COMP 6771

Image Processing

Vikram Singh Brahm

Student ID: 40241024

Contents

1. Summary of Motivation and Contributions:

The paper addresses the critical task of retinal blood vessel extraction in medical image analysis, emphasizing its significance in computer-aided diagnosis and treatment of various eye diseases. The primary motivation is to improve upon the limitations of existing methods, particularly the classical matched filter (MF), which tends to generate false detections. The paper introduces a novel method, the Matched Filter with First-Order Derivative of Gaussian (MF-FDOG) (see [6]), aiming to enhance vessel extraction accuracy, especially in the presence of abnormalities.

The contributions of the paper include the proposal of the MF-FDOG method, leveraging the symmetric Gaussian-shaped cross-section of vessels to distinguish them from non-vessel structures efficiently. The method combines the MF and FDOG with different scales, providing a simple yet effective way to handle both thick and thin vessels. The logical OR operation is employed to integrate results from multiple scales. The paper claims improved accuracy and reduced false positives compared to the classical MF and competitive performance with state-of-the-art methods.

Summary of Main Approaches: The main approach involves the use of two filters, MF and FDOG, to detect vessels. The MF-FDOG method is applied to retinal images with varying scales to address both wide and thin vessels. The response maps from MF and FDOG are combined using a thresholding scheme adjusted by the local mean of the FDOG response. The method is evaluated on two databases, STARE and DRIVE, using performance metrics like sensitivity, specificity, accuracy, and ROC curves.

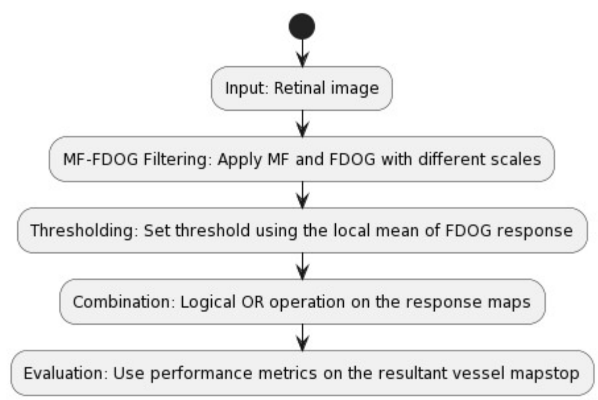


Figure 1 Flow chart showing the main approach

Critiques on Presentation of Results and Method Evaluation:

1. **Clarity in Presentation**: The paper provides a clear motivation and detailed explanation of the MF-FDOG method. However, the use of visual aids, such as a flowchart, could enhance the understanding of the proposed approach.

2. **Evaluation Metrics**: The paper employs standard metrics like True Positive Ratio, False Positive Ratio, accuracy, and ROC curves for evaluation. However, more discussion on the choice of these metrics and their relevance to the clinical context would strengthen the paper.

3. **Comparison with Existing Methods**: While the paper compares the proposed method with classical MF and state-of-the-art methods, a more detailed discussion on the strengths and weaknesses of the MF-FDOG compared to each method would provide a comprehensive understanding.

4. **Pathological Cases**: The paper emphasizes the method's effectiveness in pathological cases, but a deeper analysis of its performance in diverse clinical scenarios would enhance the paper's applicability.

2. Methodology Followed

2.1. Preprocessing of input images

In the preprocessing stage for retinal vessel extraction using a matched filter with the first-order derivative of Gaussian, a multi-step approach is employed as followed in [1]. Beginning with the loading of the retinal image, the green channel, recognized for its prominence in retinal structures, is isolated. A negative transform is then applied to enhance vessel contrast against the background. Subsequently, a white top hat transform emphasizes smaller vessels through morphological operations. Finally, Contrast Limited Adaptive Histogram Equalization (CLAHE) is employed on the green channel to enhance local contrast. These preprocessing steps collectively optimize the input image for subsequent vessel extraction algorithms, ensuring improved visibility and accuracy in the identification of retinal vessels.

2.2. Use of filters

The vessel enhancement algorithm selected for re-implementation combines Matched Filtering (MF) and First Derivative of Gaussian (FDOG) operations to highlight vascular structures in medical images. The detailed methodology encompasses the generation of matched filters and Gaussian derivative kernels, their application to the input image, and an exploration of the algorithm's sensitivity to key parameters.

