Blood Vessels and Exudates Segmentation in Eye Fundus Images based on Fourier Filtering

Luis David Lara-Rodríguez, Elizabeth López-Meléndez, and Gonzalo Urcid

Abstract—This paper presents a Fourier transform approach to segment blood vessels and exudates in eye fundus color images. The basic idea consists in an illumination enhancement using an homomorphic filter, due to non-uniform illumination conditions in the eye fundus image capture. The design of parametric Butterworth bandpass filters in the Fourier domain is applied to the green channel only, to distinguish the foreground objects from the background. To find blood vessels, the negative of the filtered image is determined to emphasize the defective vessels causing hemorrhages (spots of bleeding), fluid and exudates (fats) to escape from the blocked vessels over the retina. The blocked vessels can starve the retina from oxygen (ischaemia), leading to the growth of new abnormal vessels in the retina [1]. There are several screening exams that help to find diseases, among the exams are asmsler grid, autofluorescence, dilated eye exam, fundoscopy or ophthalmoscopy, eye fundus photography, fluorescence angiography, optical coherence tomography (OCT), and tonometry[2],[3]. In the past years, researchers have been working in eye fundus photography to find blood vessels, exudates, hemorrhages. Some of these works use diverse techniques like the Hough transform, mathematical morphology techniques, illumination correction and histogram equalization [7], [13], [8], [9], [10]. Other works enhance the image using Gaussian filters as well as the watershed transform[4], [12], [5], [6]. In this paper we use the database DIARETDB1 (Standard Diabetic Retinopathy Database Calibration Level 1) from Lappeenranta University, where each image in this database has a size of $1152 \times 1500$ pixels. Knowing that the area of the optic disk is $2.47\text{mm}^2$ (radius $= 0.88\text{mm}$), the corresponding approximate spatial resolution is of $4.746\mu\text{m}$ per pixel [11].

The purpose of the present research work is to extract blood vessels and exudates in eye fundus color images. Basically, our proposal consists of the following steps. First a binary image mask is created to obtain the boundary of the eye fundus in the acquired color image by clipping the working area taken by the camera. Second, an homomorphic filter in the Fourier domain is applied to homogenize the image illumination, after which a Butterworth bandpass filter in the frequency domain is used to distinguish between foreground objects, and the corresponding eye fundus image background. Third, two procedures are proposed for the different types of pathologies mentioned earlier. The first procedure is for blood vessels, we use a DoG filter to enhance their contrast, then a median filter is applied to reduce background noise, and image thresholding (Otsu’s method) is performed using global statistics to obtain the desired object regions including their edges. Segmentation of the blood vessels is obtained applying a morphological closing and a logical operation between the binary mask and the thresholded image. The second procedure that determines exudates, an auxiliary image is calculated from local statistics in order to emphasize the exudates from the background. Similarly, Otsu’s method is employed to binarize the auxiliary image. Also, the same logical operation between the binary mask and the thresholded image is realized to get the segmented image.

The paper is organized as follows: Section II explains in detail the different image processing steps involved in the proposed Fourier filtering based method for the segmentation of the aforementioned pathologies and several representative examples are provided. In Section III we present the segmentation results obtained including our segmentation algorithm in pseudocode format. We close the paper with Section IV of conclusions and some pertinent comments.

I. INTRODUCTION

EYES diseases (Maculopathy, diabetic retinopathy, glaucoma, etc) do not always have symptoms, early detection and treatment could prevent loss of vision. If a person has diabetes their chances of developing diabetic retinopathy are higher, large periods of high blood sugar levels cause damage to the small blood vessels in the retina at the back of the eye. If these blood vessels are damaged by high blood sugar levels and initially become defective, later they may become blocked off. The defective vessels can lead to hemorrhages (spots of bleeding), fluid and exudates (fats) to escape from the blood vessels over the retina. The blocked vessels can starve the retina from oxygen (ischaemia), leading to the growth of new abnormal vessels in the retina [1]. There are several screening exams that help to find diseases, among the exams are asmsler grid, autofluorescence, dilated eye exam, fundoscopy or ophthalmoscopy, eye fundus photography, fluorescence angiography, optical coherence tomography (OCT), and tonometry[2],[3]. In the past years, researchers have been working in eye fundus photography to find blood vessels, exudates, hemorrhages. Some of these works use diverse techniques like the Hough transform, mathematical morphology techniques, illumination correction and histogram equalization [7], [13], [8], [9], [10]. Other works enhance the image using Gaussian filters as well as the watershed transform[4], [12], [5], [6]. In this paper we use the database DIARETDB1 (Standard Diabetic Retinopathy Database Calibration Level 1) from Lappeenranta University, where each image in this database has a size of $1152 \times 1500$ pixels. Knowing that the area of the optic disk is $2.47\text{mm}^2$ (radius $= 0.88\text{mm}$), the corresponding approximate spatial resolution is of $4.746\mu\text{m}$ per pixel [11].

