CIRCLET BASED FRAMEWORK FOR OPTIC DISK DETECTION

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ABSTRACT

Optic Disc (OD) detection in retinal fundus images is a crucial stage for the automation of a screening system in diabetic ophthalmology. Most researches for automatic localization of OD benefit the regions of vessels. In this paper, we present a fast and novel method based on the Circlet Transform to detect OD in digital retinal fundus images that doesn't utilize the location of the vessels. First, each R, G and B band is enhanced using CLAHE method. Then, the enhanced image in RGB color space is converted to L*a*b one. Next, the Circlet transform is applied to the L* band, and finally, the Circlet transform coefficients are analyzed to find the location of the OD. The proposed algorithm is implemented on DRIVE dataset and the experimental results show a very well OD localization. The correct rate of the proposed method is 95% even though it doesn't utilize the vessels' structure.

Index Terms— Circlet Transform, Circlet coefficients, Digital Retinal Fundus Images, Image Enhancement, Optic Disk Detection.

1. INTRODUCTION

Retinal fundus images are widely used in the diagnosis and treatment of different eye diseases. By making the process automatic and accelerating the evaluation of dozens of fundus images, the efficiency of ophthalmologists in clinics will be improved. The Optic Disc (OD) is considered as one of the main features for a retinal fundus image [1]. The OD is the brightest region in normal retinal fundus images and has a pallid circular or oval shape. Optic disk is usually considered as a reference to detect special characteristic in fundus images as blood vessels and optic nerves are entered into the OD. For example, in some methods, for tracking blood vessel, the algorithm starts from the OD [2, 3]; the position of fovea is commonly estimated from the location of OD [4, 5] and in order to quantify abnormal structures caused by glaucoma, the dimensions of OD could be utilized. Over years many efforts have been done for the automatic detection of OD. An automatic method for the location of OD in fundus images is proposed by Li et al [6] in which some candidates are first found by clustering the brightest intensity pixels. Then, PCA is applied to the candidates and the center of OD is found by computing the minimum distance between the primary image and its projection onto "disk space". Sekhar et al [7] performed automated localization of the retinal OD using Hough Transform (HT). In their method, first, morphological operations are applied to find circular regions. Then, HT is used to detect OD among selected candidates. Detection of OD in RI via a geometrical model of vessel structure is proposed by Foracchia et al [8]. They mentioned that all Retinal Vessels (RVs) originate from the OD and their route pursue a comparable directional pattern in all images. So, they proposed a geometrical parametric model to depict the direction of RVs at any given position in the image. The parameters of their model are recognized by a simulated annealing optimization technique using vessels structure of experimental data. Using this model the center of the OD is detected. Automatic localization of OD in retinal fundus images is performed by Sinthanayothin et al [4] in which the OD is found via recognizing the region with the greatest alteration in the intensity of surrounding pixels. Automatic OD detection using Curvelet transform is performed by Esmaeili et al [9]. In their work, Digital CUrvelet Transform (DCUT) is applied on the enhanced retinal image, and then, the coefficients are modified to find candidate regions of the OD. Canny edge detector is applied on the image obtained from keeping the highest coefficients of DCUT and then some morphological operators are applied. Region that has maximum pixels in the edge map obtained by the DCUT is considered as the location of OD. A fast and robust OD detection is proposed by [10] using Pyramidal Decomposition (PD) and Hausdorff-based Template Matching (HTM). Two methods are combined: 1) a HTM technique on the edge, directed by 2) a PD for large scale object tracking. Complementary search methods are used to achieve better results. Hoover et al [11] proposed a method for the localization of OD in retinal images based on fuzzy convergence of the blood vessels. Their method utilizes the blood vessel network convergence as initial characteristic, in conjunction with the brightness of the nerve as secondary feature. Fuzzy convergence employs the endpoints of the blood vessel segments to recognize the intersection of many vessels. The detection of the OD in retinal fundus images using matching filter of vessels' direction is proposed by Abdel-Razik Youssif et al [12]. A matched filter is proposed to match the vessels' direction at the OD neighborhood. The vessels are segmented utilizing a Gaussian matched filter. Therefore, a direction map of the vessels is acquired called Vessels Direction Map (VDM). The segmented vessels are then thinned and filtered to depict the candidate OD's centers. The matched filter is resized to four separate dimensions to match the shape of vessels in various sizes. Then, the differences between these templates and a VDM are computed and the minimum measuring corresponds to the center of the OD. Approximately all the previous works utilized the vessels information for OD detection. In this paper, a fast and novel method based on the Circlet Transform is proposed to detect optic disk in the retinal fundus images that doesn't need the location of the vessels. The contributions of the proposed method are as follows:

- Developing Circlet transform for OD localization on a public dataset
- Utilizing just the OD properties and not vessels' structure for OD localization with high performance
- Proposing a method for the modification of Circlet coefficients in order to remove noise and artifacts
- Studying the effect of variation of Circlet parameters on the performance of OD localization

The study is organized as follows. Section two introduces Circlet transform that is the main focus of this work. Optic disk detection using Circlet transform is described in section three. Section four explains experimental results and discussion and finally the work is concluded in section five.