2.2.1. Matched Filtering (MF)

Matched Filtering, a spatial domain filter, was employed to enhance structures in the image that match a predefined template. In our implementation, Matched Filtering was used to emphasize vessel-like structures. The filter was applied at multiple directions to capture vessels with different orientations. Parameters such as the standard deviation (s), filter length (L), and threshold (t) were carefully chosen to optimize performance by the authors (details in [2]), and I have followed those parameters to get responses.

Definition: $f(x.y) = \frac{1}{\sqrt{2\pi}s} e^{-\frac{x^2}{2s^2}} - m$ for $|x| \leq ts, |y| \leq \frac{L}{2}$ where $m = (\int_{-t}^{+t} \frac{1}{\sqrt{2\pi}s} e^{-\frac{x^2}{2s^2}} dx)/2ts$

2.2.2. First Derivative of Gaussian (FDOG) Filter

The First Derivative of Gaussian filter, also known as the gradient of the Gaussian filter, was utilized for its ability to highlight edges and transitions in intensity. FDOG is effective in capturing vessel boundaries. Similar to Matched Filtering, FDOG was applied at various directions to ensure robust segmentation across different orientations. Parameters, including the scale parameter (s) and filter length (L), were tuned to achieve optimal results by the authors.

Definition: $g(x, y) = -\frac{1}{\sqrt{2\pi}s^3} e^{-\frac{x^2}{2s^2}}$ for $|x| \leq ts, |y| \leq \frac{L}{2}$ (more details in 6)

2.3. Filter Kernels

Filter kernels played a crucial role in defining the characteristics and orientations captured by Matched Filtering and FDOG. These kernels were generated to highlight vessel-like structures in different directions. Visual representations of the filter kernels for various orientations are depicted in Figure 2. The kernels were integral to the filtering process, aiding in the extraction of relevant features associated with vessels.

