DIGITAL IMAGE PROCESSING LABORATORY REPORT

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OPTIC DISK DETECTION IN FUNDUS IMAGES

Abstract

The optic disc (OD) is one of the main features of a retinal fundus image. The OD appears toward the left-hand or right-hand side of a fundus image as an approximately circular area, roughly one-sixth the width of the image in diameter, brighter than the surrounding area, and as the convergent area of the blood vessel network. In this project we use the properties mentioned above - shape, color, size, and convergence to the identify the OD in retinal fundus images using Hough transform.

Introduction

Detection of the OD is a key preprocessing component in algorithms designed for the automatic extraction of the anatomical structures of the retina. As mentioned earlier, the OD appears toward the left-hand or right-hand side of a fundus image as an approximately circular area, roughly one-sixth the width of the image in diameter, brighter than the surroundings, and as the convergent area of the blood vessel network. We use the DRIVE dataset for the entirety of this project.

DRIVE Dataset

The photographs for the DRIVE dataset were obtained from a diabetic retinopathy screening program in The Netherlands. The screening population consisted of 400 diabetic subjects between 25-90 years of age. The dataset comprises forty randomly selected photographs. Each image is JPEG compressed and uses 8 bits per color plane at 768 by 584 pixels. The FOV of each image is circular with a diameter of approximately 540 pixels. For each image, a mask image is provided that delineates the FOV. The set of 40 images are divided into a training and a test set, both containing 20 images.

Described below are the key concepts which have been used in our project:

YUV Color Space

YUV color space encodes a color image taking human perception into account, allowing reduced bandwidth for chrominance components, thereby typically enabling transmission errors or compression artifacts to be more efficiently masked by the human perception than using a 'direct' RGB-representation. The Y component determines the brightness of the color (referred to as luminance or luma), while the U and V components determine the color itself (the chroma). Y ranges from 0 to 1 (or 0 to 255 in digital formats), while U and V range from -0.5 to 0.5 (or -128 to 127 in signed digital form, or 0 to 255 in unsigned form). One aspect of YUV is that we can throw out the U and V components and get a grayscale image. The luminance component Y is computed as Y = 0.299R + 0.587G + 0.114B, where R, G, and B are the red, green, and blue components.

Canny Edge Detection

The process of Canny edge detection algorithm can be broken down to 5 different steps:

1. Apply Gaussian filter to smooth the image in order to remove the noise
2. Find the intensity gradients of the image ($G = \mathrm{sqrt}(G_x^2 + G_y^2)$, $\Theta = \mathrm{atan2}(G_y, G_x)$)
3. Apply non-maximum suppression to get rid of spurious response to edge detection: Non-Maximum suppression is applied to 'thin' the edge. After applying gradient calculation, the edge extracted from the gradient value is still quite blurred. Thus non-maximum suppression used to suppress all the gradient values (by setting them to 0) except the local maxima, which indicate locations with the sharpest change of intensity value.
4. Apply double threshold to determine potential edges: After application of non-maximum suppression, remaining edge pixels provide a more accurate representation of real edges in an image. However, some edge pixels remain that are caused by noise and color variation. In order to account for these spurious responses, it is essential to filter out edge pixels with a weak gradient value and preserve edge pixels with a high gradient value. This is accomplished by selecting high and low threshold values.
5. Track edge by hysteresis: Finalize the detection of edges by suppressing all the other edges that are weak and not connected to strong edges

Erosion

The erosion of a binary image f by a structuring element s (denoted f Θ s) produces a new binary image g = f Θ s with ones in all locations (x, y) of a structuring element's origin at which that structuring elements fits the input image f, i.e. g(x, y) = 1 if s fits f and 0 otherwise, repeating for all pixel coordinates (x, y). Mathematically,

$$A \Theta B = (x \in Z^2 \mid (B)_x \subseteq A)$$

Histogram Equalization

This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values.