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The paper is organized as follows: Section II explains in detail the different image processing steps involved in the proposed Fourier filtering based method for the segmentation of the aforementioned pathologies and several representative examples are provided. In Section III we present the segmentation results obtained including our segmentation algorithm in pseudocode format. We close the paper with Section IV of conclusions and some pertinent comments.

II. SEGMENTATION OF BLOOD VESSELS AND EXUDATES

A previous step builds a binary mask used to delete the working area taken by the eye fundus camera. The corresponding Algorithm 1 is given next and an example of a mask is shown in Fig. 1.

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Manuscript received July 10, 2015. *Corresponding author: Gonzalo Urcid, email: gurcid@inaoep.mx.

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Index Terms—Butterworth Fourier filtering, Color image segmentation, Eye fundus images.

ISBN: 978-988-19253-6-7
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)
Algorithm 1 Eye Fundus Mask

procedure MASK(I)
  \[I_R \leftarrow \text{ExtractChannel}(I, R)\]
  \[I_G \leftarrow \text{ExtractChannel}(I, B)\]
  \[I_Q \leftarrow I_R/(I_G + 1)\]
  \[I_Q \leftarrow \text{MedianFilter}(I_Q)\]
  \[L_{\text{MOTSU}} \leftarrow \text{OtsuThreshold}(I_Q)\]
  \[M \leftarrow \text{Binarize}(I_Q, L_{\text{MOTSU}})\]

In a segmentation process is possible to discriminate objects of interest from the background by dividing the image in regions that satisfy certain conditions [15]. In general, due to the presence of non-uniform illumination in eye fundus images, we propose the use of a Fourier homomorphic filter to homogenize this illumination. Recall that the two dimensional discrete Fourier transform (DFT) is given by,

\[
F(u, v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) e^{-j2\pi(u/M + vy/N)},
\]

where \(f(x, y)\) is an image of size \(M \times N\), \(u = 0, 1, ..., M - 1\), and \(v = 0, 1, ..., N - 1\). Also, \(f(x, y)\) is multiplied by \((-1)^{(x+y)}\) to center the transform that is computed with an FFT (Fast Fourier Transform) algorithm. The filtered image, denoted by \(g(x, y)\), is computed as follows:

\[
g(x, y) = \mathcal{F}^{-1}[F(u, v)H(u, v)],
\]

where \(\mathcal{F}^{-1}\) is the inverse discrete Fourier transform (IDFT), \(F(u, v)\) is the DFT, of the input image \(f(x, y)\), and \(H(u, v)\) is a specific Fourier homomorphic filter. For numerical computation, the functions \(F\), \(H\), and \(g\) are matrices of the same size as the given image. A high pass Butterworth homomorphic filter (HF) is given below,

\[
H_{HF}(u, v) = (\gamma_H - \gamma_L) \left( \frac{D(u, v)}{D_0} \right)^{4n} + \gamma_L,
\]

where, \(\gamma_L < 1\), \(\gamma_H > 1\), and \(n\) (filter order) is the slope of the function between the given gamma bounds. The particular values we use for filtering the eye fundus color images are \(\gamma_L = 0.75\), \(\gamma_H = 1.75\), \(n = 3\), and \(D_0 = 10\) for the cutoff spatial frequency. An example of illumination correction for an RGB color image is shown in Fig. 2 and for the green channel only appears in Fig. 3.

Fig. 1. Top: original eye fundus color images. Bottom: eye fundus binary mask.

