MI206 - Algorithmic Geometry Mathematical Morphology

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Contents

1 Introduction

The aim of this project is to propose an automatic method for segmenting the vascular network in retinal images, as shown in the example below.

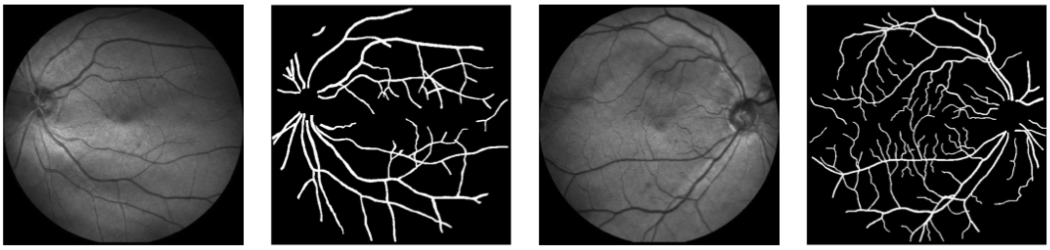

Figure 1: Expected Result - Result drawn by the doctor

The program will be written in Python, with the objective of implementing a succession of filters or actions on the image to achieve the desired result.

2 Reasoning

2.1 Pre-processing

The first step is to invert the image, i.e., black pixels become white and vice versa. Indeed, we are interested in the vascular network, which is black in the images. Moreover, the morphological filter "top-hat" (which we use later) is more effective on bright areas of interest. We also apply a mask to keep only the area of interest in the image.

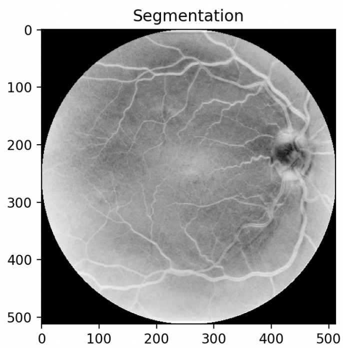

Figure 2: Inverted and masked image

2.2 Multi-scale Top-Hat

The top-hat is the morphological filter that seemed most suitable; it increases the contrast between the background and the vascular network.

As indicated in the lab instructions, I also used a multi-scale approach. To do this, I decided to take three disk-shaped structuring elements (disks gave me the best performance) with different radius sizes (chosen after several trials, taking the values that gave the best results).

For each radius, we apply the Top-Hat and combine the results by taking the maximum of each pixel across all top-hats. This ensures the highlighting of vessels of different sizes.

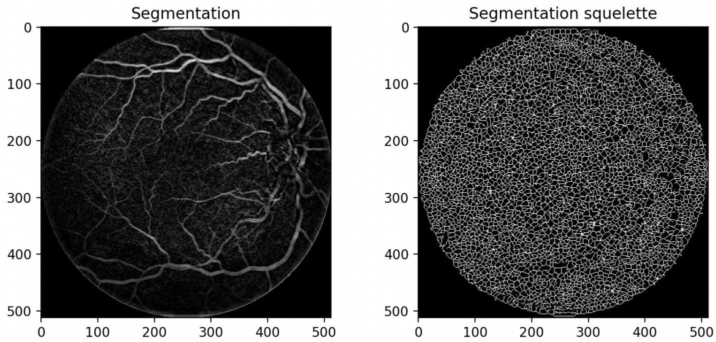

Figure 3: Noisy image after top-hat

2.3 Binary Image

I then used an intensity threshold to make the image binary (here too, the intensity threshold value was chosen to maximize performance), pixels with values below the threshold become black and others white.

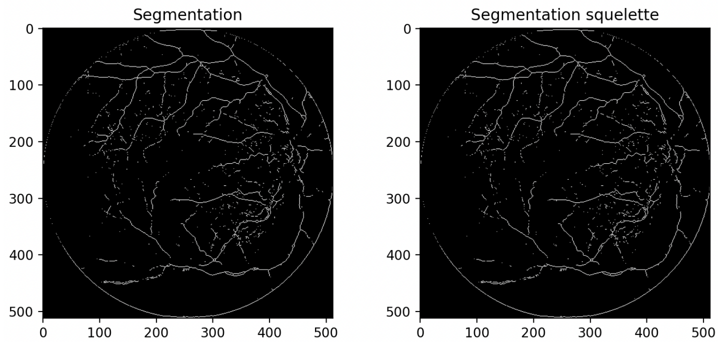

Figure 4: Noisy binary image

2.4 Connected Components

I then noticed that I was getting small single white pixel fragments. To address this problem, which I associated with noise, it is also necessary to filter components smaller than a certain threshold.

I sometimes obtained white fragments outside my area of interest, so I decided to use the circular mask again. I obtain a satisfactory segmentation (visible in the Results section).

3 Results

Accuracy measures the proportion of correctly identified vessel pixels, while recall measures the proportion of actual vessel pixels that were correctly identified. These two metrics are sufficient to show the performance of the algorithm.

The segmented image and the ground truth image are skeletonized to focus on the central pixels of the vascular structures for evaluation.

It is possible to modify certain values of the algorithm according to preferences. If we want a balanced model, with high precision and recall, we obtain Figure 5. If we want higher precision and lower recall, we obtain Figure 6. Conversely, for high recall and low precision, we have Figure 7.

