Blood Vessels Detection in Fundus photographs

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Introduction and Background

Undoubtedly, diabetic retinopathy (DR) can be considered as one of the major chronic disorder, which can also lead to the blindness. Preventively, medical imaging is assisting well to control this disease to some certain level. However, researchers are still trying to find some optimal approach which can be highly accurate. Mainly, segmentation of blood vessels is an essential step of diagnosis of diabetic retinopathy. Retinal ophthalmologists require efficient segmentation tools/applications to segment the blood vessels in the eye fundus images due to its sensitivity to vascular disorders; to analyze the several retinal based disorders.

Successively, this document details about the developed tool that is capable to segment the blood vessels in eye fundus images. The proposed methodology (discussed below in section 4) is tested on the DRIVE dataset and the segmented images are compared with the manual segmented images. Statistically, the methodology is able to segment the blood vessels with an accuracy rate of approx. 94% per image.

Research Objective

Develop a method for the segmentation of blood vessels in retinal fundus images.

State of art

In accordance to the previous studies, there are several methods/approaches have been proposed to segment the blood vessels in the fundus images. Mainly, in [1], R. Kharghanian et al used Gabor wavelet and line operator based features to extract the two feature set for image classification, wherein a feature vector of pixel intensity (four features from differently scaled Gabor wavelet transform and two features from orthogonal line operators) is developed at each pixel. Finally, they used Bayesian and Support Vector Machine (SVM) classifiers for the comparison of the classified results. Primarily, Gaussian mixture model was used to determine the class-conditional probability density functions for vessel and non-vessel whereas; a fast classification was done by the means of Bayesian classifier. DRIVE dataset was used to test the proposed algorithm. Resultantly, they found the efficient results by Gabor features and line features based combinational classifier. However, in some cases, Bayesian classifier performed better then the proposed combinational classifier. [1]

In [2], A. Mueen et al proposed an algorithm comprised the powerful pre-processing techniques (contrast enhancement) and automatic thresholding to perform the automatic segmentation of blood vessels. Generally, the contrast among the blood vessels and the retinal tissues are fuzzy in the fundus images. Contrast-Limited Adaptive Histogram Equalization (CLAHE) was implemented for contrast enhancement by limiting the maximum slope in the transformation function. Additionally, ISOData technique was used for automatic thresholding.

In [3] they presented a method for detecting blood vessels. The first step consists of applying anisotropic diffusion filtering in the initial vessel network in order to restore disconnected vessel in es and elim in noisy lines. In the second step, a multi-scale line-tracking procedure allows detecting all vessels having similar dimensions at a chosen scale. Computing the individual image maps requires different steps. First, a number of points are pre-selected using the eigen values of the Hessian matrix. These points are expected to be near to a vessel axis. Then, for each pre-selected point, the response map is computed from gradient information of the image at the current scale. Finally, the multi-scale image map is derived after combining the individual image maps at different scales (sizes). Two publicly available datasets have been used to test the performance of the suggested method. The main dataset is the STARE project's dataset and the second one is the DRIVE dataset.

In [4] they describe the simple vessel segmentation strategy, formulated in the language of wavelets, which is used for fast vessel detection. When validated using a publicly available database of retinal images, this segmentation achieves a true positive rate of 70.27%, false positive rate of 2.83%, and accuracy score of 0.9371. Vessel edges are then more precisely localized using image profiles computed perpendicularly across a spline fit of each detected vessel centerline, so that both local and global changes in vessel diameter can be readily quantified. Using a second image database, they show that the diameters output by our algorithm display good agreement with the manual measurements made by three independent observers.