2. THE CIRCLET TRANSFORM

The Circlet transform proposed by Chauris et al [13] is a state of the art and efficient transform for detecting objects with circular pattern in which binary image segmentation is no longer needed against many well-known methods such as Hough transform whither binarization is an essential task for applying them to detect round shapes. The Circlet transform, as a new transform, decomposes an image to sub-bands with different radii and frequencies. The basics of the transform are defined in the frequency domain in a way to model a circular pattern in the spatial domain. By this definition, Circlet transform generates high coefficients correspond to the circular objects in the image easier and more robust than existing transforms. In other words, Circlet transform decomposes an image into circles called *circlets* with different radii and a certain width, via a series of fast Fourier transforms. All circlet components $c_\mu(x,y)$ could be created by a basic circlet $c_{ref}(x,y)$ which can be shifted or be changed in radius or the central frequency. The circlet function can be written as (1):

$$c_\mu(x,y) = \Omega\left[2\pi f_0 (r - r_0)\right] \qquad (1)$$

where $r = \sqrt{(x-x_0)^2 + (y-y_0)^2}$. Ω is considered as a fluctuating function such as a wavelet function which is formulated to reveal discontinuities. From a practical point of view, c_μ is defined in the 2D Fourier domain [13].

Proper filters must be defined for $\hat{c}^*_\mu(\omega_1,\omega_2)$, the Fourier transform of c_μ, such that circular shapes could be achieve for basic functions $c_\mu(x,y)$. The filters are defined in the Fourier domain and 2D filters G_k are constructed by the 1D filters F_k. The F_k filters are defined as (2):

$$F_k(\omega) = \begin{cases} \cos(\omega \pm \omega_k) & , \ |\omega \pm \omega_k| \le \pi/(N-1) \\ 0 & othgerwise \end{cases} \qquad (2)$$

where N is the number of filters and $\omega_k = \pi(k-1)/(N-1)$. By considering a phase delay in order to have circular shape in the spatial domain, the G_k filters are defined as (3):

$$G_k(\omega_1,\omega_2) = e^{i|\omega| r_0} \cdot F_k(|\omega|) \qquad (3)$$

where $\omega = (\omega_1,\omega_2)$ and $|\omega| = \sqrt{\omega_1^2 + \omega_2^2}$. By the definition of the filters G_k, the formulation of a circlet in the Fourier domain will be as (4):

$$\hat{c}_\mu(\omega) = e^{i\langle\omega, x_c\rangle} \cdot G_k(\omega) \qquad (4)$$

where $x_c = (x_0, y_0)$ is the central position and r_0 is the radius of the circlet. More details about the Circlet transform, its implementation and application could be found in [13, 14].

(a) (b) (c)

Figure 1. (a) A sample of retinal image, (b) enhanced image, and (c) the L* band of (b).

3. OPTIC DISK DETECTION USING CIRCLET TRANSFORM

The application of the Circlet transform in OD localization is shown by Chauris et al [13], but they just reported on three retinal fundus images not on any dataset and also the details implementation and challenges are not explained. It is worthy to note that, based on our experiments, developing Circlet transform for OD detection especially on a dataset has some challenges that are discussed in Section 3.1.

General steps of the proposed algorithm are: 1) Reducing the noise of the image, 2) Enhancement of the R, G and B bands of the RGB image, 3) Conversion of the enhanced image from RGB color space to L*a*b color space, 4) Applying Circlet transform on L* band, 5) Analysis of Circlet transform coefficients to find the location of the OD. The details of the proposed method are explained in the following. First, the image is filtered using a median filter with 3×3 window size to reduce the noise of the image. Then, the filtered image is enhanced using Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm [15]. This algorithm is applied on each R, G and B band separately. CLAHE enhances the contrast of small windows to generate a uniform histogram. Adjacent windows are then merged utilizing bilinear interpolation to smooth the boundaries. Figure 1(a) shows a sample of retinal image and Figure 1(b) shows the enhanced image. Next, since the red, green and blue components are highly correlated and it is difficult to execute some image processing algorithms, the enhanced image from RGB color space is converted to L*a*b color space. In the next step, the Circlet transform with parameters $N = 4$ and $r_0 = \{30, 32, \cdots, 40\}$ is applied to the L* known as intensity band. Figure 1(c) shows the L* band of the Figure 1(b). It is noticeable that the Circlet transform in our method is directly applied on a gray-scale image. So, it is not limited to have a binary image in contrary Circular Hough Transform (CHT) [16]. The CHT is a well-known method for detecting circular shapes and the binary image uses for CHT is the edge map of the image. Some methods are developed for OD localization based on Hough transform [7, 17, 18] in which the information of vessel was not used that are also considered for comparison with our method in Section 4.