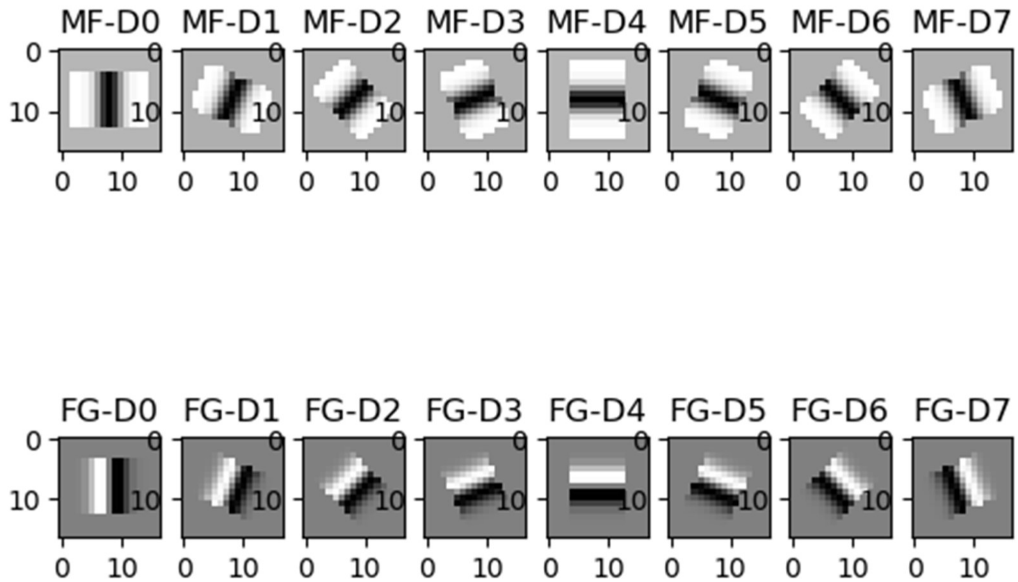
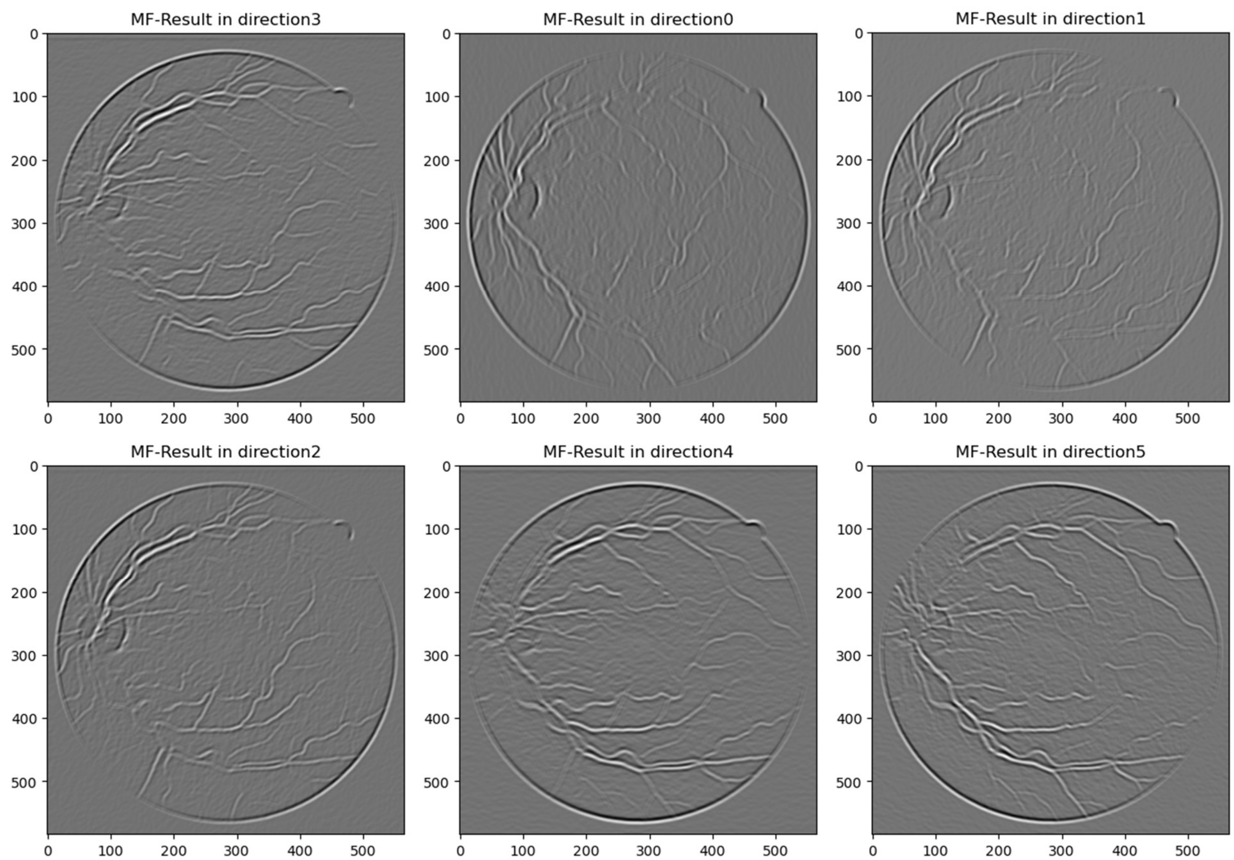


Figure 2 MF and FDOG kernels in all 8 directions at orientation difference of 15 degrees



