Department of Computer Science and Engineering

COMP 6771 - Image Processing
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Project Report - Implementation of "Retinal vessel extraction by matched filter with first-order derivative of Gaussian"

Submitted By:

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Team Contributions:

Name	Contributions

Antas Jain	● Collaboration in Algorithm Implementation of selected paper - Preprocessing Pipeline
	● Validation Testing on the algorithm
	  ○ Implementing ROC
	  ○ Manual Testing of Outputs.
	  ○ Comparing outputs for different Hyper-Parameters
	● Documentation

Rajat Sharma	● Implemented the Matched-Filter and First Derivative of gaussian
	  ○ Developed Pipeline for implementation
	  ○ Fine-tuned code and Hyper-parameters
	● Validation Testing on the algorithm
	  ○ Implementing accuracy calculation
	  ○ Research and Inferences

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Part 1

Comprehensive Review of Retinal Vessel Extraction Techniques

Paper 1: Zhang et al. - MF-FDOG Approach [1]

Motivation & Contributions: Zhang et al. focus on retinal vessel extraction, a key aspect in diagnosing retinopathy. They introduce the Matched Filter with First-Order Derivative of Gaussian (MF-FDOG), aiming to improve the accuracy of retinal vessel detection.

Approach: MF-FDOG integrates the matched filter with the first-order derivative of Gaussian, enhancing differentiation between vessel and non-vessel structures. This method reduces false positives and improves fine vessel detection.

Critique: The methodology demonstrates effectiveness, especially in reducing false positives and identifying finer vessels. However, the paper could delve deeper into its limitations in complex scenarios and compare its efficacy with more recent advancements.

Paper 2: Mallick, Kumar, and Agarwal - Modified Multiscale MF-FDOG [2]

Approach & Contributions: Building on Zhang et al.'s foundation, this paper presents a modified multiscale MF-FDOG method. It incorporates advanced preprocessing techniques, such as top-hat transform and histogram equalization, and adopts a multiscale approach for enhanced vessel detection.

Results & Comparison: This modified technique shows superior accuracy and specificity, especially in identifying finer vessels, due to its comprehensive preprocessing and multiscale analysis.

Comparative Analysis and Superiority of Results

The advancement from Zhang et al.'s method [1] to Mallick, Kumar, and Agarwal's approach [2] highlights the evolution in retinal vessel extraction techniques. The superior results in paper [2] are attributed to:

1. **Advanced Preprocessing Techniques**: The inclusion of top-hat transform and histogram equalization enhances the visibility and contrast of retinal vessels, facilitating better detection than the method in paper [1].
2. **Multiscale Analysis**: Unlike the single-scale focus in paper [1], paper [2] employs a multiscale analysis, allowing for more nuanced and accurate vessel detection across different sizes and contrasts.

These enhancements contribute significantly to the improved accuracy and specificity in retinal vessel detection demonstrated in paper [2], showcasing the importance of continuous refinement and innovation in medical image analysis.

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Part 2

Re-implementation of algorithm from “Retinal Vessel Extraction” paper [1]

➢ This part was Implemented in File “retinal_vessel_extraction.py”

Reimplementing the MF-FDOG (Matched Filter with First-Order Derivative of Gaussian) algorithm for retinal vessel extraction involved several key steps and considerations:

- **Parameter Setting**: Adjusted parameters such as sigma for Gaussian kernels and kernel sizes for both thick and thin vessel detection, we tried to play around with the sigma values to see the differences in result, before finally fixating on value given in the paper.
- **Image Preprocessing**: Included green channel extraction and contrast enhancement using CLAHE. We tried multiple methods for preprocessing the Image to get the better input for MF-FDOG kernel.
- **Vessel Extraction**: Implemented matched filtering combined with the first derivative of Gaussian for both thick and thin vessels.
- **Combining Results**: Merged the outputs from thick and thin vessel extractions to create a comprehensive vessel map.