Details about Frangi Filter

In our work, we have used Frangi filters which are successful in detecting tubular structures like vessels. Frangi filters use Hessian matrix, which is calculated by convolving image with the second partial derivates of Gaussian kernel. In the next step, eigen values are calculated (λ_1 and λ_2) to help identify the shape, specifically they are used to identify vessel-like structures. For pixels belonging to a vessel region, λ_1 will be close to zero, and λ_2 will have a large absolute value. Considering the fact that the tubular structures we are detecting have high intensity values, λ_2 will have to be negative. [5]

Vesselness function is calculated as a combination of blobness measure R_B and norm of Hessian Matrix S:

$$V_0(X,\sigma) = \begin{cases} 0, \quad \lambda_2 > 0 \\ \exp(-\frac{{R_B}^2}{2\beta^2})(1-\exp(-\frac{S^2}{2\gamma^2})) \end{cases}$$

The measures are described as follows:

$$R_B = \frac{\lambda_1}{\lambda_2}$$

$$S = \sqrt{({\lambda_1}^2 + {\lambda_2}^2)}$$

The described vesselness measure is calculated for different scales to obtain a final estimate of vessleness:

$$V(X) = \max_{\sigma_{min} \leq \sigma \leq \sigma_{max}} V(X,\sigma)$$

Proposed Methodology

We have developed an approach to segment the blood vessels in the retina fundus images. The proposed methodology has been tested on the DRIVE dataset. The flow chart of proposed methodology is illustrated in fig. 1. In the first step, an RGB input image is converted into the grayscale format, which is followed by the filtration with Frangi filters. Filtered image is then masked and thresholded. After applying morphological operations in which small segmented regions are removed, the image is divided into two images. One of the images consists only of large segments, and the other one consists of small segments. Circular elements are removed in the second image, and then the images are merged. In the last step, morphological operators of dialation and erosion are applied and the result image is given by the result.

Additionally, we have created an automatic application (illustrated in fig. 2.) based on our approach, which includes several functionalities such as automatic segmentation of blood vessels, comparative image of manually segmented image and segmented image via our approach, and statistical analysis of our approach. In our work, we have used 2- dimensional Frangi filter, which is a robust approach for the detection of tubular structures like vessels. Frangi filter use Hessian matrix, which is calculated by convolving image with the second partial derivates of Gaussian kernel.