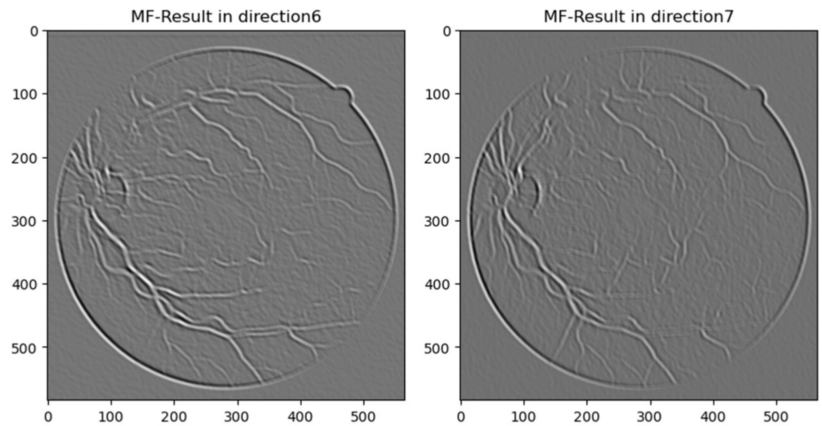
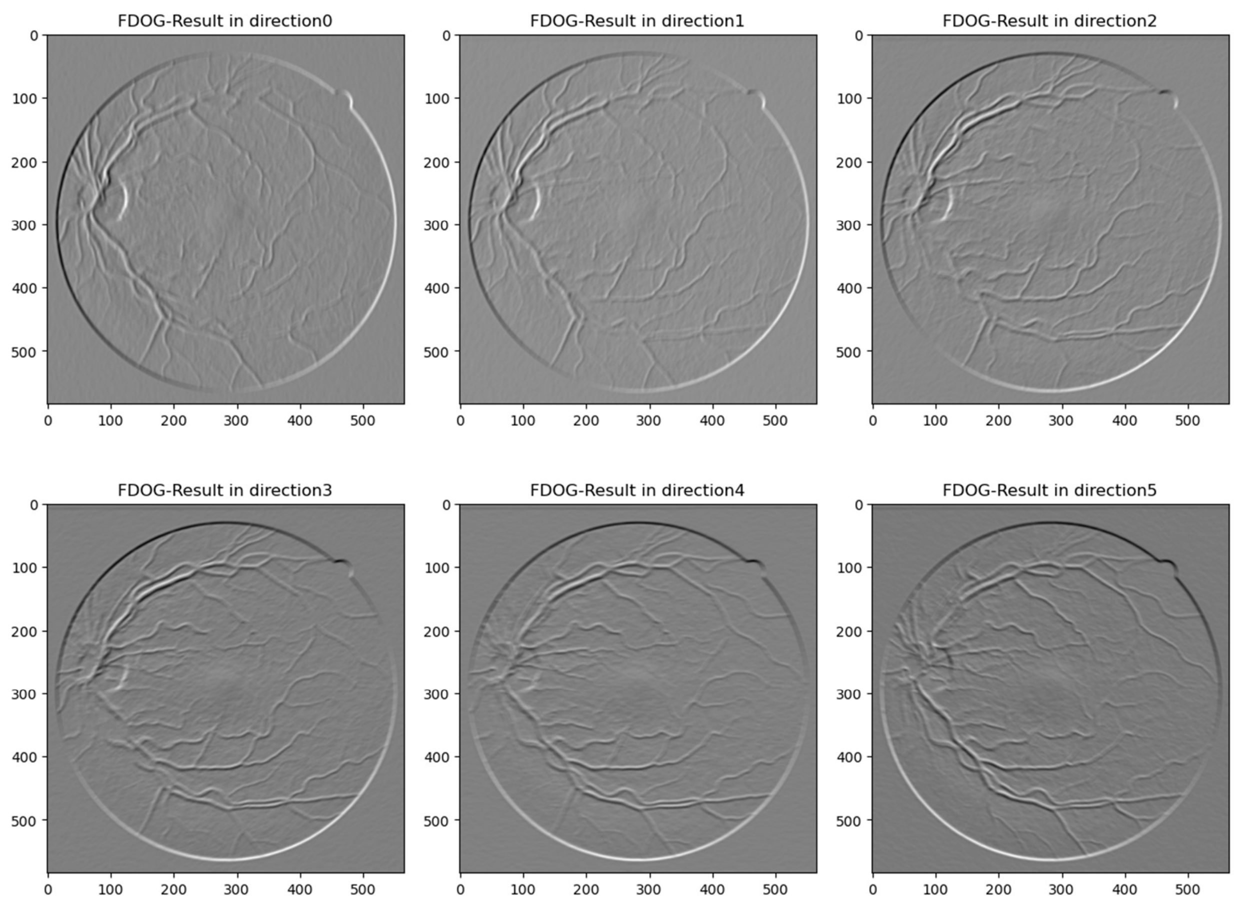


Figure 3 Application of MF on input

The application of matched filters to the input image results in a set of enhanced images, each emphasizing vessels from a specific direction. Figure 3 depict the outcomes of applying the MF filter at different angles, showcasing the algorithm's ability to capture vessels at various orientations.



