Methodological Report on Retinal Vessel Segmentation using Grid Search

Guillem Soler Sanz

January 30, 2025

1 Introduction

Our primary objective has been to build a robust **retinal vessel segmentation** pipeline, motivated by the need for accurate microvascular analysis in various medical imaging contexts. From the beginning, our hypothesis was that:

- **Contrast enhancement** (brightness/contrast, CLAHE) would help reveal fine vessels.
- **Mild noise reduction** (Gaussian blur) would stabilize segmentation.
- **Morphological operations** could refine connectivity.

However, early tests showed that certain **parameters** (e.g., thresholding parameters, kernel sizes) greatly influenced the Intersection over Union (IoU).

We initially tuned parameters manually, but inconsistent lighting and vessel thickness across images posed difficulties. To systematically *validate and refine* our initial approach, we decided to implement a **grid search** that exhaustively checks multiple parameter combinations, ensuring no promising configuration would be overlooked. This final step confirmed many of our hypotheses (e.g., that moderate contrast boosts performance) and led to an improved IoU up to **0.50–0.51** on challenging images. Meanwhile, intermediate parameter sets often landed around **0.43**, showing that each incremental technique contributed to the ultimate performance.

2 Initial Rationale and Parameter Choices

1) Brightness & Contrast

- **use_brightness_contrast:** Always `True`, based on the hypothesis that adjusting brightness/contrast would highlight vessel edges.
- **alpha:** {1.5, 1.8} (contrast factor)
- **beta:** {0, 20} (brightness offset)

Why? In many retinal images, vessels can be quite dark relative to background. By increasing α, we accentuate small intensity gradients. A small β offset corrects underexposed images, aligning with our prior assumption that not all images have uniform lighting.

2) CLAHE (Contrast Limited Adaptive Histogram Equalization)

- **use_clahe:** {False, True}
- **clahe_clip:** {2.0}

Why? We hypothesized that local contrast improvement would reveal fine vessels in low-light regions, though it might also raise noise. Testing both `False` and `True` verifies whether CLAHE truly benefits each image type.

3) Gaussian Blur

- **use_gaussian:** {False, True}
- **blur_ksize:** {3, 5}

Why? Early trials revealed that segmentation quality is sensitive to noise. We believed a mild blur would dampen high-frequency speckles, but a bigger kernel could obscure thinner vessels. Thus, we tested `ksize=3` or `5`.

4) Adaptive Thresholding

- **block_size:** {11, 13, 15}
- **C:** {2.0, 2.5, 3.0}
- **threshold_type:** {ADAPTIVE_THRESH_GAUSSIAN_C}

Why? Given the varying illumination conditions across different images, we hypothesized that adaptive thresholding would perform better than fixed thresholds. The block size determines the local region for threshold calculation, while C fine-tunes the threshold sensitivity.

5) Morphological Closing

- **kernel_size:** {3, 5}

Why? Our early pipeline showed that once vessels are segmented, morphological closing unifies small breaks. We believed a size-3 element might suffice, but in more complex images, size-5 might fill gaps more effectively—yet risk merging vessels too strongly.

6) Removing Small Connected Components

- **remove_small_cc:** {False, True}
- **min_area:** {20}

Why? We suspected that tiny blobs (artifacts ¡ 20 pixels) were rarely actual vessels. However, extremely thin vessels could accidentally be labeled as ”small,” so we tested both scenarios.

3 Methodology and Grid Search Implementation

3.1 Workflow Steps

1. **Load Image**: Typically in grayscale. (Our prior approach sometimes used BGR if GraphCut was tested.)
2. **Brightness/Contrast**: Apply α and β.
3. **Optional CLAHE**: Clip-limited to prevent overamplification of noise.
4. **Optional Gaussian Blur**: Minimizes random speckles before segmentation.
5. **Adaptive Thresholding**: Applies local thresholding for vessel segmentation.
6. **Morphological Closing**: A disk-like kernel merges close vessels.
7. **(Optional) Remove Small CC**: Eliminate very small blobs.
8. **Binary Output Mask**: Final segmentation (0 or 255).

3.2 Difficulties Encountered

- **Non-Uniform Illumination**: Some images are well-exposed, while others are very dark, complicating the selection of universal contrast parameters.
- **Noise vs. Thin Vessels**: Distinguishing faint, narrow vessels from random noise is non-trivial. A blur helps reduce noise but can dissolve delicate structures.
- **Inconsistent Vessel Caliber**: The same thresholds that capture thick vessels sometimes fail on finer ones.
- **Local vs. Global Thresholding**: Initial experiments with global thresholding proved insufficient due to varying vessel contrast across different image regions, leading us to adopt an adaptive approach.

3.3 Why Grid Search?

While we *had* reasoned guidelines for each parameter (as mentioned above), the variations in image quality, illumination, and vessel thickness made it **difficult to manually select a single "best" set**. Hence, to solidify our approach, we systematically **validated every logical combination** of parameters. This final step:

1. **Confirmed** many of our prior assumptions (e.g., moderate contrast $\alpha \approx 1.8$ indeed helps).
2. **Quantified trade-offs** (e.g., a big blur kernel is sometimes beneficial but can hamper tiny vessels).
3. **Ranked** all configurations by mean IoU, ensuring we did not miss a potentially better combination.