(a) (b) (c)

Figure 2. (a) the absolute CT coefficients of Figure 1.(a) correspond to radius $r_0 = 32$ and frequency $k = 2$, (b) searching area correspond to Figure 2(a), and (c) detected OD by CT.

3.1 Analysis of the Circlet transform coefficients

As it is expected, the optic disk location corresponds to the maximum coefficient of the Circlet transform. In the case of retinal images, there is a challenge in finding desired maximum coefficient of the Circlet transform since Region Of Interest (ROI) is a sharp circle. The border of ROI is highlighted with yellow color in Figure 1(a) for better understanding. The border of ROI, as a full circle, produces high undesired coefficients which form a ring shape in the Circlet transform coefficients for all radii and all frequencies. For example, Figure 2(a) shows the absolute Circlet transform coefficients correspond to the radius $r_0 = 32$ and frequency $k = 2$. As it is seen in Figure 2(a), high intensities that are appeared as a full ring are unwanted coefficients generated due to the border of ROI and must be omitted. In order to remove undesired coefficients and tend the searching area to restriction, we have proposed a method as the following. Our proposed method for the modification of the Circlet coefficients is based on the thresholding and morphological operations. For the modification of the Circlet coefficients and limiting searching area, the mask of the ROI is needed. This mask is simply achieved by applying Otsu thresholding algorithm on the L* band follow by the Hole filling operator to correct the missing area within the ROI. Opening morphological operator with a disk shape structure element with radius 50 is applied on the mask in order to smooth the boundary and is named Mask-I. Erosion morphological operator with a disk shape structure element of radius r_i is applied on Mask-I and is named Mask-II. i denotes the i th radius of radius rang $r_0 = \{r_1, r_2, \cdots, r_n\}$ where n is the number of radii considered for Circlet transform. Mask-II is subtracted from Mask-I and the result is named Mask-III. The edge of Mask-III is detected using Sobel method. Dilation morphological operator with a disk shape structure element of radius 10 is applied to the edge and the result is named Mask-IV. Finally the Searching Area (SA) is obtained by equation (5):

$$\text{SA} = \sim\left(\text{Mask-IV} \;+\; \sim\text{Mask-I}\right) \tag{5}$$

where $+$ and $\sim$ denotes OR and NOT logical operator, respectively. The SA corresponds to Figure 2(a) is depicted in Figure 2(b). When the corresponding SAs are applied on the coefficients for all radii and all frequencies, the maximum coefficient within SAs is found which determines the location and radius of the optic disk. Figure 2(c) illustrates the detected OD of Figure 1(a) using Circlet transform.

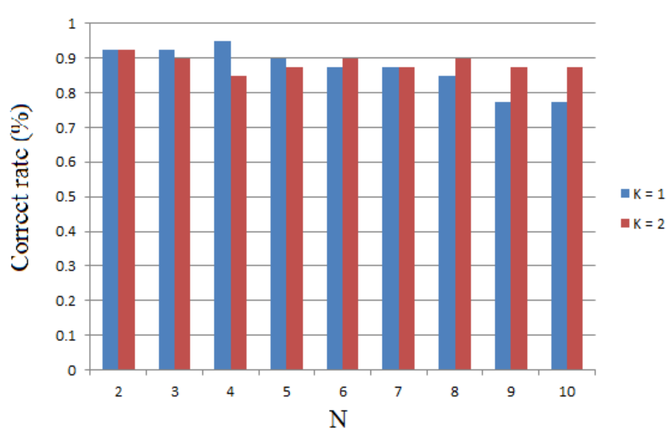

Figure 3. The correct rate (%) for the changes of N between 2 and 10 and for frequencies k=1 and k=2.

