Original Research Article

Evaluation of vessel diameters in processed medical retinal images

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International Archives of Integrated Medicine, Vol. 11, Issue 12, December, 2024.
Available online at http://iaimjournal.com/
ISSN: 2394-0026 (P) **ISSN: 2394-0034 (O)**

Received on: 11-12-2024 **Accepted on:** 21-12-2024
Source of support: Nil **Conflict of interest:** None declared.

DOI: **10.5281/zenodo.14565458**

How to cite this article: Cristian-Dragoș Obreja. Evaluation of vessel diameters in processed medical retinal images. Int. Arch. Integr. Med., 2024; 11(12): 1-8.

Abstract

This study focuses on evaluating image processing techniques for measuring retinal vessel diameters, a critical aspect of medical image analysis for diagnosing vascular abnormalities such as diabetic retinopathy. Four algorithms, Canny Edge Detection, Marr-Hildreth Filter, Watershed Segmentation, and Chan-Vese Algorithm, were assessed for their segmentation performance and measurement accuracy. A dataset of 70 retinal images from the DRIVE database, comprising both healthy and diabetic retinopathy cases, was used. Each algorithm was implemented in MATLAB and tailored to address challenges like noise, intensity variations, and weak boundaries. Vessel diameters were calculated using a custom MATLAB algorithm based on the full width at half maximum (FWHM) of intensity profiles, with linear interpolation refining the measurements. This work highlights the potential and limitations of these algorithms in achieving accurate and reliable vessel segmentation for medical imaging applications.

Key words

Retinal image processing, Diabetic retinopathy, Edge detection, Chan-Vese algorithm, Image segmentation.

Introduction

Retinal vessel segmentation and diameter measurement are essential components of medical image analysis, particularly for diagnosing and monitoring conditions such as diabetic retinopathy. Automated and accurate segmentation techniques play a critical role in quantifying vascular changes that serve as biomarkers for systemic and ocular diseases [1-3].

The accurate measurement of vascular abnormalities, especially those associated with diabetic retinopathy, remains challenging due to vessel asymmetry and the complexity of the background, which often result in measurement errors. Current algorithms for blood vessel detection are predominantly based on segmentation, probing, or edge detection. These approaches utilize gradient masks to locate edge points and apply morphological operations to produce precise edge maps, even under noisy conditions. Threshold-based segmentation further isolates the foreground (blood vessels) from the background, enabling enhanced vessel delineation [2-5].

This study evaluates the performance of various image processing algorithms, including the Canny edge detection method, Chan-Vese algorithm, Marr-Hildreth filter, and Watershed segmentation, for retinal vessel analysis. These methods are tested on a dataset comprising 70 retinal images from the DRIVE database, with 35 ground truth images, 25 healthy subjects and 10 diabetic retinopathy cases [5-9].

Each algorithm is implemented in MATLAB and tailored to segment retinal vessels efficiently while addressing challenges like noise, intensity variations, and weak boundaries. The segmentation quality and accuracy are assessed by comparing vessel diameters extracted from algorithm outputs against ground truth images. The vessel diameters are calculated using a custom MATLAB algorithm based on the full width at half maximum of the vessel's intensity profile. Linear interpolation further refines the measurements, enabling precise diameter estimation even in narrow regions. This paper presents a comparative analysis of the algorithms, focusing on their segmentation capabilities and error rates in vessel diameter measurement. The study underscores the importance of selecting robust segmentation methods for medical imaging applications, particularly for diseases like diabetic retinopathy, where precision is paramount [10, 11]. This paper is organized as follows: section 2 outlines the materials and methods, sections 3 present the experimental results and discussion, and section 4 provides the conclusions.

Materials and methods

Database

A total of 70 retinal images from the DRIVE digital retinal image database were used [12]. This database includes 35 randomly selected retinal images and 35 manually segmented images used as ground truth. These images are categorized as follows: 25 correspond to healthy subjects, while 10 are diabetic retinopathy retinal images.

Chan-Vese Algorithm (CVA)

The Chan-Vese algorithm is a region-based image segmentation method that extends classical active contour models by focusing on intensity homogeneity rather than edge detection. It uses energy minimization to segment images into regions with distinct intensity averages, making it robust for noisy images and weak boundaries. Widely applied in medical imaging, texture analysis, and object recognition, it excels in scenarios where edge-based methods falter [9].