Hough Circles

The circle Hough Transform (CHT) is a basic technique used in Digital Image Processing, for detecting circular objects in a digital image. It is a specialization of Hough Transform. The purpose of the technique is to find circles in imperfect image inputs. The circle candidates are produced by 'voting' in the Hough parameter space and then selecting the local maxima in a so-called accumulator matrix.

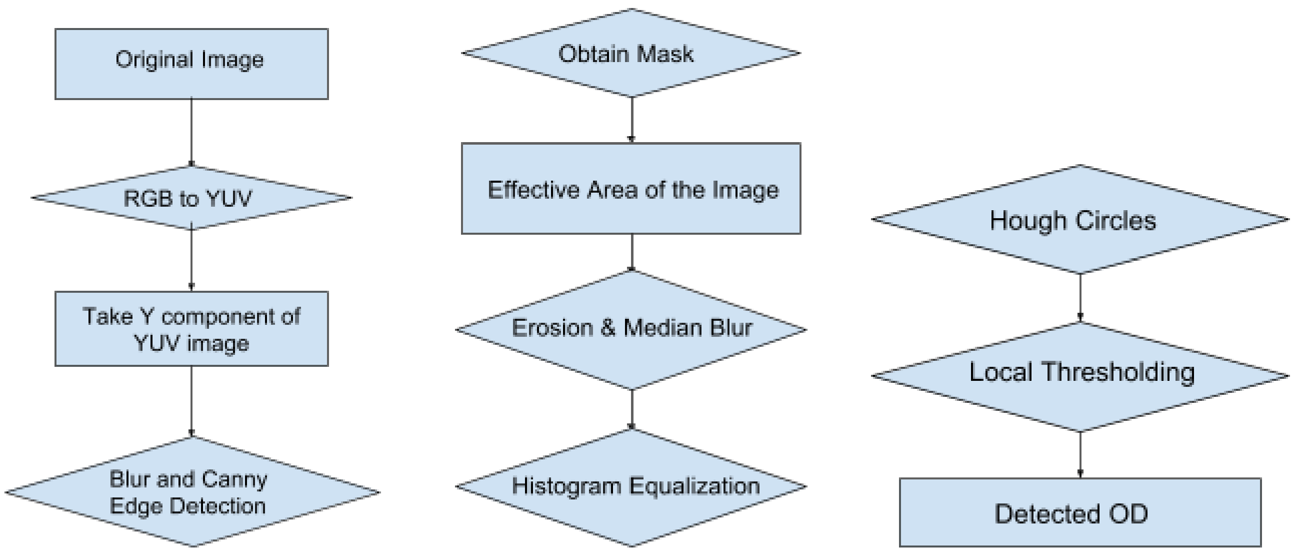
In a two-dimensional space, a circle can be described by:

$$(x-a)^2 + (y-b)^2 = r^2$$

where (a,b) is the center of the circle, and r is the radius. If a 2D point (x,y) is fixed, then the parameters can be found according to the above equation. The parameter space would be three dimensional - (a, b, r) and all the parameters that satisfy (x, y) would lie on the surface of an inverted right-angled cone whose apex is at (x, y, 0). In the 3D space, the circle parameters can be identified by the intersection of many conic surfaces that are defined by points on the 2D circle. This process can be divided into two stages. The first stage is fixing radius then find the optimal center of circles in a 2D parameter space. The second stage is to find the optimal radius in a one dimensional parameter space.

An accumulator matrix is introduced to find the intersection point in the parameter space. First, the parameter space is divided into 'buckets' using a grid and an accumulator matrix is initialized according to the grid. The element in the accumulator matrix denotes the number of 'circles' in the parameter space that pass through the corresponding grid cell in the parameter space. The number is also called 'voting number'. Initially, every element in the matrix is zeros. Then for each 'edge' point in the original space, we can formulate a circle in the parameter space and increase the voting number of the grid cell which the circle passing through. This process is called 'voting'. After voting, we can find local maxima in the accumulator matrix. The positions of the local maxima are corresponding to the circle centers in the original space.

