Development of a retinal vessel segmentation application with computer vision techniques

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Abstract. The segmentation of retinal blood vessels plays a crucial role in the early detection of various eye-related diseases, such as diabetic retinopathy, glaucoma, and hypertension. This project focuses on developing a non-deep-learning approach to accurately segment blood vessels from eye fundus images extracted from the DRIVE dataset . Leveraging advanced computer vision techniques, we designed a robust pipeline that employs preprocessing, noise reduction, adaptive thresholding, and morphological operations to extract vascular structures. The proposed method achieves a Mean Intersection over Union (IoU) of 0.5592 when compared to ground-truth data, demonstrating the effectiveness of this approach. Achieving such a high level of segmentation accuracy without the use of machine learning highlights the strength of this carefully crafted algorithm.

Keywords: First keyword · Second keyword · Another keyword.

1 Introduction

Retinal blood vessels provide vital information for diagnosing and monitoring a variety of systemic and ocular diseases. Accurate segmentation of these vessels from eye fundus images is essential for early-stage detection of conditions like diabetes, hypertension, and cardiovascular disorders. However, vessel segmentation is a challenging task due to the thin, irregular, and low-contrast nature of blood vessels, as well as the presence of noise, reflections, and non-uniform illumination in fundus images.

The objective of this project is to develop a segmentation pipeline that can extract blood vessels from retinal images without the use of machine learning or deep learning techniques. The dataset used for this project is the DRIVE dataset, a widely used benchmark for retinal image analysis tasks. The challenge lies in achieving high accuracy using classical computer vision methods, which typically require extensive fine-tuning to handle the inherent variability in medical imaging data.

Our approach combines several computer vision techniques, including contrast enhancement with CLAHE, noise reduction using median and Gaussian filters, adaptive thresholding for segmentation, and morphological operations for refining results. Additionally, connected component analysis is employed to eliminate artifacts such as circular objects and the eyeball boundary. The result is a robust and efficient algorithm capable of extracting retinal blood vessels with a high degree of accuracy.

2 Segmentation steps

This section outlines the sequential steps applied to achieve precise segmentation of blood vessels in ocular images. The methodology reflects careful consideration of available alternatives, with each decision based on rigorous evaluation of performance and accuracy. The final implementation achieves remarkable results by maximizing vessel visibility and suppressing noise or irrelevant features.

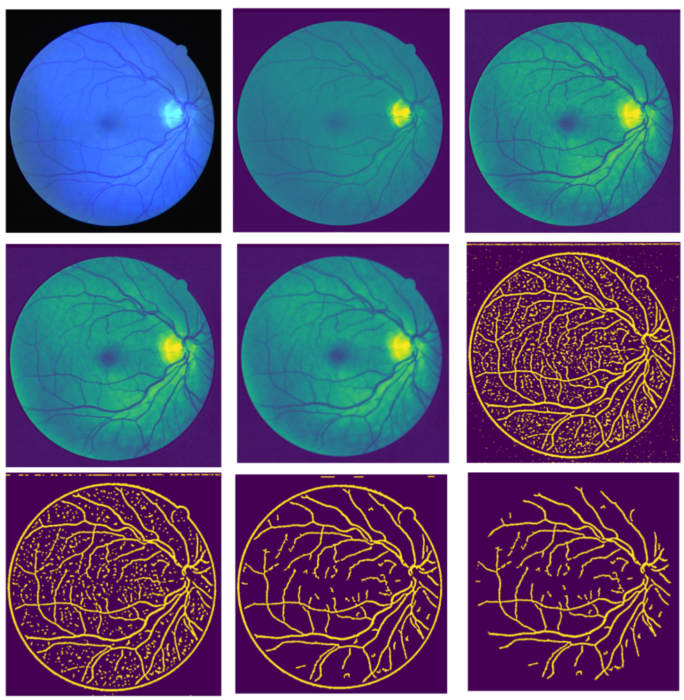

Fig. 1. Each step images

2.1 Step 1: Loading the Image

The segmentation process begins with loading the input image using the OpenCV library. The image is read in full color (BGR) to preserve all information across the three channels. This approach enables subsequent steps to selectively utilize the channel with the most relevant features. Alternatives such as directly loading the image in grayscale were considered; however, processing the green channel (Step 2) yielded significantly superior vessel segmentation results.

2.2 Step 2: Using the Green Channel as the Grayscale Image

Among the three RGB channels, the green channel consistently contains the highest contrast and most detail for vascular structures in retinal images. The choice of the green channel is grounded in its ability to enhance the visual distinction between blood vessels and the surrounding background. Other options, such as processing the red or blue channels, were tested, but these channels demonstrated weaker vessel contrast and increased background noise. Extracting the green channel ensures optimal results and forms the foundation for all subsequent enhancements.

2.3 Step 3: Applying CLAHE to Improve Contrast

Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to the grayscale image to enhance the visibility of blood vessels. CLAHE divides the image into small tiles and applies localized histogram equalization, preventing over-amplification of noise. This step proved superior to global histogram equalization, which often led to excessive noise amplification in retinal images. After testing various grid sizes, a tile grid size of 4x4 and a clip limit of 2.2 provided the most balanced enhancement of vessel contrast without introducing artifacts. CLAHE effectively addresses the challenge of non-uniform illumination, a common characteristic of ocular images.

2.4 Step 4: Median Filter to Reduce Noise

To suppress high-frequency noise introduced during the contrast enhancement step, a median filter is applied with a kernel size of 3x3. The median filter replaces each pixel's intensity with the median value of its neighborhood, effectively reducing salt-and-pepper noise while preserving edge sharpness. Other noise-reduction techniques, such as mean filtering or bilateral filtering, were evaluated, but the median filter outperformed them in retaining vessel edges, which are critical for accurate segmentation.