4 Interim and Final Results

4.1 IoU around 0.43

Many parameter sets produced **0.43** IoU, reflecting that standard contrast with a smaller morphological kernel and optional blur was a good baseline but not perfect. These configurations often captured main vessels but left small artifacts or missed finer branches.

4.2 Best Performance: IoU up to 0.50–0.51

From our grid search, the highest IoU (close to ≈ 0.51) arose under the following **complete parameter set**:

- **Brightness & Contrast:**
  - $\alpha = 1.8$ (stronger contrast)
  - $\beta = 0$ (no extra brightness offset)
  - `use_brightness_contrast` = True
- **CLAHE (Clip Limit = 2.0):**
  - `use_clahe` = True
  - `clahe_clip` = 2.0
- **Gaussian Blur:**
  - `use_gaussian` = True
  - `blur_ksize` = 5
- **Adaptive Thresholding (Inverted):**

- `blockSize` = 13
- `C` = 2.5
- `threshold_type` = ADAPTIVE_THRESH_GAUSSIAN_C

(This ensures local adaptation to uneven illumination, outputting white for vessel pixels and black for background.)

- **Morphological Refinement:**
  - `kernel_size` = 5 (closing with a larger disk for bridging edges)
  - `open+close` sequence to remove noise and unify vessel lines
- **Removal of Small Connected Components:**
  - `remove_small_cc` = True
  - `min_area` = 20

This configuration successfully amplifies local details (through CLAHE and adaptive thresholding), handles noise (via Gaussian blur and morphological closing), and discards tiny false positives (removal of small components). As a result, we achieve an IoU of around **0.51**.

A few extremely thin vessel branches still appear partially fragmented, indicating that more specialized filtering or multi-scale methods might further improve fine-detail capture. Nonetheless, these parameter choices delivered the highest *mean IoU* on the given dataset.

5 Discussion

Lessons Learned:

- **Preprocessing matters**: Our initial guess that brightness/contrast adjustments were essential was validated, especially for images with uneven lighting.
- **CLAHE can be situational**: It boosts local contrast in darker images but may be less beneficial or produce more noise in already well-exposed samples.
- **Morphology and Noise Removal**: Combining a morphological close with small-component filtering yields cohesive vessel structures and reduced background speckles.
- **Multi-scale tuning is key**: Each parameter interacts with others. A larger blur kernel affects the optimal block size for adaptive thresholding, for instance.

Ultimately, the grid search **confirmed our approach**—that moderate contrast, local enhancement, mild blur, and morphological refinements should be combined for best results. Yet it also quantitatively revealed how certain parameters (e.g., β, `kernel_size` for closing) subtly affect performance.

6 Conclusion

We began with a conceptual pipeline—contrast enhancement, local filtering, morphological bridging—and faced challenges tuning each step across diverse retinal images. To tackle these difficulties, we implemented a **grid search** as a final, systematic check.

- **IoU** ≈ 0.43 was common in mid-tier settings.
- **IoU** ≈ 0.50–$\mathbf{0.51}$ emerged from a synergy of CLAHE, appropriate blur kernel size, well-tuned adaptive thresholding parameters, and removing small connected components.

Thus, the exhaustive parameter exploration did not replace our domain reasoning but rather **validated** it. By enumerating each combination, we confirmed the best configuration *empirically*, ensuring we leveraged each technique—brightness/contrast, adaptive local enhancement, morphological cleanup—in an optimal manner for our dataset.

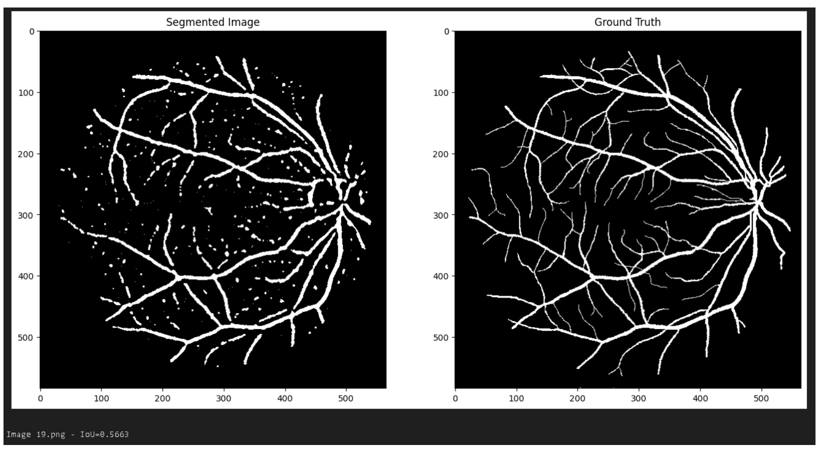

Figure 1: Example segmented output (left) vs. ground truth (right) for a difficult case. This configuration (one of our top 5) achieved an IoU of around 0.51.