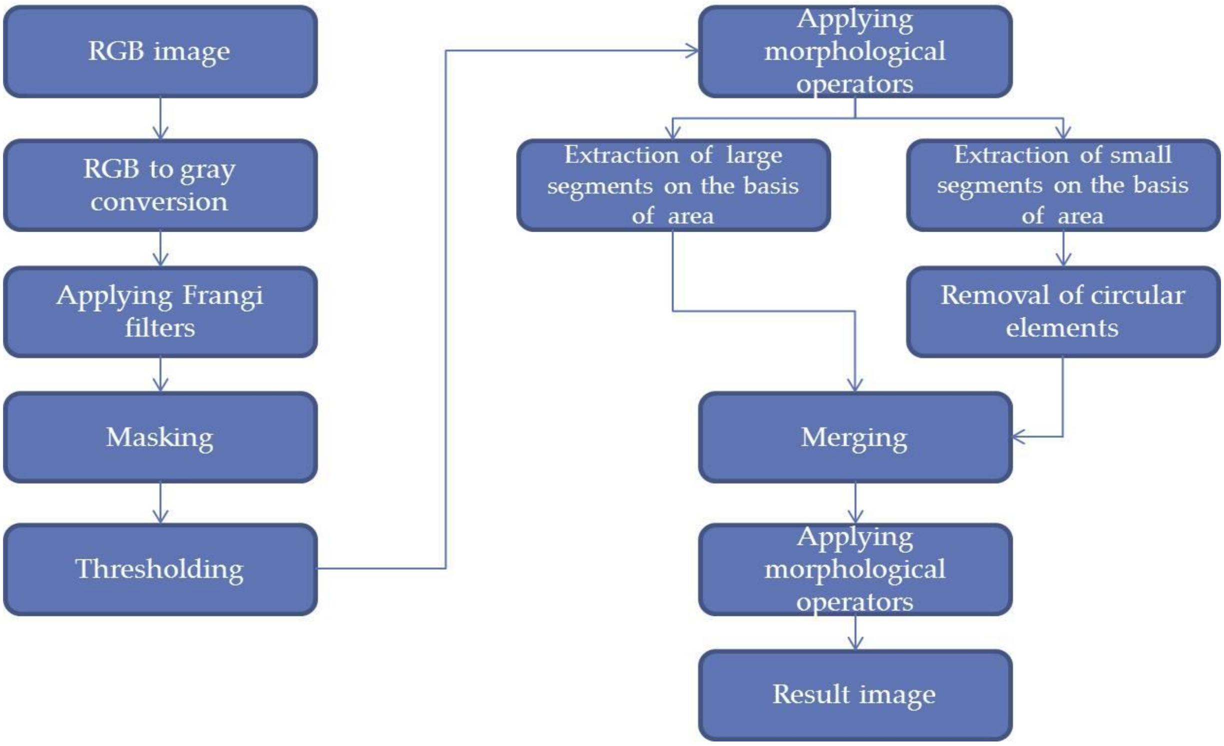


Fig. 1. Systematic flow chart of proposed methodology

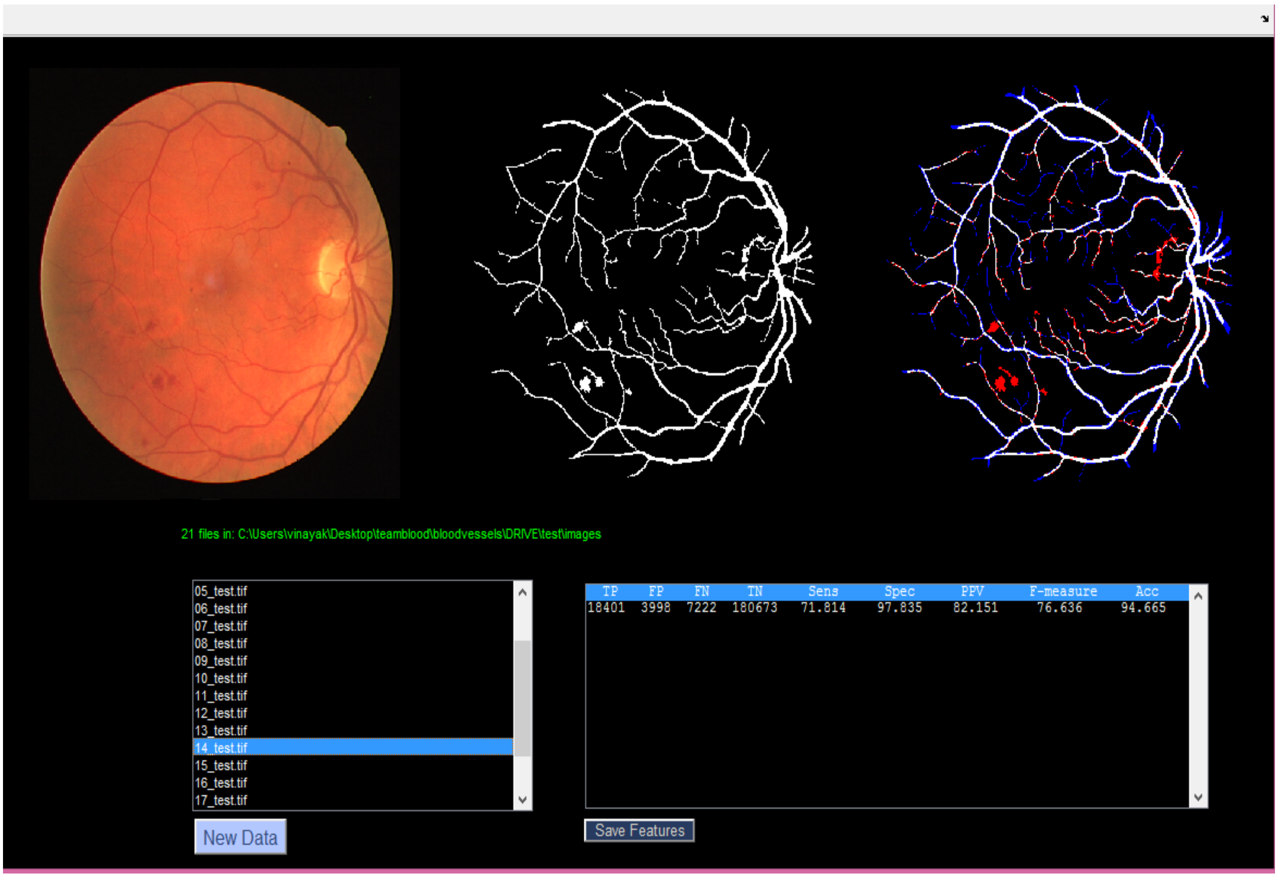


Fig.2. Design Consideration of User interface

Results

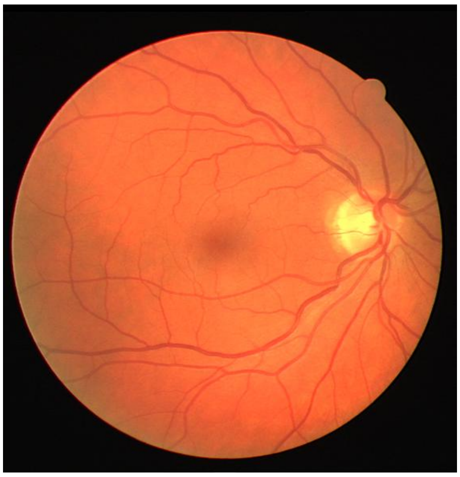