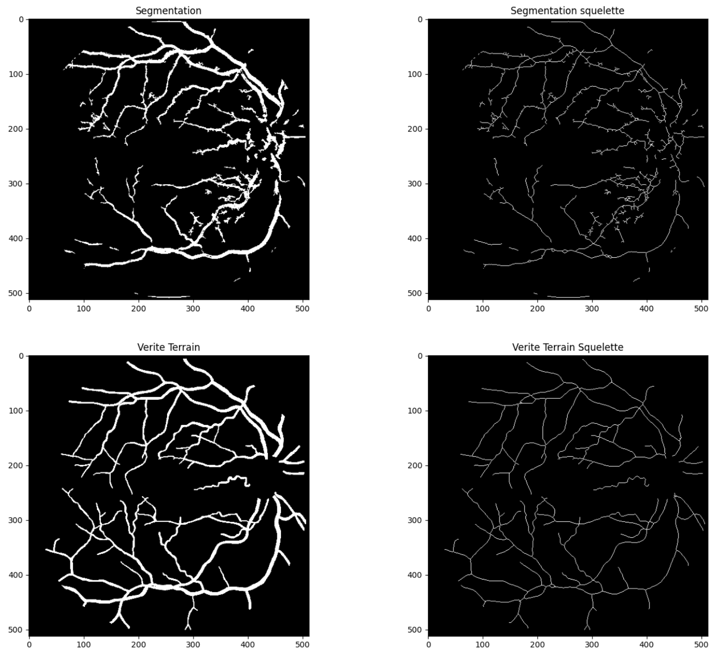

Figure 5: Scales = [3,5,7], Threshold = 20, Component-size > 30, Accuracy = 0.73, Recall = 0.73

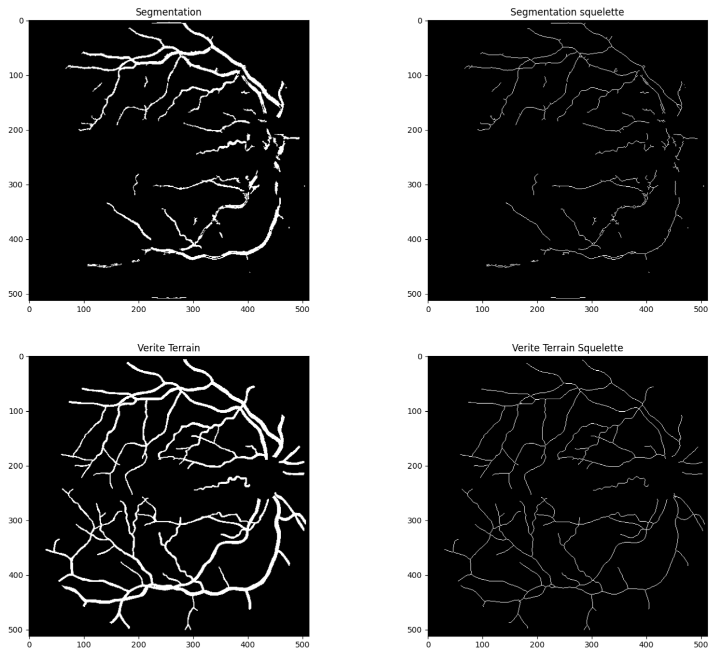

Figure 6: Scales = [4,5,6], Threshold = 25, Component-size > 30, Accuracy = 0.88, Recall = 0.56

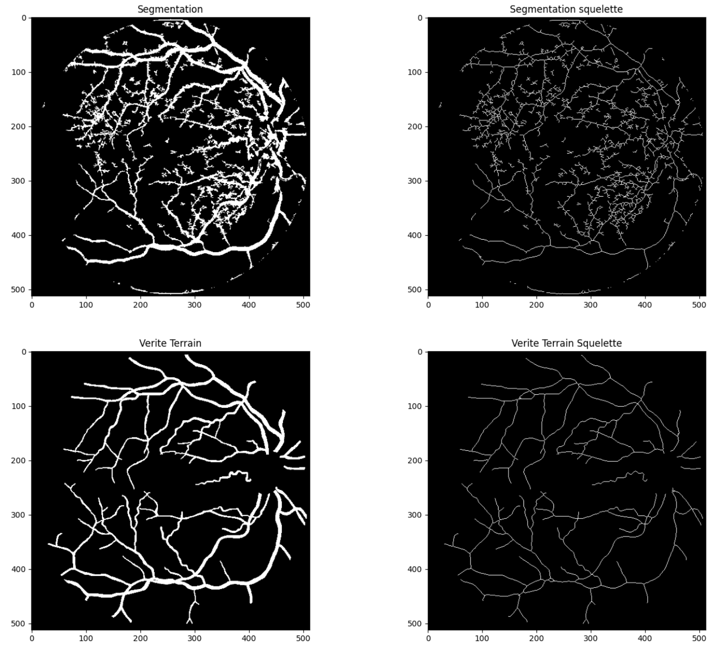

Figure 7: Scales = [3,5,7], Threshold = 20, Component-size > 25, Accuracy = 0.47, Recall = 0.87

The most judicious choice seems to be the most balanced profile, as it remains precise with good recall. However, the model with higher recall may allow a doctor to see the entire network and then refine the precision.

To improve this algorithm, one could try to further optimize the parameters or consider using neural networks, even though this second approach is more resource-intensive and computationally expensive.