Fig. 2. Top: example color image. Bottom: illumination corrected color image.

Fig. 3. Top: example green channel gray scale image. Bottom: illumination corrected green channel gray scale image.

Once we have corrected the image illumination, the segmentation process is facilitated by filtering in Fourier’s
domain to intensify the foreground objects against the surrounding background of the corresponding green channel of a given eye fundus color image. Specifically, we use a Butterworth bandpass \( BP \) filter given by,

\[
H_{BP}(u, v) = \frac{(WD(u, v))^2}{(WD(u, v))^2 + (D(u, v)^2 - D_0^2)^2},
\]

where, \( n \) is the order of the filter, \( W \) is the bandpass width, \( D(u, v) = \sqrt{(u-M/2)^2 + (v-N/2)^2} \) is the Euclidean distance from the center of the filter, and \( D_0 \) is the cutoff spatial frequency. In the present case, the chosen values used are \( n = 3 \), \( W = 100 \), and \( D_0 = 75 \). The resulting image after Fourier inversion is given by the following equivalent spatial expression,

\[
g_{BP}(x, y) = [I_{G}(x, y) * h_{BP}(x, y)] * h_{BP}(x, y).
\]

To visualize the type of filter applied to the green channel eye fundus image, Fig. 4 displays the Butterworth bandpass filter and the magnitude of the Fourier spectrum of the filtered image. The filtering step in Fourier’s domain is the same for the segmentation of blood vessels and exudates. The specific steps to segment each type of pathology is described next.

A. Segmentation of Blood Vessels

In order to remark blood vessels, we take the negative of the previous filtered image computing, \( g_{\text{BP}}(x, y) = (L - 1) - g_{\text{BP}}(x, y) \), where \( L \) is the maximum value of the corresponding grayscale range. Then, a DoG[14] operation is used to emphasize objects edges; the mathematical expression are given by,

\[
\text{DoG}(x, y; \sigma_1, \sigma_2) = e^{-((x^2+y^2)/2\sigma_1^2)} - e^{-((x^2+y^2)/2\sigma_2^2)},
\]

\[
g_{\text{DoG}}(x, y) = \text{DoG}(x, y) * g_{\text{BP}}(x, y).
\]

The values used for the DoG spatial filter are \( \sigma_1 = 2 \) and \( \sigma_2 = 1.7 \), with a mask of \( 11 \times 11 \) pixels and \( 5 \times 5 \) pixels, respectively. Furthermore, the resulting image is enhanced with a median filter of size \( 7 \times 7 \) pixels to reduce the noise introduced by the DoG filter. The filtered image is symbolized by \( g_{\text{DoG}}(x, y) \). In the next step, an image thresholding is performed using Otsu’s[15] method to obtain a binary image using the global threshold value provided by Otsu’s method, recalling that it is based on global and local statistics. Specifically, the binary output image is computed as,

\[
B_{V}(x, y) = \begin{cases} 
0 & \text{if } g_{\text{DoG}}(x, y) < L_{\text{VOtsu}}, \\
1 & \text{otherwise}.
\end{cases}
\]

A binary closing morphological operation [16] is used to connect object edges in the corresponding regions of \( B_{V}(x, y) \), i.e., \( B_{V} \circ S = (B_{V} \oplus S) \circ S \), where the structuring element \( S \) is an square of size \( 7 \times 7 \) pixels. Finally, the segmented image \( S_{V} \) containing the blood vessels is obtained by masking the previous image. Hence, \( S_{V} = B_{V} \land M \), where \( \land \) is the logical AND operation. An example is shown in Fig. 5.

B. Segmentation of Exudates

For this type of pathology, we use image \( g_{\text{BP}} \) to compute an auxiliary image based on its local statistics, with the purpose to emphasize contrast of exudates present in the image. This auxiliary image, represented by \( C_{\text{aux}} \), scans \( g_{\text{BP}} \) with a \( 3 \times 3 \) neighborhood and is given by the following expression,

\[
C_{\text{aux}}(x, y) = \mu_{L}(x, y) + \alpha \sigma_{L}(x, y),
\]
Again, Otsu’s method is used to calculate a global threshold value for the $C_{aux}$ grayscale image. In particular, the binary output image is determined as,

$$B_{E}(x,y) = \begin{cases} 0 & \text{if } C_{aux}(x,y) < L_{EOtsu} \\ 1 & \text{otherwise}. \end{cases} \quad (10)$$

The segmented exudates image is found by masking the previous image with the initially binary mask $M$. That is to say, $S_{E} = B_{E} \land M$. An illustrative example of exudates is displayed in Fig. 6.