Image preprocessing begins with CLAHE, which enhances contrast in low-intensity regions, and Gaussian smoothing, which reduces noise while preserving edges. A rectangular mask is initialized to cover most of the vascular area, setting the starting point for segmentation. The Chan-Vese algorithm iteratively evolves this contour using active contour, isolating the vascular system. Post-processing removes small artifacts (bwareaopen) and fills vessel holes (imfill) to create a complete map [13, 14].

The algorithm optimizes a functional based on the Mumford-Shah model, which balances data fidelity, contour smoothness, and regularization. However, it assumes piecewise constant regions, which may limit its effectiveness in complex textures, and its performance is sensitive to initial contour placement.

Considering an image $I(x, y)$, the mathematical function is defined as:

$$E(c_1, c_2, C) = \mu \cdot \text{Length}(C) + \nu \cdot \text{Area}(\Omega_{\text{in}}) + \lambda_1 \int_{\Omega_{\text{in}}} |I(x, y) - c_1|^2 \, dxdy + \lambda_2 \int_{\Omega_{\text{out}}} |I(x, y) - c_2|^2 \, dxdy$$

where C is the contour, $\Omega in, \Omega out$ are the regions inside and outside the contour, c_1, c_2 represent the mean intensities inside and outside and $\mu, \nu, \lambda 1, \lambda 2$ are the parameters controlling smoothness, area, and fidelity [14, 15].

Watershed Segmentation (WS)

Watershed segmentation is a region-based algorithm inspired by topographical landscapes, where pixel intensities represent peaks and valleys. The method uses the gradient of the image to identify areas of rapid intensity change, which typically correspond to object boundaries. The algorithm simulates a flooding process, where water starts from low-intensity regions (valleys) and gradually fills basins. When basins meet, boundaries or "dams" are created to prevent merging, forming watershed lines that separate regions. This process makes the algorithm particularly effective for segmenting overlapping or touching structures, such as cells or objects with shared edges [16].

In medical imaging, watershed segmentation is widely used for tasks like separating touching cells, delineating organs, or identifying tumors in modalities like CT, MRI, or histological images. Its ability to segment overlapping objects is critical in fields such as cytology, where tightly packed cells often need precise boundaries for analysis. Marker-based watershed techniques are commonly applied to guide the segmentation, where predefined markers act as seeds for the flooding process. This approach enhances accuracy, especially in noisy or complex images, such as separating overlapping blood vessels or identifying tumor margins in radiological scans [16, 17].

The algorithm relies on a mathematical function that computes the gradient magnitude of the image to highlight regions of intensity change. The gradient map is treated as a topographical surface, and local minima serve as starting points for the flooding simulation. Pre-processing steps like noise reduction or smoothing are often required to ensure that the gradient represents meaningful boundaries. While watershed segmentation can sometimes over-segment images, combining it with advanced pre- and post-processing techniques allows for more robust and clinically relevant results. Its adaptability and effectiveness make it a staple in medical image analysis, ensuring precise segmentation for diagnostic and research purposes [18].

Marr-Hildreth Filter (MHF)

The Marr-Hildreth filter is a classical edge detection algorithm used in medical imaging to enhance boundaries and detect significant structures. By combining Gaussian smoothing with the Laplacian operator, it identifies edges through zero-crossings in the Laplacian of a smoothed image. This method captures fine details while reducing noise, making it effective for analyzing medical images with variability and subtle features. Its ability to delineate boundaries makes it valuable for detecting anatomical structures, segmenting tissues, and identifying abnormalities [19].

In medical imaging, the Marr-Hildreth filter is used to detect tumor boundaries, enhance organ edges, and segment biological structures. In X-rays and CT scans, it highlights bone outlines and organ shapes to aid diagnosis and surgical planning. Similarly, in MRI and histological images, it emphasizes soft tissue contrasts or cellular structures for better visualization. Its noise suppression and edge-detection capabilities are particularly useful for identifying low-contrast regions like early-stage lesions or subtle abnormalities, supporting early diagnosis and treatment planning.

Mathematically, the Marr-Hildreth filter operates by first applying a Gaussian filter to smooth the image, reducing the impact of noise and small variations. This smoothed image is then processed with the Laplacian operator, which measures the second derivative of intensity to identify regions of rapid change. Edges are detected by locating zero-crossings in the resulting image, which correspond to significant intensity transitions. The scale of the Gaussian filter plays a critical role, determining the level of detail captured, and must be carefully tuned for specific medical applications. By leveraging its mathematical robustness, the filter remains a cornerstone for edge detection in medical image analysis [19, 20].