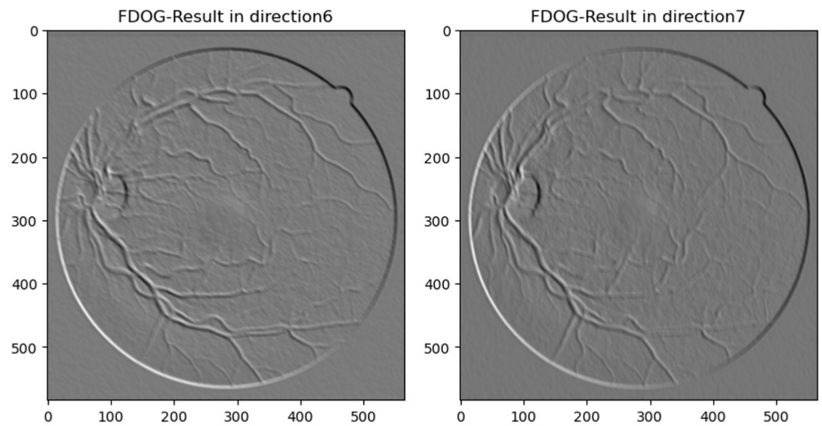


Figure 4 Application of FDOG on input

The application of Gaussian derivative filters to the input image yields a set of enhanced images, each highlighting vessel edges from a distinct angle. Figure 4 depict the outcomes of applying the FDOG filter at different orientations, illustrating the algorithm's effectiveness in emphasizing vessel boundaries.

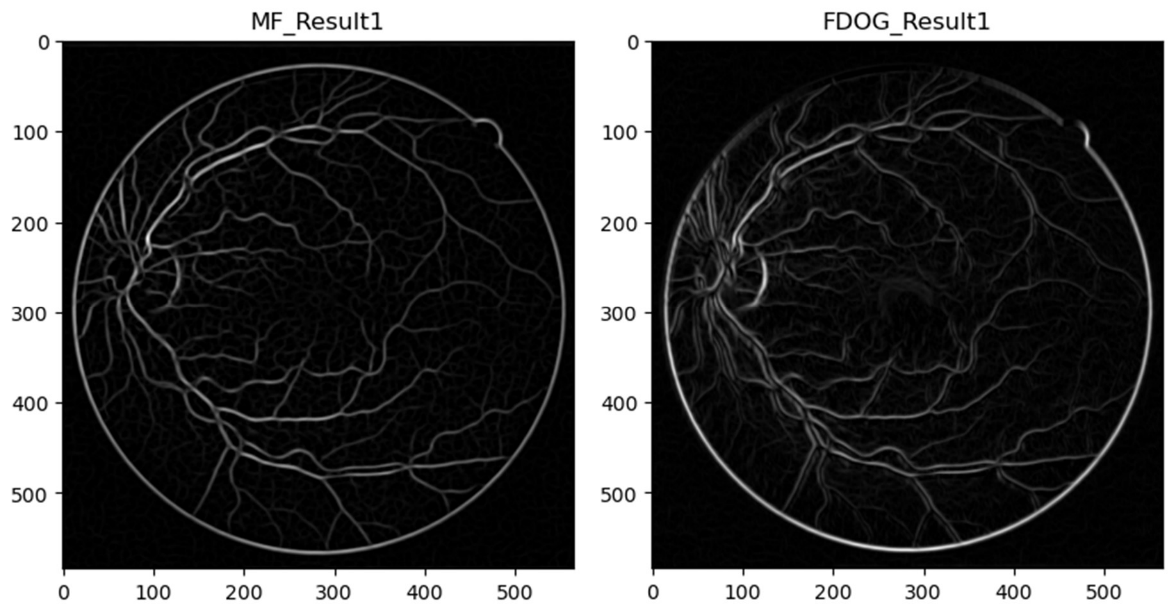


Figure 5 MF and FDOG results with s=1.5, L=9

2.4. Obtaining H and D from the image bank

Matrix H is constructed by taking the maximum response at each pixel location from the set of enhanced images resulting from the application of match filters on various directions. Mathematically, for each pixel (i, j) in the image:

$$H(i,j) = \max\left(H_1(i,j), H_2(i,j). H_3(i,j) \ldots H_n(i,j)\right)$$

Where $H_x(i,j)$ represent the enhanced images obtained from applying MF in different directions.