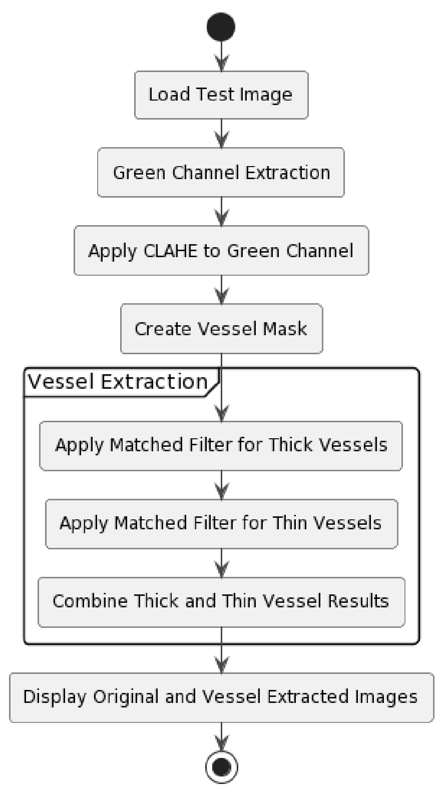

Fig. 1 - Retinal vessel Extraction pipeline

Results of Re-Implementation

The implementation of the algorithm from paper [1] was tested against the subset of DRIVE Dataset [3], which is a profound dataset for Retinal Vessel Segmentation/Extraction operations.

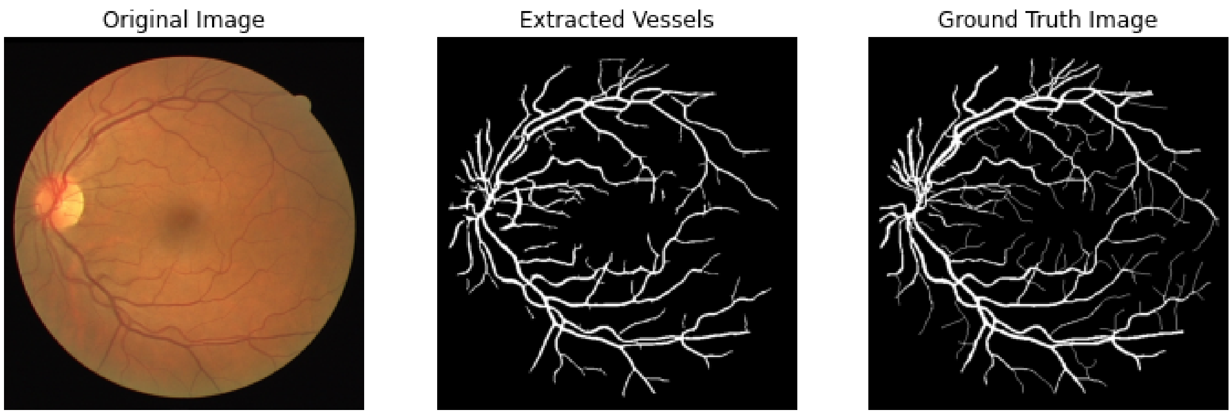

Fig 2 - Output Comparison between Extracted Vessels and Ground Truth Image

The accuracy of the Extracted Vessels against the Ground Truth Image was approximately 95%.

Validation Testing of Re-implemented Algorithm

Validation testing of the re-implemented MF-FDOG algorithm involved the following key aspects (Portrayed in Fig 3):

- **Dataset Processing:** Applied the algorithm to a *subset* of retinal images from DRIVE Dataset[3], ensuring a wide representation of test cases. *This subset of images is attached with this document*.
- **Ground Truth Comparison:** Each output was compared against manually annotated ground truth images to assess accuracy.
- **Accuracy Metrics:** Computed standard metrics like accuracy, sensitivity, and specificity for each image, providing a quantitative measure of the algorithm's performance.
- **Average Performance Calculation:** We determined the average performance across the dataset to gauge overall effectiveness.
- **Consistency Check:** Ensured the algorithm's consistency across varied image conditions and vessel characteristics.

The Output is given in the table below, the average accuracy on the dataset, with parameters:

➔ Sigma (thin) = 1, L (thin) = 5
➔ Sigma (thick) = 1.5 and L (thick) = 9
➔ C = 2.3, Directions = 8 and Window Size = 31*31

Resulted as **96.29%**, which suggests that algorithm along with preprocessing is working almost as coherently as expected according to the paper's findings.

