AUTOMATED RETINAL VESSEL SEGMENTATION

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ABSTRACT

The study of the vascular tree in retinal fundus images is the quintessential preliminary step in the inspection of ophthalmic diseases and abnormalities in patients. In this work, an automatic retinal blood vessel segmentation method is proposed based on the following pipeline: green channel extraction, gamma correction, background subtraction, edge-preserving denoising, contrast enhancement, top-hat filtering, and Otsu's thresholding. This method yields fast and satisfactory results from the experiments carried on three open datasets, namely STARE, CHASE_DB1 and DRIVE. The accuracies obtained for these datasets are 95.00%, 94.03% and 94.02%, respectively. Additionally, a simple method to detect the optic disk location based solely on the segmented vascular tree is presented.

Index Terms— retinal vessel segmentation, fundus image, morphology

1. INTRODUCTION

Ophthalmology is the branch of medicine that specializes in the anatomy, functions, and diseases of the human eye.

A common instrument used by specialists in this field is the fundus camera which captures photographs of the back of the eye. Fundus images play an important role for diagnosing multiple ocular diseases such as glaucoma, diabetic retinopathy and macular degeneration as they allow to see and examine the optic disk, fovea, macula and vascular tree [1].

The retinal vascular tree is not only important to diagnosing eye ailments but can also help in detecting signs of cardiovascular diseases and hypertension [2]; hence, there has been a surge of proposed automatic methods to extract these networks of vessels. These methods are generally classified as either supervised or unsupervised methods.

Supervised methods rely widely on machine learning algorithms and seek to separate vessels from the background following a set of rules derived from the computation of pixel-wise features [3][4]. The drawback of these methods is mainly the high computational cost.

Unsupervised methods make use of one or more concepts in image processing including mathematical morphology, clustering, convolution and match filtering [5][6]. However, they often suffer from high noise sensitivity.

This paper proposes an unsupervised method based mainly on median filtering, non-local means denoising and morphological top-hat filtering.

2. MATERIALS

This work is based on three databases that are commonly used by the research community to test their segmentation algorithms. They have the advantage to be freely accessible and are packed with manual segmentation of the vasculatures performed by an expert which serve as ground truth for this study. Here is a short description for each database.

DRIVE: The Digital Retinal Images for Vessel Extraction (DRIVE) database consists of 40 images from an original of 400, taken randomly following a diabetic retinopathy screening program in The Netherlands [7]. The dimensions of images are 565x584 and were captured with a Canon CR5 non-mydriatic 3CCD camera with a 45-degree field of view (FOV). This database comprises binary mask images delineating the FOV.

STARE: The Structured Analysis of the Retina (STARE) database consists of 20 images as a result of a 1975 initiative by the University of California, San Diego [8]. The dimensions of images are 700x605 and were captured with the TopCon TRV-50 fundus camera with 35-degree FOV. This database does not include mask images; therefore, they were individually generated.

CHASE_DB1: The Child Heart And health Study in England DB1 (CHASE_DB1) database consists of 28 images [9]. The dimensions of images are 999x960 and were acquired using the Nidek NM 200D fundus camera with 35-degree FOV. This database comprises binary mask images delineating the FOV.

The implementation of the segmentation pipeline was done in C++ and leveraged the capabilities of the OpenCV v2 library. A Graphical User Interface (GUI), built with the QT widget toolkit, was added on top to ease the manipulation and testing of the program (see Fig. 4).

3. METHODS

The devised segmentation pipeline is shown in Fig. 1 and a description of it is detailed below.

First, the fundus images, which are RGB color images, are converted to grayscale to enable further processing. Generally, the grayscale of an RGB image refers to the weighted sum of the three channel images. However, each channel image is at the base a grayscale image. For fundus images, the green channel captures the highest contrast between the vessels and the background; therefore, it is directly extracted while the contribution of other channels is dismissed.