Matrix D is constructed by taking the maximum response at each pixel location from the set of enhanced images resulting from the application of first derivative of gaussian filters on various directions. Mathematically, for each pixel (i, j) in the image:

$$D(i,j) = \max\left(D_1(i,j), D_2(i,j). D_3(i,j) \ldots D_n(i,j)\right)$$

Where $D_x(i,j)$represent the enhanced images obtained by applying FDOG in different directions.

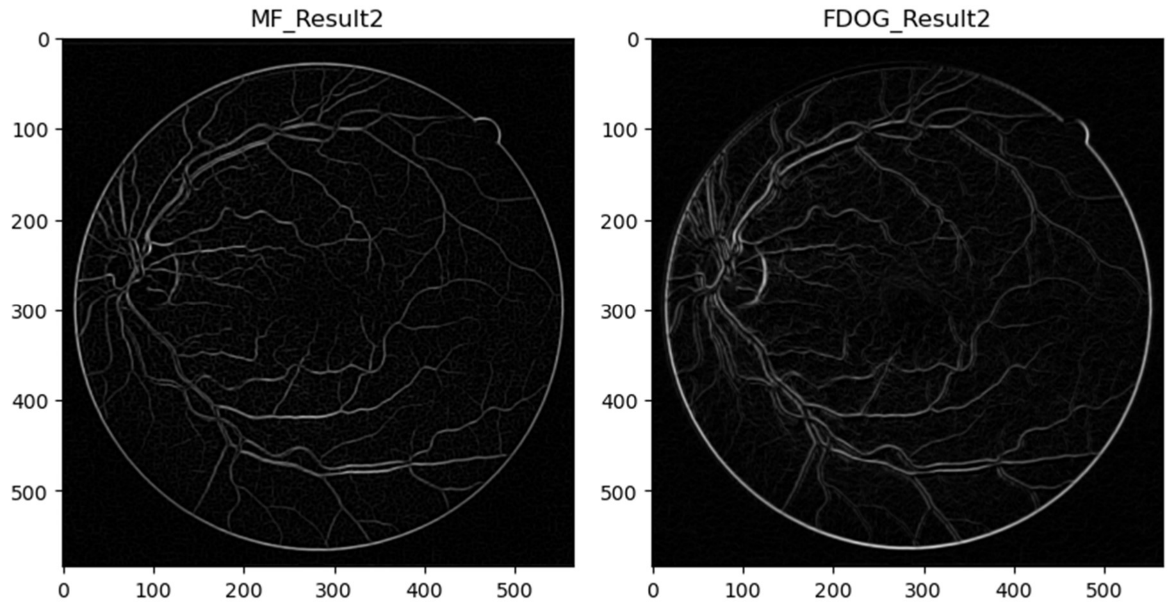


Figure 6 MF and FDOG results with s=1, L=5

2.5. Final Results from our implementation:

After this we do bitwise or operation on the response images returned after applying the `final_processing` function on both MF and FDOG results with s=1.5, L=9 and MF and FDOG results with s=1, L=5. In this function the response maps of both MF and FDOG are combined using a thresholding scheme implemented in the code.