Algorithm



Step 1 **Step 2** **Step 3**

1. The image is initially converted from RGB space to YUV space.
2. Only the Y component is used for further processing.
3. Blurring and Canny Edge Detection is performed on the Y component using the process mentioned in the Introduction.
4. Mask is obtained using the same by which we get the effective area of the image.
5. Erosion and Median Blurring is performed.
6. Histogram Equalisation is performed.

7. Hough Circles are found using Hough Transform on which Local Thresholding is performed to get the Optic Disk.

Results

The proposed method was tested with the 40 images form the DRIVE database. Figure 1 - Figure 6 show outputs at various stages of the algorithm. (a) part corresponds to rightly detected OD while (b) part corresponds to undetected OD. Figure 7 contains images where multiple disks get detected. Using the Canny edge detector, the success rate, including both good and acceptable detections, is 33 out of 40 images, or 82.5 %. (17 out of 20 from training dataset and 16 out of 20 from test dataset).

Conclusions

We tested a method for automatic detection of the OD in fundus images of the retina. A comparison of two methods of edge detection, the Sobel operators and the Canny method, was performed. It was found that Canny operator leads to better detection of the OD using the Hough Transform. Among the 40 images in the DRIVE database, the proposed method correctly detected in 82.50% of the cases. The proposed method did not work well in cases where the OD is not circular and/or where bright exudates are present.

References

1. Xiaolu Zhu and Rangaraj M. Rangayyan, “Detection of the Optic Disc in Images of the Retina Using the Hough Transform,” In *Proceedings of the 30th Annual International IEEE EMBS Conference*, pp.3546-3549, Vancouver, Canada, August 20-24, 2008
2. DRIVE: Digital Retinal Images for Vessel Extraction, http://www.isi.uu.nl/Research/Databases/DRIVE/, accessed on February 15, 2018

Step - by - step display of the obtained results

1. Original Images

Figure 1(a)

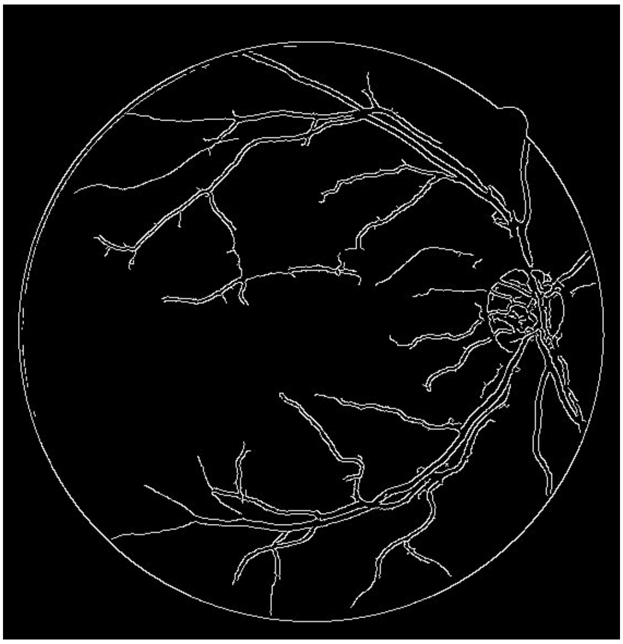
Figure 1(b)

2. Y Component of converted image

Figure 2(a)

Figure 2(b)