Next, the overall brightness is adjusted nonlinearly by applying a gamma correction, i.e. raising the pixel intensities to a power γ. The γ picked is different for each dataset, but they are all lower than 1 giving enlightened fundus images since the mapping of input intensities, by the gamma function, is weighted more to higher values. Although this technique is widely used to optimize images for the the human visual perception, it is applied here to globally enhance the images. The resulting image is inverted such that the vessels become brighter than the background.

To get rid of background elements that are not of interest such as the optic disc and persistent luminance inhomogeneities, the background is subtracted from the image. This is done by approximating the background through median filtering with a large kernel – which also eliminates the vessels – and then subtracting the obtained image from the initial image.

At this stage, the image consists only of the vessels and small noise patches on top of a very low intensity background. Smoothing will further alleviate the noise; however, the vessel lines/edges need to be preserved. For this purpose, the non-local means technique was adopted.

Next, the image contrast is improved using Contrast Limited Adaptive Histogram Equalization (CLAHE) with which different regions of the image have their own histogram computed to enhance local contrast and improve greatly the definitions of vessels.

The caveat of applying CLAHE is that noise gets relatively enhanced as well. The vessels therefore need to be further enhanced with regards to the noise. For this, the sum of twelve top-hat transforms applied on the image is computed each using the same structuring element but oriented differently at intervals of 15° to span a 360° search of vessels (2 x (12 x 15) = 360). The structuring element is a rectangular kernel of width 1 and height larger than the vessels' thickness.

At this point, the retinal vasculature is well defined and highly contrasted compared to the background noise. The segmentation is achieved using Otsu's thresholding method and the vascular tree is obtained as a binary image.

The final step is to trim the FOV contour to remove unwanted encircling edges. This is done by eroding the FOV mask with a circular kernel resulting in a FOV mask with reduced radius which is then applied to the segmented image to retain only the pixels within the reduced FOV.

Fig. 2 shows the aftermath of each processing step applied to a sample image from the DRIVE database.

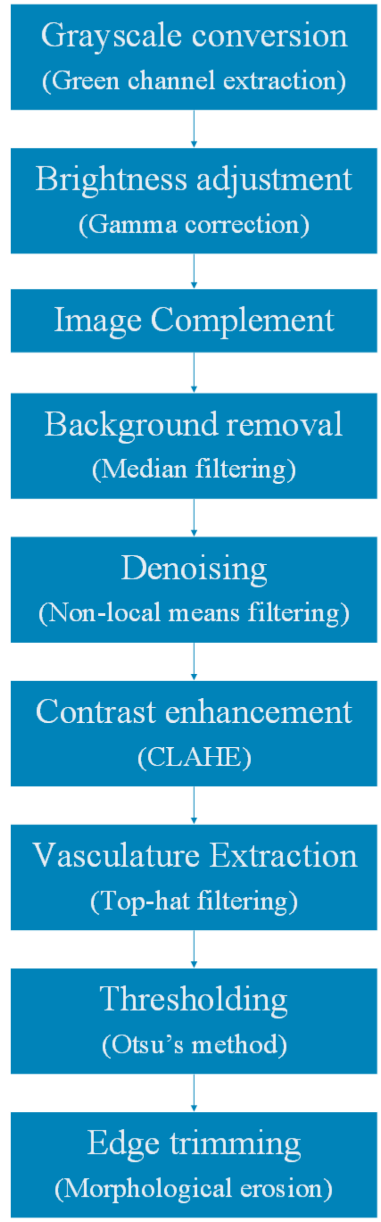

Fig. 1. Proposed segmentation pipeline

4. RESULTS

To measure the efficiency and performance of the proposed segmentation method, the accuracy score is computed from comparing the obtained binary results with their corresponding ground truth images. When a pixel in the segmented image has the same value as the corresponding pixel in the ground truth image, it is considered a correct match, either as true positive – if the intensity is 1 or white – or true negative – if the intensity is 0 or black. The accuracy is computed as follows:

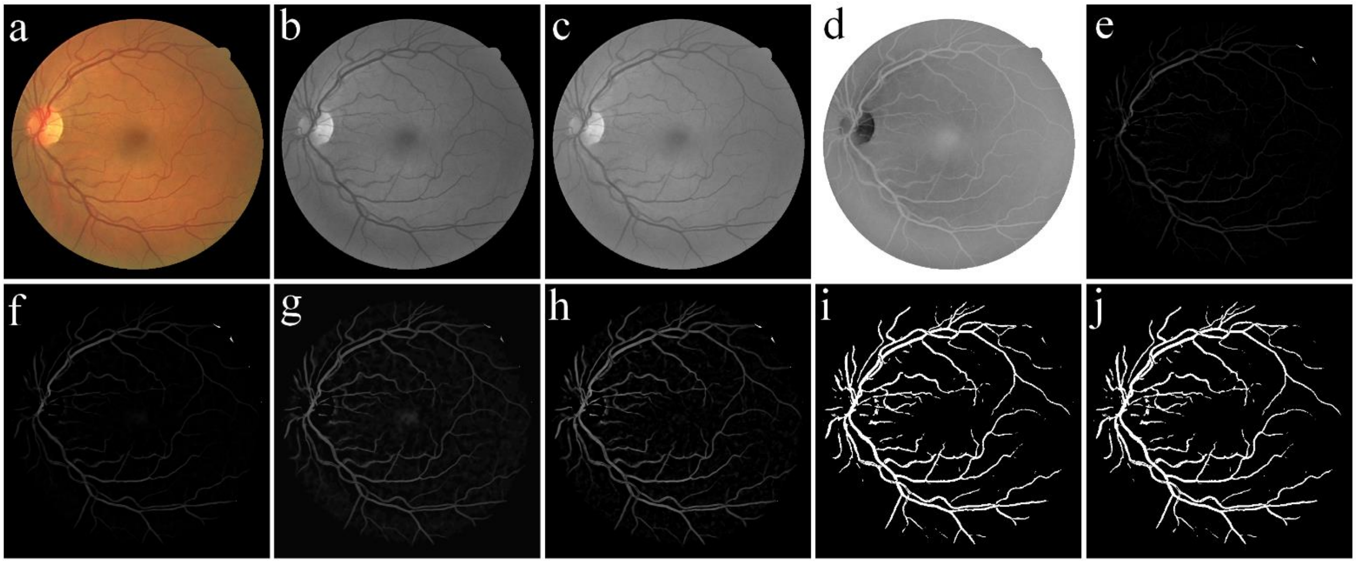

Fig. 2. Processing steps on a sample fundus image of the DRIVE database: a) fundus image, b) green channel, c) gamma correction, d) image complement, e) background removal, f) non-local means denoising, g) CLAHE, h) sum of top-hats, i) Otsu's thresholding, j) FOV contour trimming.

$$Accuracy = \frac{True\ Positives + True\ Negatives}{Total\ Pixels}$$

Table 1 shows the accuracy score obtained from running the experiment over all images of each database.

TABLE I. ACCURACY SCORES

Database	Accuracy
STARE	95.00 %
CHASE_DB1	94.03 %
DRIVE	94.02 %

5. DISCUSSION

The highest accuracy score was with the STARE database (95%) while with the DRIVE and CHASE_DB1 the score was slightly lower (about 94%). These results are close to the scores from state-of-the-art methods found in the literature. It shows that the proposed method, though a simple and unsupervised one, is robust and effective while yielding relatively prompt results even on today's average PCs.

The use of median filter for background suppression was useful to get rid of a lot of artefacts. Thresholding at that stage would lead to fair results – around 93% for accuracy. Further processing steps were taken to increase the contrast of the vessels and improve the definition of their edges and thickness.

The non-local means filtering helps in removing granular or gaussian-like white noise left from the background subtraction. Bilateral filtering is an effective and sometimes faster alternative, but the former provided optimal results.