Fig.3. The original image

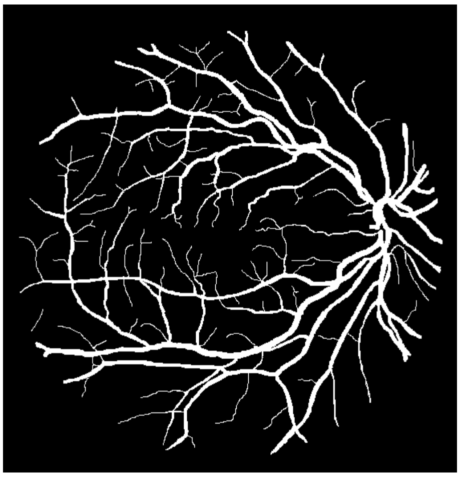


Fig. 4.The manual image

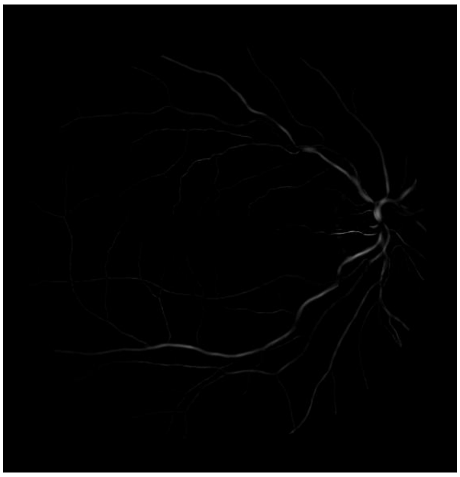


Fig.5. After FrangiFilter

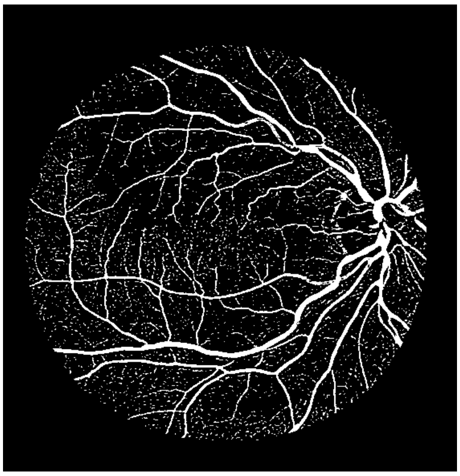


Fig. 6. Segmented image