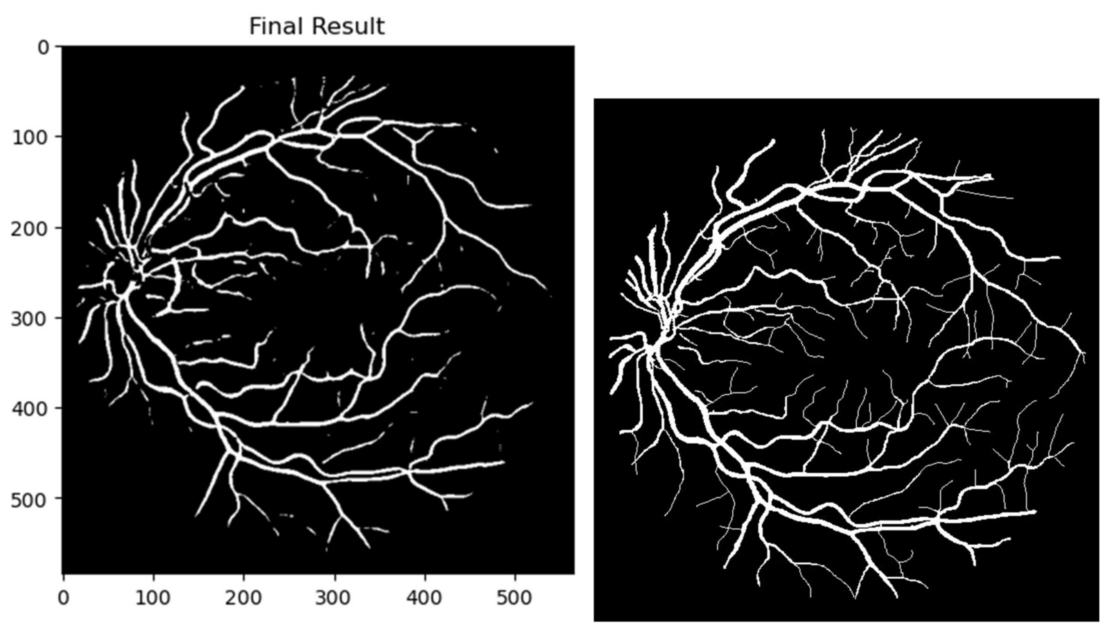


Figure 7 Comparison of the final result obtained after doing bitwise operation and the ground truth of image 1 in RITE Dataset

Method	Average Accuracy	Average TPR	Average FPR
MF	90.75651594132623	0.6013062344873275	0.008960525739213996
MF-FDOG	92.14950297005697	0.52568767427837	0.004686631934490926

Table 1 Averages of Accuracy, TPR, FPR on RITE dataset

As shown above the algorithm has been implemented correctly. For further increase, we can do add some more preprocessing steps. So, as we can see that the FDOG-MF algorithm was able to improve the accuracy than the MF filter, we have implemented the main idea behind the paper.

3. Challenges faced in reimplementation.

While the re-implementation of the vessel enhancement algorithm proved to be successful, the process was not without its challenges. I faced the following challenges:

- **Integration of Mathematical Formulas**: Translating the mathematical formulations from the research paper into executable code posed challenges, especially in handling intricate operations like rotated coordinate calculations and kernel generation based on Gaussian derivatives. Ensuring the accuracy of these implementations required a thorough understanding of the underlying mathematical concepts.
- **Debugging and Validation:** The debugging process was intricate due to the complexity of the algorithm and the multiple stages involved. Ensuring that each component operated as intended, and validating the intermediate and final results against expectations, required meticulous attention. Debugging became a systematic process involving stepwise validation and cross-referencing with the original research paper.

4. Pros and cons of the research article

Pros:

- **Multi-Directional Sensitivity:** The designed algorithm was able to capture vessel structures from diverse orientations.
- **Parameter Adaptability:** With this approach we will be able to fine-tune performance based on input image characteristics as it allows adjustments to parameters like s, L, and t.
- **Sensitivity to Vessel Features:** Constructs M_h for comprehensive vessel representation using both Match Filter and First Derivative of Gaussian Filter and captures both broader and finer vessel structures using bitwise or operation on images.

Cons:

- **Computational Intensity:** Application of two filters contributes to computational load which may pose challenges if we ever deal with large medical image datasets in the future.
- **Sensitivity to Image Quality:** Performance of this approach is directly influenced by variations in image quality.
- **Might Require Preprocessing:** May require pre-processing to mitigate noise and artifacts.
- **Parameter Dependency:** Performance highly dependent on optimal parameter selection and would require careful experimentation for generalizability.
- **Interpretability of Parameters:** Understanding implications of certain parameters can be challenging as it requires a deeper grasp of underlying mathematical formulations.

5. Comparison of Two Retinal Blood Vessel Segmentation Approaches

Paper 1: "Retinal Vessel Extraction by Matched Filter with First-Order Derivative of Gaussian" (Zhang et al., 2010) (6)

Paper 2: "Fast and Efficient Retinal Blood Vessel Segmentation Method Based on Deep Learning Network" (Boudegga et al., 2021) (4)

Methods

1. **Method followed in paper 1:** Utilizes a matched filter with the first-order derivative of Gaussian for retinal vessel extraction. Filters are applied to enhance vessel structures based on the response to vessel-like patterns.
2. **Method followed in Paper 2:** Proposes a novel deep learning architecture for retinal blood vessel segmentation. It uses a U-form deep learning network with lightweight convolution modules.