4. RESULTS AND DISCUSSION

The proposed algorithm is tested on the DRIVE publicly available dataset [19]. This dataset contains 20 training and 20 test images, in total 40 retinal images. Our method is applied on all 40 images. The performance of the method in localizing OD is evaluated by an expert and the results are reported as correct rate. We've also studied the effect of variations of the number of filters, N, and frequencies, k in the performance. The correct rate (%) for the changes of N between 2 and 10 and for frequencies k=1 and k=2 is shown in Figure 3. It is seen from Figure 4 that the correct rate for different value of N and for k=1 and k=2 is above 77.5% and 85%, respectively. It is also inferred that for k=1, increasing the number of filters, N, decreasing the correct rate while for k=2, correct rate is more robust to changes of N. This is because of the fact that for k=1, by increasing N the bandwidth will quickly decrease leading to more artifacts in Circlet coefficients. In on our experiments, maximum correct rate for k>2 was 10% because in higher frequencies the effect of noise will increase; in addition curved vessels generate high coefficients in higher frequencies lead to missing the OD and decreasing correct rate. As a result, for values N less than 5, k=1 is suitable and for values N higher than 4, k=2 is more appropriate for OD localization using Circlet transform. The maximum correct rate in our experiment is 95% for N=4 and k=1. Our result is compared with previous works on DRIVE dataset in Table I. From Table I, it is seen that our proposed method outperforms previous works that didn't utilize the information of vessels [7, 17, 18]. It must be noted that our proposed method also doesn't exploit the info of vessels' structure for the localization of the OD while the methods proposed by Esmaeili et al [9] and Youssif et al [12] that achieved 100% correct rate, took the advantageous of vessels' shape. The performance of the proposed method could be improved by using vessels' structure's info. Figure 4 shows the result of our method for some samples of the dataset. Top row and four RIs in bottom left of Figure 4 depict the images with the correct localization of OD and two RIs in bottom right of Figure 4 exhibit the images with missing OD's localization. As it is seen in Figure 4, the proposed method produces a well localization of OD and the presented circle could be used as an initial contour for deformable models to segment the OD with high accuracy.

TABLE I. COMPARISON OF RESULTS OF OD LOCALIZATION WITH PREVIOUS WORKS ON DRIVE DATASET.

Method	Correct rate
Youssif et al [12]	100.0 %
Esmaeili et al [9]	100.0 %
Our proposed method	**95.00 %**
Park et al [18]	90.25 %
Sekhar et al [7]	90.00 %
Zhu et al [17]	90.00 %

5. CONCLUSION AND FUTURE WORK

In this paper, a novel method based on Circlet transform was proposed for the detection of OD in the retinal fundus images. The Circlet transform tool is directly applied on a gray-scale image and no further process for binary segmentation is needed. Our algorithm tested on 40 images of DRIVE dataset and a very well localization of OD achieved with 95% of correct rate. Our method doesn't need the information of vessels and actually use the information of circular shape of the OD. Our proposed method outperformed previous works that they also didn't utilize the information of vessels. In the future works, we aim to develop and evaluate our method on more complicated retinal fundus image datasets (such as STARE) and modify the algorithm to detect optic disks which are deformed from a full circle. We will also combine the information of vessels with our method to improve our results. In addition, we will use the circle produced by our method as initial contour for a level set model to exactly segment the OD, as done in [20].

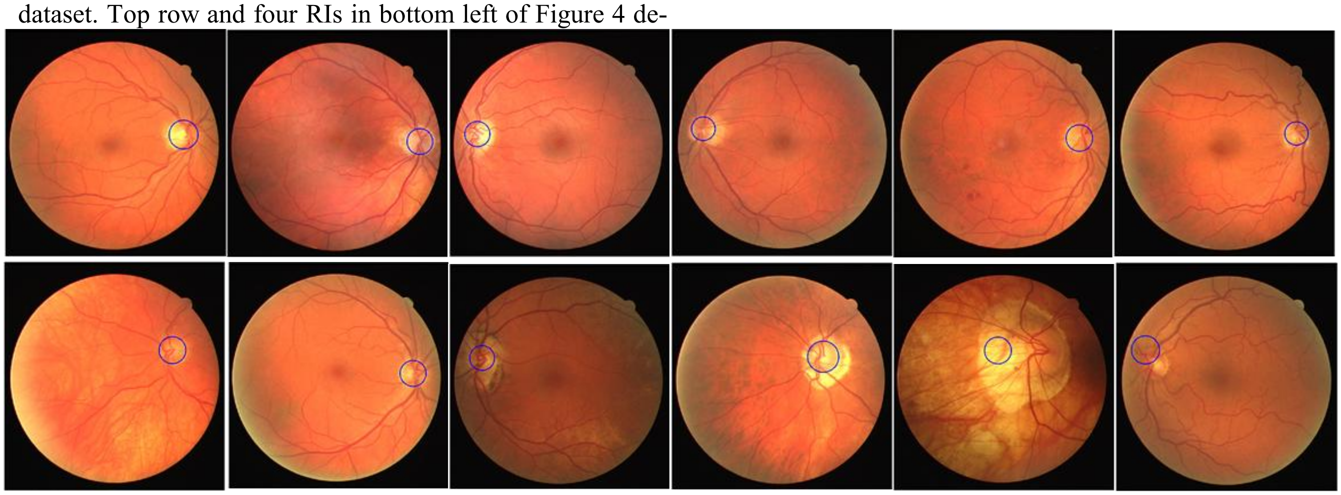

Figure 4. The result of our algorithm for some samples of the dataset. Top row and four RIs in bottom left depict the images with exact location of OD and two RIs in bottom right exhibit the images with close location.

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