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Formula used to Calculate Accuracy:

$$Accuracy \ = \# \, Pixels \, Matching \, in \, Extracted \, and \, Ground \, Truth \, Images / \, Total \, Pixels$$

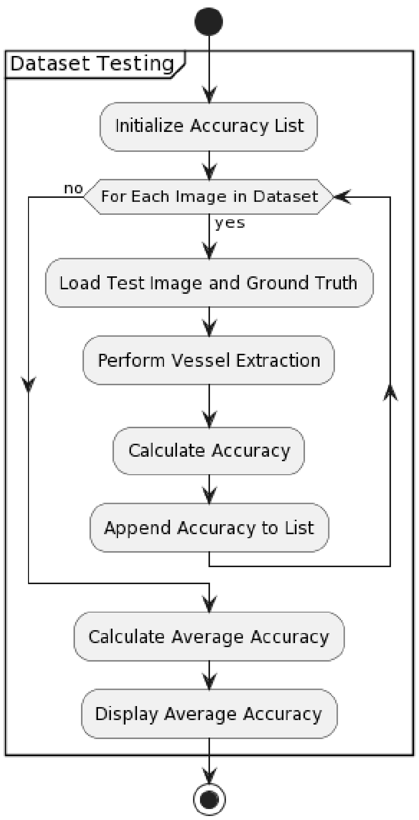

Fig. 3

```
Image 01 – Accuracy: 96.38%
Image 02 – Accuracy: 96.64%
Image 03 – Accuracy: 96.01%
Image 04 – Accuracy: 96.69%
Image 05 – Accuracy: 97.09%
Image 06 – Accuracy: 95.70%
Image 07 – Accuracy: 96.37%
Image 08 – Accuracy: 95.82%
Image 09 – Accuracy: 96.25%
Image 10 – Accuracy: 96.99%
Image 11 – Accuracy: 96.18%
Image 12 – Accuracy: 96.43%
Image 13 – Accuracy: 95.53%
Image 14 – Accuracy: 96.55%
Image 15 – Accuracy: 95.62%
Image 16 – Accuracy: 96.59%
Image 17 – Accuracy: 96.61%
Image 18 – Accuracy: 96.33%
Image 19 – Accuracy: 96.26%
Image 20 – Accuracy: 95.72%
Average Accuracy: 96.29%
```

Fig. 4

Fig. 3 : Pipeline for validation of MF-FDOG Algorithm on subset of DRIVE Dataset [3]
Fig. 4: Accuracy Table for Algorithmic Validation on subset of DRIVE Dataset [4]

Receiver Operating Characteristic Graph

➢ This part of analysis was implemented in file "additional_analysis.py"

The following graph Fig 5 represents the ROC Graph for the algorithm applied on DRIVE Dataset's Test Fundus Images.

Inference from the graph:

- **Overall Performance**: The curve is well above the diagonal line of no-discrimination. Indicating that the vessel extraction algorithm is performing well in distinguishing between the vessel and non-vessel pixels.
- **True Positive Ratio (TPR)**: The TPR values are relatively high across all thresholds(y-axis), starting from around 0.94 and going up to almost 1.00. This means the algorithm is correctly identifying a high percentage of the actual vessels as vessels.

- **False Positive Ratio (FPR)**: The FPR values(x-axis), are also quite low. They start just above 0.2 and go up to 0.6. While there is an increase in FPR as the threshold becomes less stringent, the FPR does not approach 1, which means the algorithm is not incorrectly classifying many non-vessel pixels as vessels.
- **Area Under the Curve (AUC)**: The AUC appears to be quite high, suggesting good performance of the vessel extraction algorithm.
- **Selection of Threshold**: The curve suggests that even at lower thresholds, the system maintains a relatively high TPR while keeping the FPR in check.
- **Trade-off**: There is a trade-off between sensitivity and specificity. As the algorithm becomes more sensitive (higher TPR), it also becomes less specific (higher FPR).