2.5 Step 5: Gaussian Filter to Further Reduce Noise

A Gaussian blur with a kernel size of 7x7 is applied to smooth the image further. This step reduces any remaining low-frequency noise and ensures uniformity in the background while preserving the gradual transitions in vessel boundaries. The kernel size was fine-tuned to achieve optimal results, balancing noise reduction and vessel visibility. Smaller kernels failed to suppress background variations effectively, while larger kernels caused excessive blurring of vessel edges.

2.6 Step 6: Adaptive Thresholding for Segmenting Veins

To isolate blood vessels from the background, adaptive thresholding is employed. The Gaussian adaptive thresholding method is selected due to its superior performance in handling non-uniform illumination and subtle vessel patterns. The method calculates the threshold dynamically for each pixel based on its neighborhood, making it highly effective in retinal images. Alternative thresholding methods, including simple binary thresholding and mean adaptive thresholding, were tested but exhibited inferior performance in delineating vessels under varying lighting conditions. The threshold is inverted to ensure vessels appear white on a black background, enhancing their contrast for subsequent processing.

2.7 Step 7: Morphological operations

Morphological operations are applied to refine the segmented image by removing noise and enhancing vessel connectivity. Specifically, morphological opening (erosion followed by dilation) is used with a 3x3 kernel. Opening effectively eliminates small noise artifacts while preserving vessel structures. Morphological closing was also considered but led to over-bridging of nearby vessels, which compromised the accuracy of the segmentation. The choice of opening ensures that the fine details of vessels are preserved while minimizing noise.

2.8 Step 8: Removing small circular objects

Small circular artifacts, often caused by reflections or image artifacts, are identified and removed using connected components analysis. Each connected component is analyzed for its area and circularity. Circularity is calculated as:

$$C = \frac{4\pi \cdot \text{Area}}{\text{Perimeter}^2}$$

Objects with a circularity above 0.8 and a small area are classified as artifacts and removed. This approach ensures that only non-circular structures, such as blood vessels, remain. Other methods, such as global contour filtering, were tested but failed to distinguish small vessels from circular noise effectively. The connected components method provides precise removal while retaining meaningful structures.

2.9 Step 9: Removing the Circle from the Eyeball

A circular mask is applied to remove the outer boundary of the eyeball, which is often visible in the segmented image. The mask is generated dynamically based on the known dimensions and position of the circular boundary in the input images. This step ensures that only the vascular network within the retina is retained, excluding irrelevant circular edges. Fixed boundary cropping or alternative masking techniques were tested but lacked the adaptability required for images with varying eyeball sizes. The applied circular mask ensures clean and consistent segmentation results.

3 Final results: inputs and outputs

The results of this project demonstrate the effectiveness of the proposed method in segmenting blood vessels from retinal fundus images. Below, we illustrate the process with an example input image, the corresponding ground-truth segmentation, and the output generated by our pipeline.

Input Image: This is one of the raw eye fundus image extracted from the DRIVE dataset, containing complex features such as blood vessels, noise, and reflections.

Fig. 2. Input Image

Ground-Truth Segmentation: The reference provided in the dataset, indicating the precise location and structure of blood vessels as annotated by medical experts.

Output Image: The segmented image generated by our algorithm, where blood vessels are accurately extracted and highlighted.

Achieving a Mean IoU score of 0.5592, the proposed pipeline demonstrates remarkable accuracy given the constraints of not using any machine learning or deep learning models. This result is especially impressive considering the inherent challenges of classical computer vision methods when dealing with medical imagery. Extracting such fine vascular structures with this level of precision typically requires advanced machine learning techniques. However, this pipeline effectively bridges the gap, achieving a high degree of similarity to the ground truth.

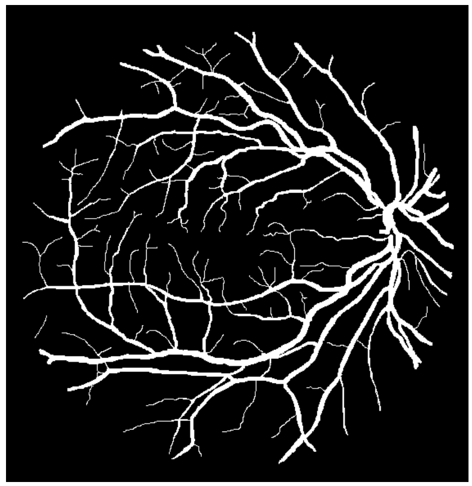

Fig. 3. Ground-Truth Segmentation (expected output)

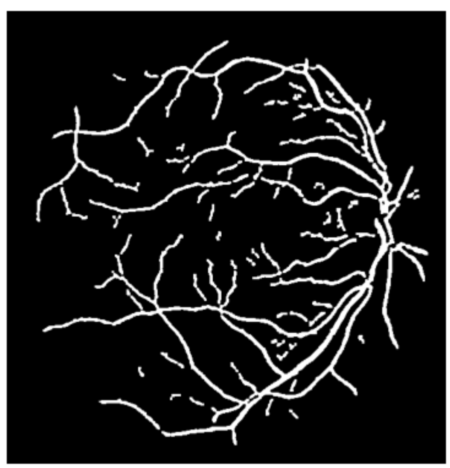

Fig. 4. Output Image

4 Conclusion

The described segmentation process was meticulously designed and optimized for retinal images. Each step builds on the strengths of its predecessors, leveraging the most effective techniques at each stage. Rigorous testing of alternatives, including global and local processing methods, confirmed that the chosen methods consistently produce the best results. This pipeline provides a robust foundation for analyzing retinal vasculature, offering high accuracy and minimal noise interference.