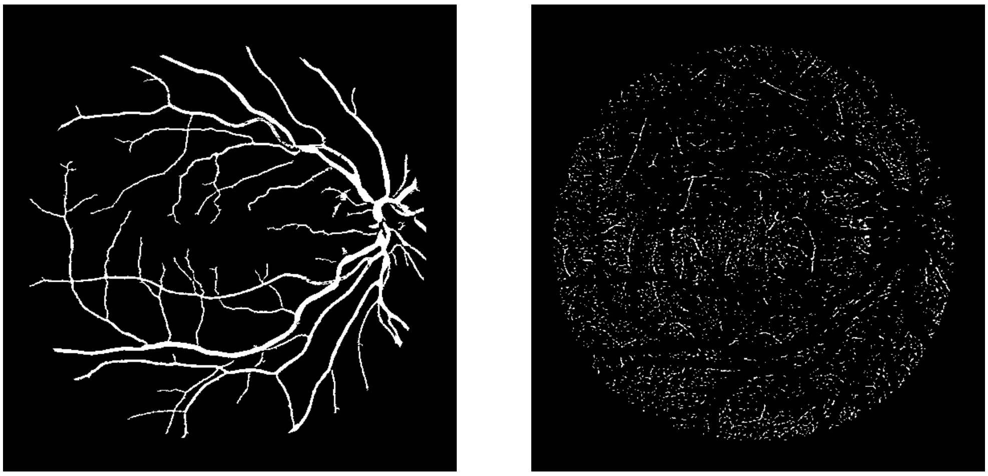


Fig.7. After sorting the "large" and "small" segmented vessels

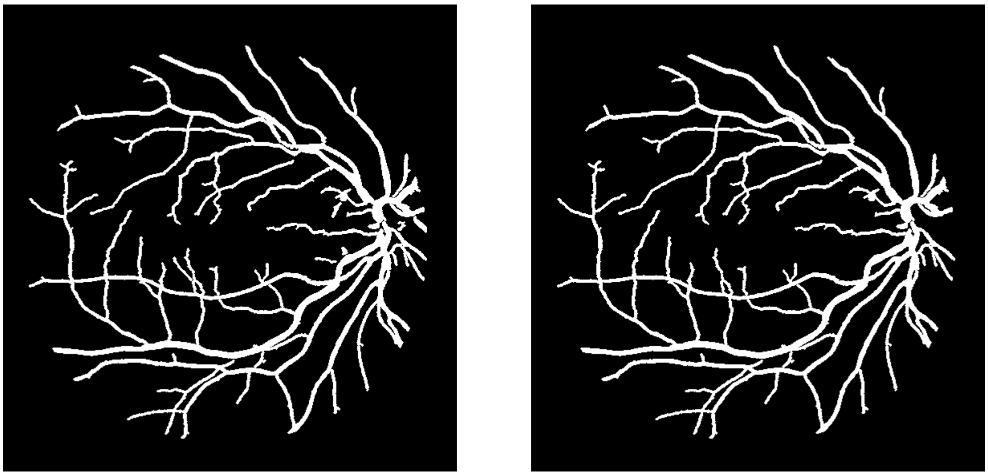


Fig. 8. After dilation and using another blob analysis based on “area”