3. **Canny Edge Detection output**



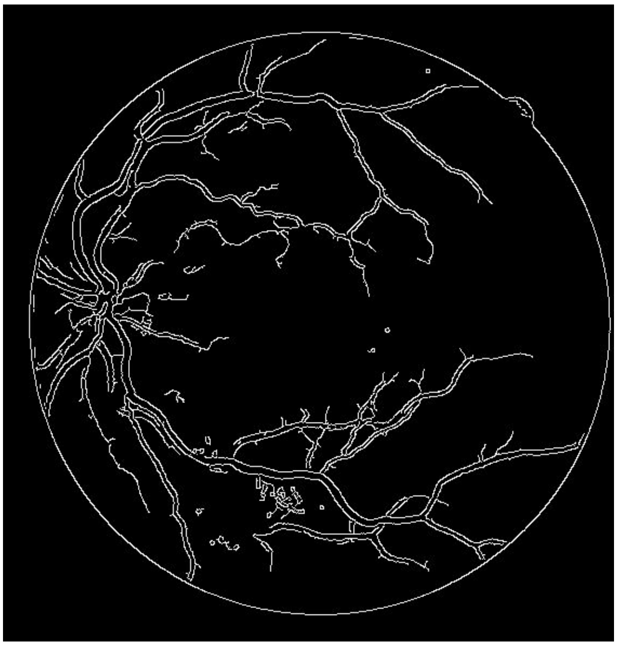


Figure 3(a)

Figure 3(b)

4. **Image after masking**

Figure 4(a)

Figure 4(b)

5. **Image after performing erosion**

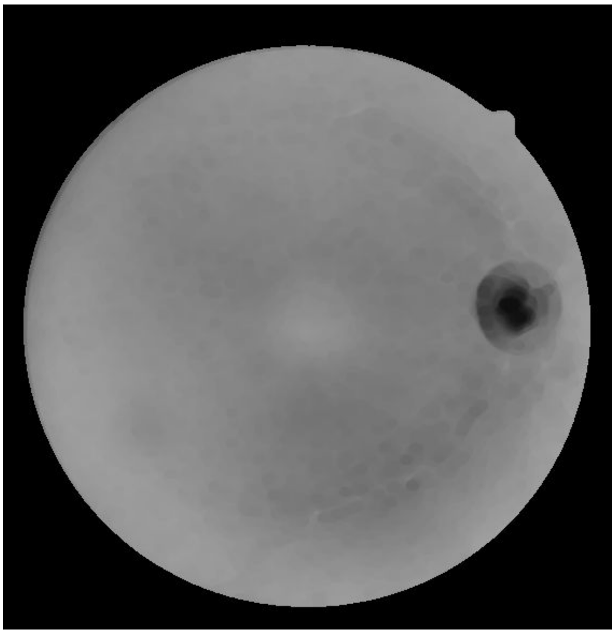


Figure 5(a)

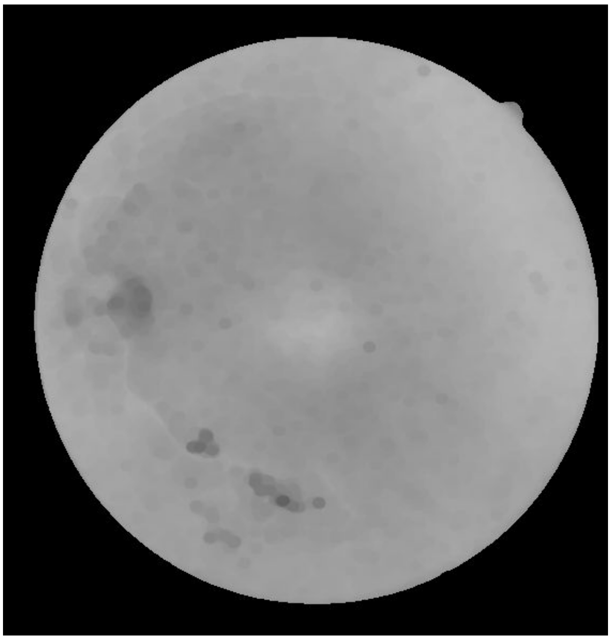


Figure 5(b)

