Blood Vessel Detection in Retinal Fundus Images

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Abstract :This thesis addresses the pivotal task of blood vessel detection in retinal fundus images, employing a comprehensive methodology for image preprocessing, contrast enhancement, and morphological operations.

This approach demonstrates promising results, showcasing improved blood vessel detection compared to existing methodologies. The methodology's effectiveness is evaluated through a series of image processing steps, emphasizing the significance of each stage in contributing to the overall success of the automated blood vessel segmentation.

In conclusion, this research contributes a robust and comprehensive solution for blood vessel detection in retinal fundus images. The combination of haze reduction, contrast enhancement, and morphological operations, followed by Bernsen thresholding, offers a sophisticated and automated framework for precise blood vessel segmentation, with potential applications in early disease diagnosis and monitoring.

1. Rezumat in limba romana/Summary in an European language

Această lucrare se concentrează pe detectarea vaselor de sânge în imagini de fundus retinian, un aspect crucial în diagnosticul și monitorizarea afecțiunilor oftalmologice. Procesul propus începe cu extragerea canalului verde și îmbunătățirea contrastului. Prin aplicarea operațiilor morfologice, obiectivul este de a evidenția trăsăturile specifice ale vaselor de sânge.

Etapa finală implică utilizarea pragului Bernsen pentru segmentarea precisă a acestora. Această abordare automatizată are potențialul de a îmbunătăți diagnosticul precoce al bolilor oftalmologice, contribuind astfel la progresul în domeniul medical.

2. State of the Art

Another state of the art can be the U-Net Architecture presented in the article [1] . It contains the performance of 20 recent techniques published on relevant venues for vessel segmentation on three show well-established datasets, and then show that a simple cascaded extension of the U-Net architecture, referred to here as W-Net, results in outstanding performance when compared to baselines. It establish a rigorous evaluation protocol, aiming to correct previous pitfalls in the area. It test the approach in a large collection of retinal datasets, consisting of 10 different databases showing a wide range of characteristics.

SVM(Support Vector Machine) based methods

Ricci and Perfetti [2] presented a method to segment vessels by means of line operators and SVM. A line detector at different directions was passed into the target pixel of green component. In addition, two orthogonal line detectors were also applied to build a feature vector for SVM to segment blood vessels and this method performed the local differential calculation of line strength for making the strong line detector. The algorithm's behavior was quite acceptable along with central reflex.

3. Theoretical Fundamentals

We will use the algorithm presented in article [4] that takes an input I(x,y)RGB fundus image and after a series of methods that provide the processing of the image that lead to the vessel extraction, it will result the output of the blood vessels map of the input image.

For the blood vessel extraction we will have the following steps:

a. *Select the green channel*. In preprocessing, first the green channel of the image is extracted. The retinal images are usually low contrast images. Microaneurysms are clearly visible in green channel due to high contrast. Preprocessing is performed in order to enhance the contrast of green channel.

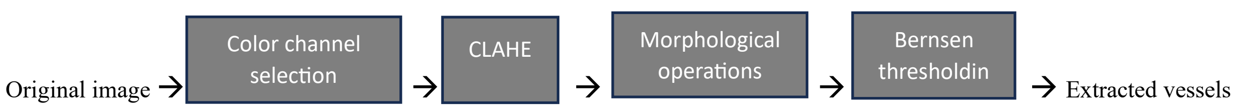
b. *Apply the contrast limited adaptive histogram equalization algorithm [7] known as CLAHE (C(x,y))*.It is used for de-noising and contrast enhancement of retinal fundus image.

c. Apply a linear structuring element with a length of 150 pixels and eight orientations from 0 to 360 degrees in steps of 45° using ($M_1(x,y)$, … , $M_8(x,y)$)

d. Sum up the eight responses using Eq. (1) ($M_{total}(x,y)$). All the responses are summed up (Mtotal(x, y)) to turn out the retinal image's blood vessels [6].

$$M_{total}(x,y) = M_1(x,y) + M_2(x,y) + M_3(x,y) + \ldots + M_8(x,y) \quad (1)$$

e. We apply the Bernsen thresholding [5] to extract the blood vessels(V(x,y))



4. Implementation

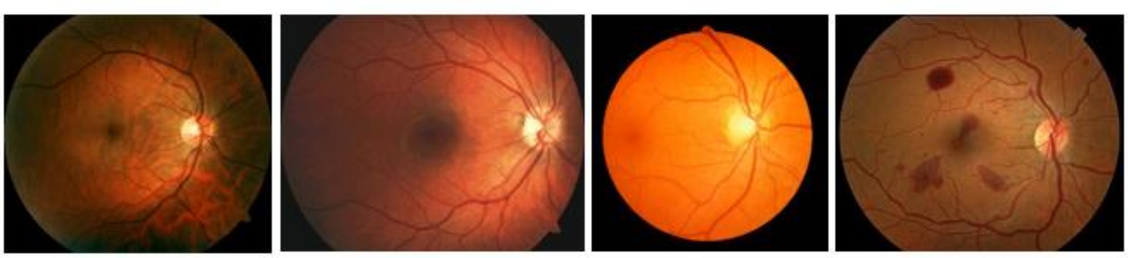
For the implementation part we used Matlab and we started to transform the theory from [4] into a practical code. In the first part of the code we give the input to our software. More exactly an RGB image is uploaded, which can be any type of image such as .jpg, .jpeg, .png, etc. After this first step we will read the image and go through the processing.