This segmentation algorithm relies on the fine tuning of parameters for the different processing steps: gamma value, size of the median filter, size of the weights and search windows for non-local means in addition to the filter strength, and the grid size and the degree of contrast limiting for CLAHE. The ideal is to adapt these parameters for each image; however, it is a difficult task and not practical especially when seeking an automatic solution. Therefore, the parameters were fixed at the database level.

6. OPTIC DISC DETECTION

A tentative to find the approximate location of the optic disk given only the vascular tree of the retina is described in this section.

The ground truth image is processed instead of the output from the segmentation procedure since the foremost represents the most accurate vascular tree and there is no dependency on executing the segmentation process as a preliminary step.

The binary image is smoothed using a large median filter which results in removing structures with low to medium thickness while increasing the density of vessels in regions where there is high concentration of branches – notably around the optic disk area. A search is then performed within a limited vertical range of the image's center using a top-to-bottom left-to-right sliding window computing the total number of non-zero pixels (i.e. vessel pixels). The area with highest density of positive pixels is assumed to be the optic disc location. Fig. 3 demonstrates an example.

The outcome is not perfect as in certain images there are areas other than the optic disc which displays a high number of connected vessels. Also, the assessment is subjective and depends on the visual judgement.

Experimenting on CHASE_DB1, this algorithm provides correct results over all images. On the other hand, the optic disk in 36 out of the DRIVE's 40 images were adequately located while the other 4 images delimited the optic disk a little less effectively.

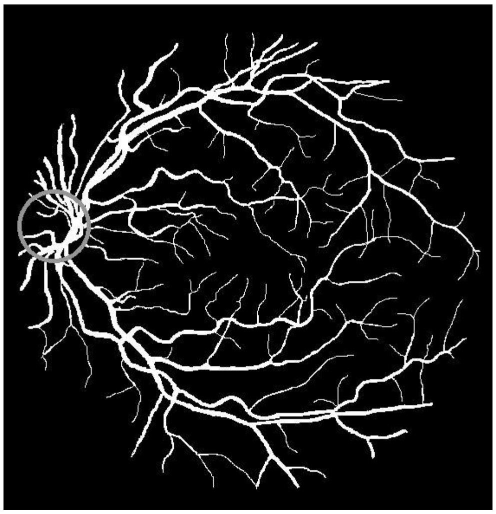

Fig. 3. Automatic optic disk detection from vascular tree.

7. CONCLUSION AND FUTURE WORKS

In this paper, an unsupervised method for the automatic segmentation of blood vessels of the retina from fundus images is presented and described. The method consists of a sequence of basic image processing techniques mainly around edge-preserving smoothing and mathematical morphology. The method was applied on three public databases and it yielded accuracy scores of at least 94% which is deemed satisfactory for a simple and unsupervised method. However, there is still room for improvement and the algorithm can be redevised to further eliminate noise that are persistent on certain images more than others by refining certain stages of the pipeline and/or adding new ones. It is believed that an accuracy of at least 95% for each dataset can be secured with a little more work on the algorithm and parameters tuning.

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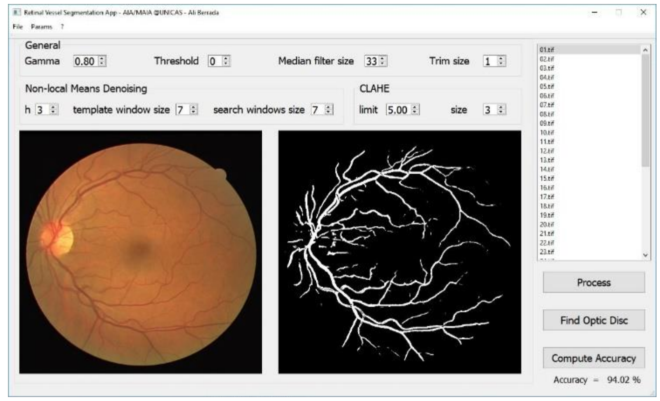

Fig. 4. GUI interface of the implemented algorithm

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