Contributions and innovations:

- **Contributions and innovations in paper 1:** Presents a traditional approach based on matched filtering and Gaussian derivatives. This approach introduced a specific filter combination for retinal vessel extraction.
- **Contributions and innovations in paper 2:** Introduces a deep learning-based method for efficient retinal blood vessel segmentation. Used a Novel U-form architecture using lightweight convolution modules for improved segmentation performance and reduced computation.

3. Results:

Paper 1:

Dataset	DRIVE DATASET	STARE DATASET
Accuracy	94.39%	93.84%

Table 2 Results from Zhang et al

Paper 2:

Dataset	DRIVE DATASET	STRE DATASET
Accuracy	97.8%	98%

Table 3 Results from Boudegga et al

4. **Thoughts on Differences in Results:** Paper 1 relies on traditional methods, while Paper 2 leverages the power of deep learning networks. The advancements in deep learning contribute to the improved performance of Paper 2. Moreover, paper 2's U-form architecture with lightweight convolution modules allows for better adaptability to the complex structures of retinal vessels compared to the fixed filters in Paper 1 and the use of data augmentation and preprocessing steps contributes to the network's ability to handle a variety of retinal image characteristics, leading to robust segmentation.

The shift from traditional methods in Paper 1 to deep learning in Paper 2 marks a significant evolution in retinal blood vessel segmentation. Paper 2 strikes a balance between accuracy and computation time, making it efficient for clinical applications. Its adoption of deep learning and innovative architecture positions it as a more promising and contemporary approach for accurate and efficient retinal image analysis.

6. Conclusion

In conclusion, the paper proposes the MF-FDOG method for retinal blood vessel extraction, aiming to enhance classical matched filtering. The method combines matched filtering and Gaussian derivative operations, demonstrating improved accuracy and reduced false positives. While the paper provides a comprehensive methodology, visual aids and a more thorough comparison with existing methods would enhance clarity. Challenges in reimplementation underscore the intricacies of translating mathematical formulations. Pros include multi-directional sensitivity and parameter adaptability, while cons involve computational intensity and parameter dependency. Comparing with a deep learning approach reveals the evolving landscape in retinal image analysis, with contemporary methods offering superior accuracy and efficiency. Overall, the paper contributes significantly, but careful consideration is needed regarding computational demands and evolving technology trends in retinal image segmentation.

7. References

1. D. Mallick, K. Kumar and S. Agarwal, "Blood Vessel Detection Using Modified Multiscale MF-FDOG Filters for Diabetic Retinopathy," 2019 International Conference on Applied Machine Learning (ICAML), Bhubaneswar, India, 2019, pp. 82-86, doi: 10.1109/ICAML48257.2019.00024.
2. Chaudhuri, Subhasis & Chatterjee, Shankar & Katz, Norman & Nelson, Mark & Goldbaum, Michael. (1989). Detection of blood vessels in retinal images using two-dimensional matched filter. Medical Imaging, IEEE Transactions on. 8. 263 - 269. 10.1109/42.34715.
3. Mallick, Debojyoti & Kumar, Kundan & Agarwal, Sumanshu. (2019). Blood Vessel Detection using Modified Multiscale MF-FDOG Filters for Diabetic Retinopathy.
4. Boudegga, Henda & Elloumi, Yaroub & Akil, Mohamed & Bedoui, M.H. & Kachouri, Rostom & Ben Abdallah, Asma. (2021). Fast and efficient retinal blood vessel segmentation method based on deep learning network. Computerized Medical Imaging and Graphics. 90. 101902. 10.1016/j.compmedimag.2021.101902.
5. Zhang, Bob & Zhang, Lin & Zhang, Lei & Karray, Fakhri. (2010). Retinal vessel extraction by matched filter with first-order derivative of Gaussian. Computers in biology and medicine. 40. 438-45. 10.1016/j.compbiomed.2010.02.008.