational approach to edge detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *PAMI-8*(6), 679–698. https://doi.org/10.1109/TPAMI.1986.4767851

Frangi, A. F., Niessen, W. J., Vincken, K. L., & Viergever, M. A. (1998). Multiscale vessel enhancement filtering. *Medical Image Computing and Computer-Assisted Intervention—MICCAI'98*, 130–137.

Samuel, P. M., & Veeramalai, T. (2021). Vssc net: Vessel specific skip chain convolutional network for blood vessel segmentation. *Computer Methods and Programs in Biomedicine*, *198*, 105769. https://doi.org/10.1016/j.cmpb.2020.105769

Zuiderveld, K. (1994). Contrast limited adaptive histogram equalization. In *Graphics gems iv* (pp. 474–485). Academic Press.