6. **Optic disk detection**

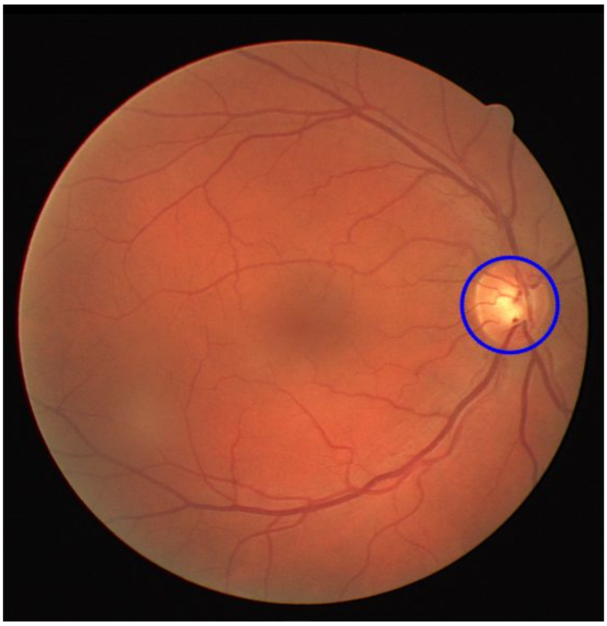


Figure 6(a)

Figure 6(b)

7. False Positives

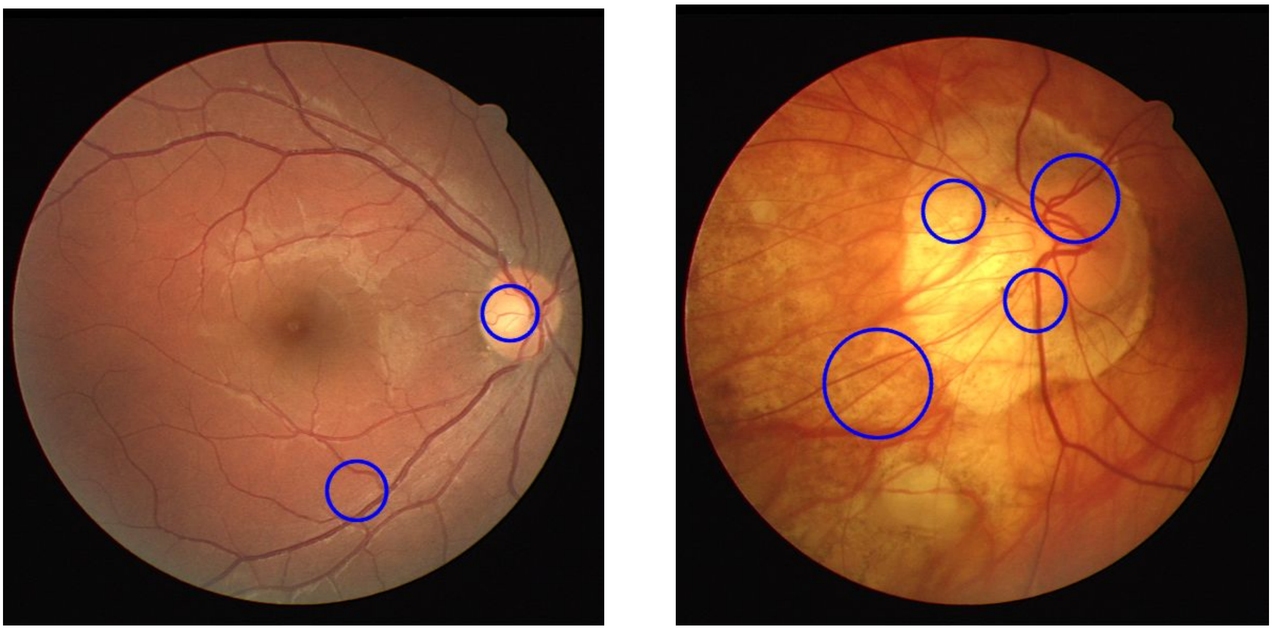


Figure 7