![Fig. 6. Top: original eye fundus color image with exudates. Middle: Butterworth bandpass filtered exudates image. Bottom: segmented exudates in an eye fundus image.](image)

### III. RESULTS

To test our proposed segmentation technique, we use four eyes fundus color images taken from the public domain database DIARETDB1. The database consists of 89 eye fundus color images, from which 84 images contain at least mild non-proliferate signs of diabetic retinopathy. The other 5 images are considered normal since these do not contain any signs of diabetic retinopathy, according to all experts who participated in the evaluation. The eye fundus color images were captured using the same 50 degree field-of-view digital fundus camera with varying imaging settings [18]. As mentioned earlier, each image has a size of $1152 \times 1500$ pixels, with an approximately spatial resolution of 4.756 micrometers per pixel. We remark that the global threshold value obtained by applying Otsu’s method is different for each image. Figures 7 and 8 show another illustrative example, respectively, of blood vessels and exudates segmentation. As we can see in Fig. 8, the exudates (foreground objects) are brighter than the background. Notice that the difference between blood vessels and exudates segmentation is that in the second pathology there is no need in to apply a closing operation. Table I lists the segmentation parameters and numerical values used in these examples and Algorithm 2 provides the sequence of steps of our technique.

![Fig. 7. Top: original color eye fundus image with blood vessels. Middle: Butterworth bandpass filtered blood vessels image. Bottom: segmented blood vessels in an eye fundus image.](image)

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<th>Segmentation Parameters for Blood Vessels</th>
<th>Segmentation Parameters for Exudates</th>
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<td>Homomorphic filter</td>
<td>$\gamma_L = 0.75, \gamma_H = 1.75, n = 3, D_0 = 10$</td>
<td>$\gamma_L = 0.75, \gamma_H = 1.75, n = 3, D_0 = 10$</td>
<td>$\gamma_L = 0.75, \gamma_H = 1.75, n = 3, D_0 = 75$</td>
</tr>
<tr>
<td>Butterworth BP filter</td>
<td>$n = 3, W = 100, D_0 = 75$</td>
<td>$n = 3, W = 100, D_0 = 75$</td>
<td>$n = 3, W = 100, D_0 = 75$</td>
</tr>
<tr>
<td>DoG filter</td>
<td>$\sigma_1 = 2 (11 \times 11), \sigma_2 = 1.7 (5 \times 5)$</td>
<td>$\mu_L, \sigma_L, \alpha = 3$ for each $(x,y)$</td>
<td>$\mu_L, \sigma_L, \alpha = 3$ for each $(x,y)$</td>
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<tr>
<td>Otsu’s threshold</td>
<td>$L_{EOtsu} \in (0,1)$</td>
<td>$L_{EOtsu} \in (0,1)$</td>
<td>$L_{EOtsu} \in (0,1)$</td>
</tr>
<tr>
<td>Morphological closing</td>
<td>$7 \times 7$ square structuring element</td>
<td>$7 \times 7$ square structuring element</td>
<td>$7 \times 7$ square structuring element</td>
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frequency processing using a Butterworth bandpass filter with carefully selected parameters, to achieve an adequate contrast of the foreground objects versus the background. Additionally, spatial DoG filtering helps to emphasize edges for blood vessel detection while in the case of exudates this step is not need it. The binarized image is determined using simple statistics (Otsu’s method). We remark that before the final masking operation is realized, a different intermediate operation is used for blood vessels and exudates extraction. In the former case, a closing morphological operation is required and for exudates an auxiliary image formed by a linear combination of local statistics is needed. We have provided a few illustrative examples to visualize the results we obtained with the proposed method. Future work contemplates extending the number of tests on the same clinical public database and doing qualitative and quantitative comparison with other known methods for segmenting pathologies in eye fundus color images.

REFERENCES