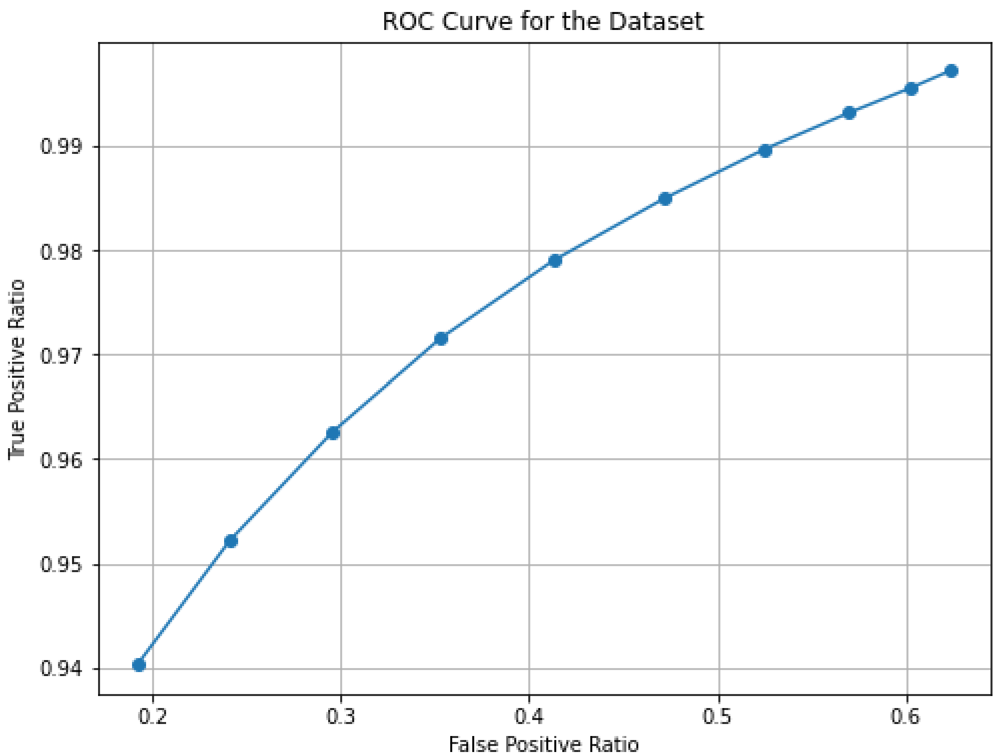

Fig. 5 - ROC Curve for MF-FDOG for DRIVE Test Subset

Where True Positive Ratio (TPR) is Calculated as:
$TPR = [TP/(TP + FN)]$
$FPR = [FP/(FP + TN)]$

Comparison with different configurations of Hyper-parameters:

The implemented algorithm was tested by tuning the parameters several time with multiple configurations, here is a subset and its resulting output:

Configuration name	S_thin	S_thick	L_thin	L_thick
Config - 1	3	5	8	15
Config - 2	1	1.5	5	9
Config - 3	0.5	1	4	8

Table 1. Hyper-parameters Configurations sample

Using these parameters, we calculated the Accuracies of the algorithm on a subset of DRIVE Dataset [3] which is represented in Fig 6.