Canny Edge Detection (CED)

The Canny edge detection algorithm is a widely used image processing method, known for its precision and robustness in identifying edges. In medical imaging, it plays a crucial role in detecting boundaries for diagnosis and treatment planning. The method combines Gaussian smoothing to reduce noise, gradient computation to detect intensity changes, and non-maximum suppression to refine edges. Double thresholding and edge connectivity ensure only meaningful edges are retained, producing clear and continuous results [21, 22].

In applications like CT and MRI scans, the Canny algorithm aids in delineating bones, organs, and soft tissues, supporting tasks like tumor segmentation and surgical planning. It is also effective in retinal images for detecting blood vessel networks. Its adaptability and accuracy make it essential for preprocessing in automated diagnostic systems.

The Canny algorithm relies on a sequence of operations. Gaussian smoothing minimizes noise and small variations, followed by gradient computation to measure intensity changes in multiple directions. Non-maximum suppression ensures that only the strongest gradient points in the edge direction are preserved. Finally, double thresholding classifies edges into strong and weak categories, allowing weak edges to be retained if they are connected to strong edges. This multi-step approach, guided by mathematical rigor, ensures a balance between sensitivity to faint edges and robustness against noise, making the Canny method a cornerstone in medical image analysis [22, 23].

Vessel Diameter Measurement

To evaluate the performance of Canny, Marr-Hildreth, Watershed and Chan-Vese methods, the retinal vessel diameters were measured. A custom Matlab algorithm was employed for this purpose. The algorithm extracts a vessel’s cross-sectional intensity profile and generates three perpendicular crossing lines that intersect the vessel edges at two distinct points. The diameter of the vessel is calculated using the full width at half the maximum (FWHM) of the intensity profile. Linear interpolation is then applied to estimate the minimal diameters at three critical narrow locations [11].

Performance Evaluation

To estimate theerror rate of themeasurement, thepercentageerrorwasused as follows:

$$e = \frac{|M_R - M_i|}{M_R} \cdot 100\%$$

where, M_R is the vessel diameter derived from ground truth images, and M_i is the vessel diameter obtained from measurements using the Canny, Marr-Hildreth, Watershed and Chan-Vese methods outputs. [7]

Results and Discussion

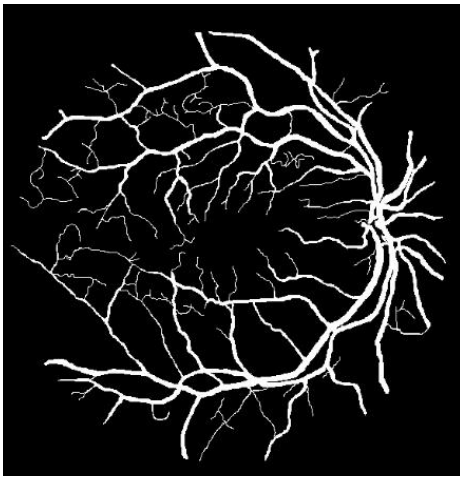
To test the performance of the proposed algorithms, the measurements were performed on 35 randomly selected retinal images. In **Figure - 1**, examples of the vascular map generated with Canny edge detection method, Chan-Vese algorithm, Marr-Hildreth Filter and Watershed segmentation algorithmare shown.

Measurements of retinal vessel diameters were conducted for both healthy subjects and patients suffering from diabetic retinopathy. The implementation of these techniques was carried out in the MATLAB environment.

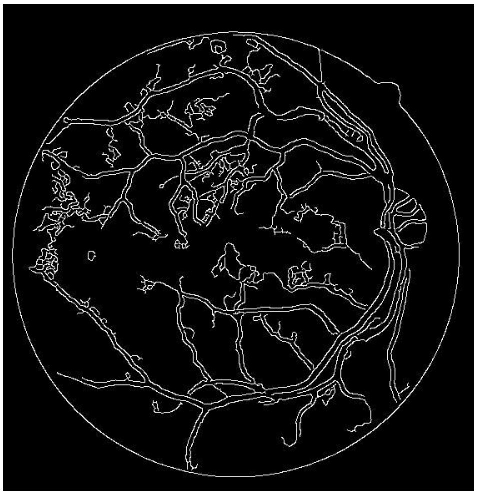
<u>Figure – 1</u>: Original, manually segmented and processed retinal images.