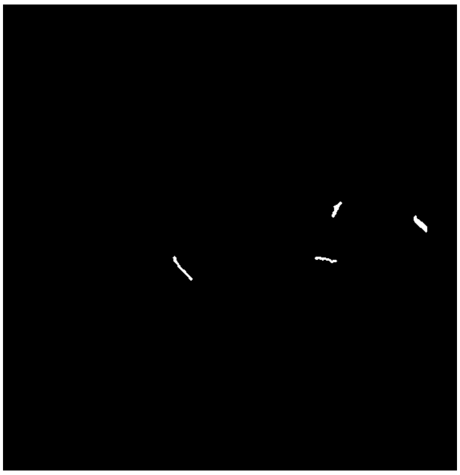
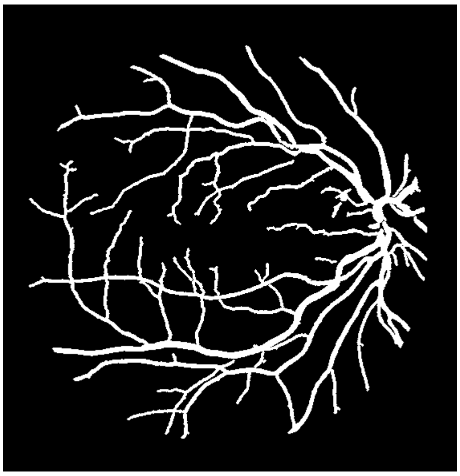


Fig.9. The sorted small parts of vessels

Fig.10. The non-circural objects



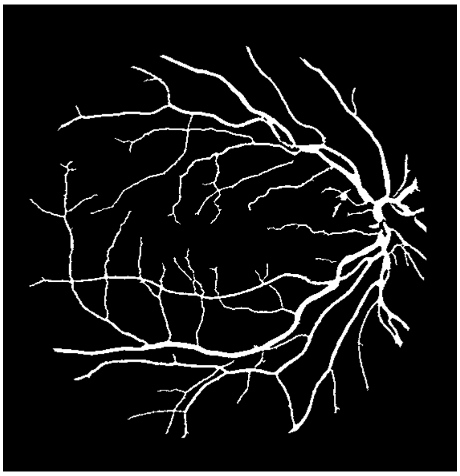
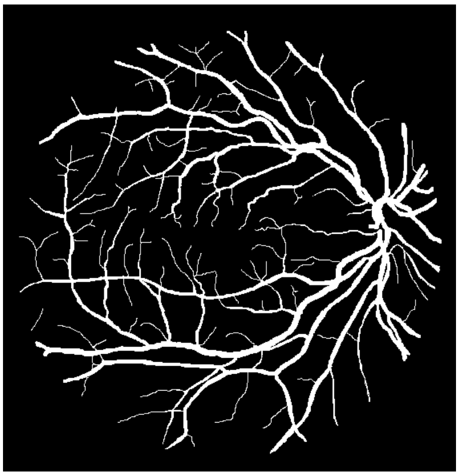


Fig. 11. After putting back the potential vessels and final image



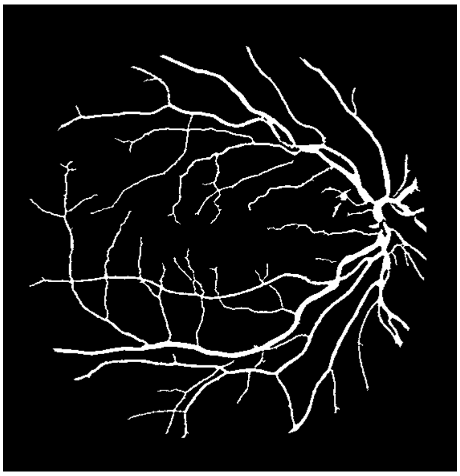


Fig. 13. Basically we lost the thin vessels, but we got a clear image with thicker vessels, which is approximately uniform with the manual image.

Conclusion

In this work we have developed an application based on proposed approach, which is a combination of Frangi filters and segmented and enhancement based morphological operations. Previous researches have shown some promising results but yet these techniques need some optimization to achieve better efficiency. However, our results also need some optimization to a certain extent. Statistically, we have achieved 75% F-score rate.

Future Work

In future, there should be some optimization done on the method for detecting thin vessels. And also, since we have encountered problems with the optic disk, it should be extracted separately. Specifically, using images from people with retinal disease as an input, lesions were mistaken for vessels, so there should be some optimization done on that part.

References

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