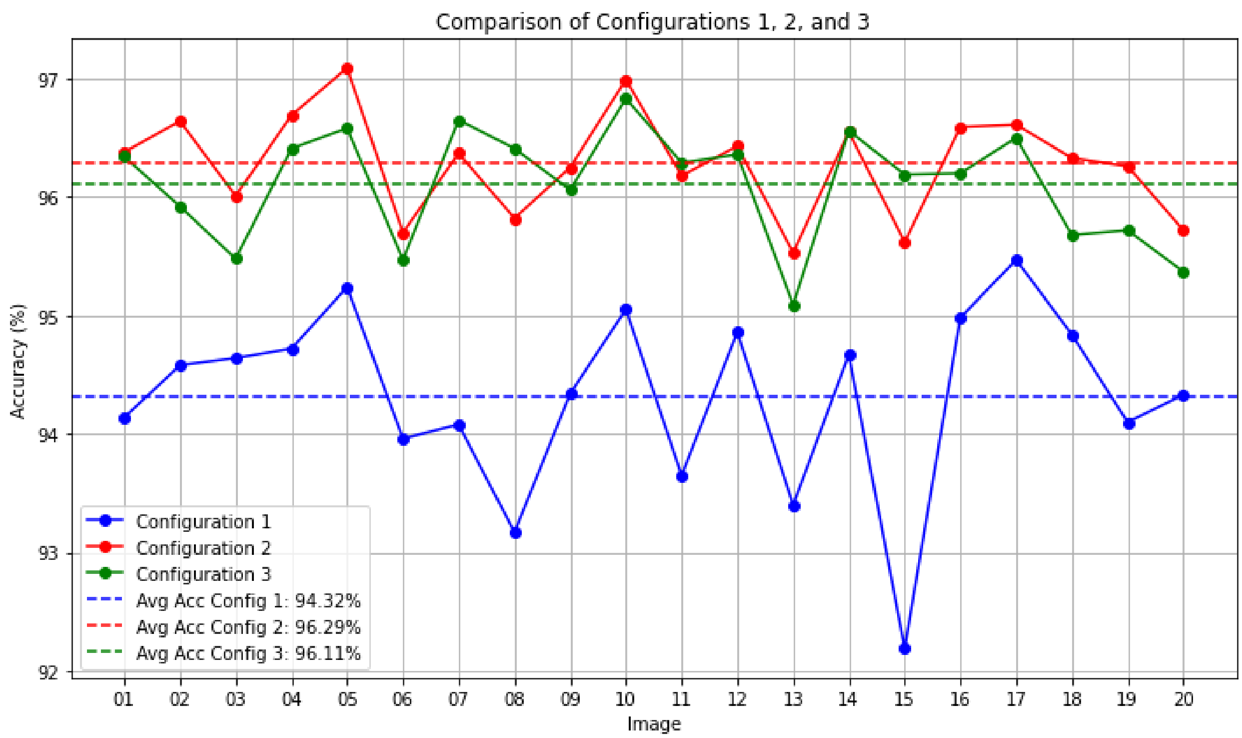

Fig. 6 - Comparison of accuracies with different parameters

This comparison was done manually, on the algorithm, and based on these parameters, It was inferred that the Specific values given in paper[1] were well suited for the algorithm as it gave the highest average accuracy, and hence the main specifications were kept at that of Configuration 2.

Reflection on the Re-implementation of the algorithm:

Here is an analysis from the re-implementation of the Paper [1] for demonstrating the MF-FDOG method of vessel extraction.

Pros:

- **Multi-scale Approach**: The method's ability to process images at multiple scales is highly beneficial for capturing vessels of varying widths, particularly distinguishing between thick and thin vessels in retinal images.
- **Enhanced Accuracy**: By combining matched filtering with the first-order derivative of Gaussian, the algorithm effectively enhances the contrast of vessels against the background, leading to better vessel detection accuracy.
- **Robustness**: The method is relatively robust to noise and variations in image quality, making it suitable for real-world medical imaging scenarios where such variations are common.
- **Applicability to Different Imaging Conditions**: The approach is versatile and can be adapted to various imaging conditions and different types of retinal images.

Cons:

- **Computational Complexity**: The multi-scale approach, while beneficial for accuracy, increases the computational load. Processing time can be significant, especially for high-resolution images.
- **Parameter Sensitivity**: The effectiveness of the algorithm depends heavily on the correct tuning of parameters like sigma, kernel size, and thresholds. Finding the right set of parameters can be challenging and may require manual tuning or optimization methods.

Self-Reflectance on Re-Implementation Difficulty:

- **Understanding the Algorithm**: Fully understanding the theoretical concepts of the MF-FDOG approach required careful study. The combination of matched filtering and Gaussian derivatives is conceptually complex.
- **Matched Filtering**: This technique is fundamental in signal processing and image analysis. Understanding how matched filtering enhances the regions of the image that correspond to the shape of the filter (in this case, retinal vessels) was crucial.
- **Coding Challenges**: Implementing the multi-scale aspect in code demanded careful consideration of efficiency and accuracy. Ensuring that the code was not only functionally correct but also efficient enough to process images in a reasonable time was a significant challenge.
- **Validation**: Validating the reimplementation involved comparing the output with standard datasets and existing methods, which was crucial for ensuring the correctness of the algorithm.
- **Multiple Implementation attempt**: Implementation was first tried using MATLAB, but do to lack of resources on MATLAB Online, switching to Python was considered

Conclusion

In conclusion, the project aimed at reimplementing the MF-FDOG algorithm for retinal vessel extraction, as described in the original paper, has been successful and enlightening. The objective was to replicate the algorithm's ability to differentiate between vessel and non-vessel structures within retinal images, and this was achieved through diligent coding, testing, and validation.

References

[1] B. Zhang et al., "Retinal vessel extraction by matched filter with first-order derivative of Gaussian," Computers in Biology and Medicine, vol. 40, pp. 438–445, 2010.

[2] P. Mallick, A. Kumar, and A. Agarwal, "Blood Vessel Detection using Modified Multiscale MF-FDOG Filters for Diabetic Retinopathy," 2019 International Conference on Applied Machine Learning (ICAML), 2019. DOI: 10.1109/ICAML48257.2019.00024

[3] Drive Dataset :
https://www.kaggle.com/datasets/andrewmvd/drive-digital-retinal-images-forvessel-extraction

[4] Matched filters with OpenCV: http://funcvis.org/blog/?p=51

[5] Stack Overflow:
https://stackoverflow.com/questions/19369658/gaussian-smoothing-window-size-and-digital-image-processing

[6] Subudhi A, Pattnaik S, Sabut S. Blood vessel extraction of diabetic retinopathy using optimized enhanced images and matched filter. J Med Imaging (Bellingham). 2016 Oct;3(4):044003. doi: 10.1117/1.JMI.3.4.044003. Epub 2016 Nov 30. PMID: 27981066; PMCID: PMC5127812.