(a) original image;

(b) ground truth image;

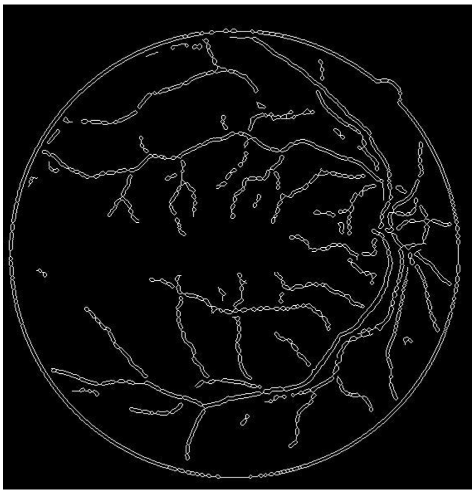


(c) Canny Edge Detection;



(d) Chan-Vese Algorithm;

(e) Marr-Hildreth Filter;



(f) Watershed Segmentation.

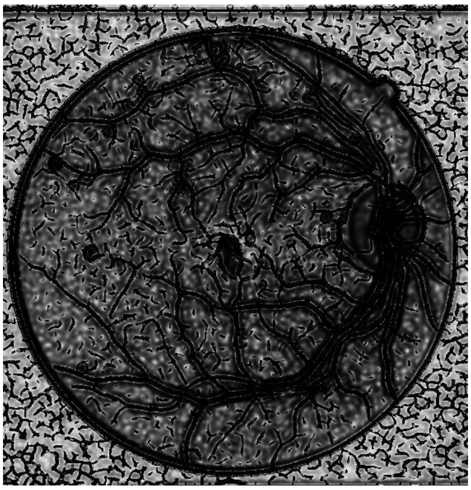


Table - 1 summarizes the average vessel diameter measurements and associated errors for both healthy and diabetic retinopathy images. The listed values correspond to results from the

Canny, Marr-Hildreth, Watershed and Chan-Vese algorithms. Analysis indicates that the Chan-Vese method consistently exhibits the lowest average percentage error rate.

Table – 1: The average vessel diameter values and the average percentage error, for healthy subjects and diabetic retinopathy patients.

	Healthy person	**Diabetic retinopathy**
Ground truth	2.201	2.240
CVA	2.161	2.322
e_{CVA}%	1.818	3.506
WS	2.332	2.381
e_{WS}%	5.909	6.223
MHF	2.491	2.578
e_{MHF}%	13.182	14.629
CED	3.604	3.001
e_{CED}%	63.636	34.036

The primary goal of this study was to assess the techniques outlined in the preceding section to identify the optimal approach for enhancing the quality and improving vessel edge detection of retinal images.

In **Table – 1**, we analyzed the error rate for every algorithm, for both healthy subjects and diabetic retinopathy patients. The smallest error is returned by Chan-Vese Algorithm, for both healthy and diabetic retinopathy affected subjects. The error values for CVA processed images are 1.818% for healthy subjects and 3,506% for diabetic retinopathy patients. The second most accurate algorithm is Watershed segmentation, for both normal and diabetic retinopathy, with a error rate values of 5.909% and 6.223%.

The largest error is generated by Canny edge detection, with a value of 63.636% for healthy subjects and 34.036% diabetic retinopathy affected subjects. In the situation of CVA, WS and MHF methods we can observe that the percentage error rate for healthy persons is smaller compared to the error generated over the processed images of diabetic retinopathy patients. It can be observed that the only exception is Canny edge detector.

At a visual analysis, we can observe that even if the vessel diameter error rate is smaller for CVA and WS algorithms, they also generate a large number of image artifacts. Moreover, both of them generate broken edges. The best results, from a visual analysis, are generate by the MHF method, with uninterrupted edges and no artifacts in the final image.

This study is subject to certain limitations. The accuracy of vessel dimension measurements may be affected by variables such as age, gender, image quality, and the presence of artifacts like noise. Furthermore, the reliance on a single projection limits the scope of the findings. Ideally, such projections should be correlated with circular cross-sectional profiles, but obtaining these images presents significant challenges.

Conclusions

This study evaluated the performance of four image processing algorithms, Canny Edge Detection, Marr-Hildreth Filter, Watershed Segmentation, and Chan-Vese Algorithm for measuring retinal vessel diameters. The results demonstrated that the Chan-Vese Algorithm consistently delivered the smallest average percentage error, making it the most accurate method for vessel diameter estimation among the tested algorithms. The Marr-Hildreth filter provided superior visual results, producing continuous edges and minimizing image artifacts, but it exhibited higher error rates compared to CVA and WS.

The study also highlighted inconsistencies in the performance of the tested algorithms, particularly for images affected by diabetic retinopathy, where background complexity and noise significantly influenced segmentation accuracy. These findings underscore the importance of selecting robust methods like CVA for clinical applications where precision is paramount.

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