Further on we will apply the steps described in Theoretical Fundamentals. In a color image, each pixel is typically represented as a combination of Red, Green, and Blue (RGB) values. The green channel, represented by the second dimension in the image array, often contains information related to vegetation and blood vessels. By isolating the green channel, you focus on the part of the image that is sensitive to the presence of blood vessels as presented in [5].

The histogram equalization is a technique explained in [7] used to enhance the contrast of an image by redistributing pixel intensities. However, standard histogram equalization may lead to over-amplification of noise. Adaptive Histogram Equalization (AHE) divides the image into small tiles and applies histogram equalization to each tile separately, which can enhance local contrast. To prevent the over-amplification of noise in AHE, Contrast Limited AHE (CLAHE) introduces a clipping limit ('clipLimit'). Pixels exceeding this limit have their values scaled down. This helps control the contrast enhancement and reduces the impact of noise. The 'Rayleigh' distribution parameter in this context specifies the distribution of pixel values after contrast enhancement. The choice of distribution can affect the appearance of the final image.

5. Experimental Result

For the experimental part we used a set of images 5 images that we managed to test our algorithm on. The following images were the one used and also we will continue with an example of an image which is taken through the whole steps of the implementation.



a) b) c) d)

Figure 1 Retinal Fundus Original Images

The implementation of the method it is illustrated starting with figure 1. We used a data set of 5 images out of which we are going to present in this part one of them that is going through the whole process.

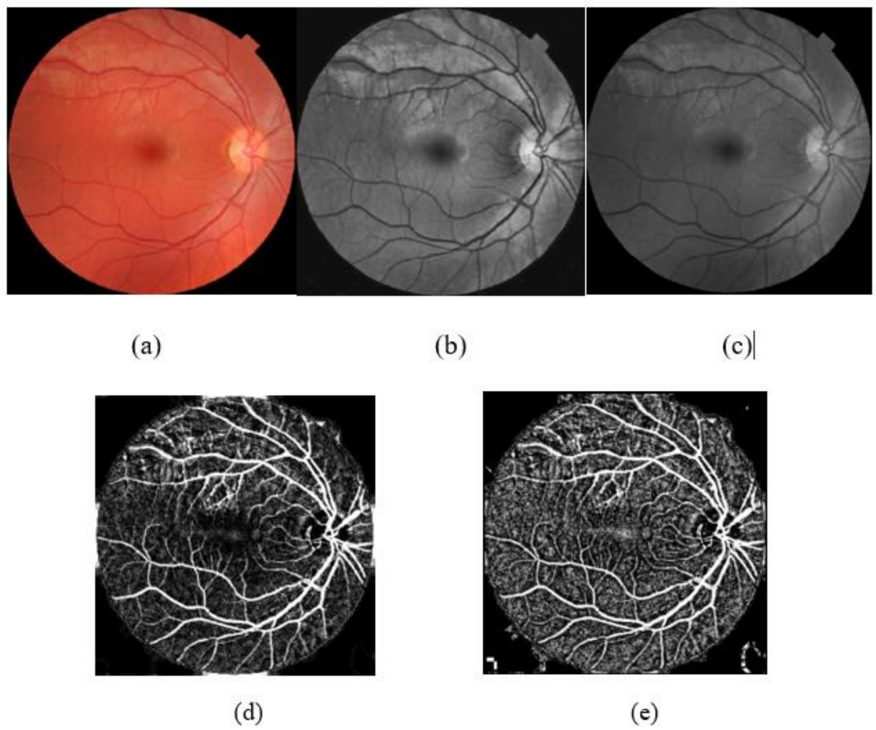


Figure 2 a) original image, b) image with green extraction, c) CLAHE , d) Response image to morphological functions, e) Image after Bernsen Thresholding

The analysis begins with the selection of a retinal fundus image as the initial input for blood vessel detection. The chosen image from Figure 2 (a) serves as the baseline for subsequent processing steps. The image is further processed by isolating the green channel from Figure 2(b). This step is crucial as it focuses on the spectral characteristics of the image, specifically targeting the green components associated with blood vessels. In Figure 2 (c) The Contrast Limited Adaptive Histogram Equalization (CLAHE) is employed on the green channel-extracted image.

This adaptive enhancement technique ensures improved local contrast, accentuating subtle details, including blood vessels. In Figure 2 (d) Morphological operations, specifically dilation and erosion, are iteratively applied using linear structuring elements at various orientations. This process enhances blood vessel features by accentuating their elongated structures, leading to the creation of a cumulative response image. Figure 2 (e) involves Bernsen thresholding applied to the accumulated response image from the morphological operations. This adaptive thresholding method considers local contrast, producing a binary image highlighting blood vessels.

6. Conclusion

In summary, the proposed methodology showcases notable advantages in the realm of blood vessels detection in retinal fundus images. Its inherent robustness allows for exceptional performance, even in challenging scenarios, setting a new benchmark for accuracy in vessel detection and segmentation. This method's excellence is particularly noteworthy in clinical applications, where it demonstrates effectiveness without requiring constant expert intervention for image analysis. The amalgamation of robust performance, cutting-edge results, and applicability in clinical settings positions this approach as a significant stride forward in the field of retinal image analysis. The efficiency of the suggested algorithm is improved by numerical evaluation parameters as compared with other literature methods.

7. References

7.1 Articles

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