Optic Disc Localization from Retinal Fundus Image using Discrete Cosine and Hough Transforms

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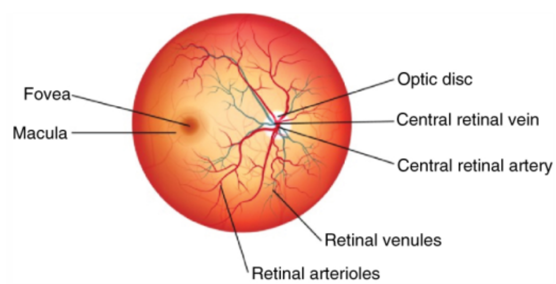
***Abstract*—Diabetic retinopathy, resulting from diabetes mellitus, is one of the main causes of global blindness and visual impairment. The integration of artificial intelligence in the analysis of retinal images helps healthcare professionals, with the precise location of the optic disc being essential for detecting vital components of the retina. In this paper, we present a method that uses the cosine transform in conjunction with the circular Hough function. This method also involves converting retinal images from the RGB color space to adapted grayscale, focusing only on the Red and Green channels. The dataset used for the experiment was RIGA, consisting of the subsets Messidor, Magrabia and BinRushed. The results showed 100% accuracy for Messidor, 97.87% for Magrabia, and 98.46% for BinRushed, achieving an overall accuracy of 99.33%.**

***Index Terms*—optic disc localization, cosine transform, hough transform, eye disease.**

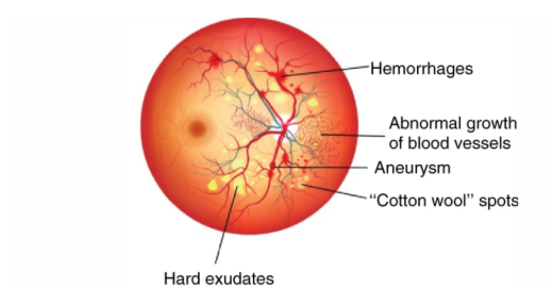
I. Introduction

Diabetic Retinopathy (DR) is an eye disease caused by diabetes mellitus (DM) and is considered one of the main causes of blindness and visual impairment, having a significant impact on global health [1]. It affects approximately 30% to 40% of diabetic patients worldwide, affecting more than 100 million individuals living with the condition [2]. Diabetes affected approximately 537 million people (aged between 20 and 79) in 2021 and this figure is expected to rise to 643 million in 2030 and 784 million by 2045 [3]. Early detection and appropriate follow-up in many cases are fundamental to preventing vision loss and improving the patient's quality of life. Normally, images from ophthalmological examinations showing the presence of ocular pathologies, when analysed using Computer Aided Diagnostic Systems (CADs), can help to make early predictions more effective and efficient [4], [5].

Fig. 1 depicts two examples of human retinal fundus image. Fig 1a shows the anatomy of a normal human retina. A normal retina has some visible features such as fovea, macula, central retinal vein, central retinal artery, retinal venules, retinal arteriolis and optic disc. Fig 1b shows a diseased retina in which ocular lesions, abnormal blood vessels, microaneurysms (MA), cottony spots, exudates and haemorrhages are visible. Pathological features (Fig. 1.b) stand out visually, allowing identification changes occurring in affected retina by clinical condition [6].



(a) Normal retinal anatomy



(b) Abnormal retinal anatomy

Fig. 1: Two illustrations of a human retina image. Adapted from [7].

Optic disc (OD) is an anatomical structure in the retinal image that is characterised by its greater light intensity compared to others parts (Fig 1a) [8]. OD Localization is essential for diagnosing eye diseases and for effectively distinguishing between large exudates or other lesions, since it can be confused with these structures [5], [7].

Many approaches, in recent years, have been presented by researchers for OD localization using using classic digital image processing techniques. For instance, in [6] a three-stage workflow was presented to OD localization: (i) Obtaining bright regions in retinal image; (ii) Obtaining keypoints with SURF algorithm and, afterwards, applying invert process to the regions corresponding to these keypoints; (iii) Deciding which one of these regions is OD by performing texture analysis.

In [17], an algorithm for optic disk (OD) detection is proposed which relies on structured learning. Initially, a classifier model is trained using structured learning. A classifier model is trained and employed to generate an edge map. This map is then thresholded to yield a binary image. Finally, to approximate the boundary of the OD, the circle Hough transform is utilized.

[18] a hierarchical technique for the efficient and accurate localization and segmentation of the Optic Disc in retinal images. The approach starts with the delineation and removal of retinal vasculature and pathologies using morphological operations. Following this, the Circular Hough Transform is applied for Optic Disc localization. The exact boundary of the Optic Disk is then discerned by defining the region of interest and utilizing a unique polar transform-based adaptive thresholding.

In [11], the method is based on morphological operations, the circular Hough transform, and the grow-cut algorithm. Morphological operators are used to emphasize the optic disc and eliminate retinal vasculature and other pathologies. The circular Hough transform estimates the center of the optic disc, while the grow-cut algorithm ensures accurate segmentation of the optic disc boundary. In [16], introduced an automatic algorithm for localizing and segmenting the optic disc (OD). The methodology uses morphological filtering to remove blood vessels and bright regions, leaving only the (OD).

In [8] a method was proposed in which fundus images are converted from the RGB color space to a new color space using an artificial bee colony algorithm. Next, a feature matrix is created to obtain regions that have optic disc. This matrix is obtained from the color pixel values of the image patches that contain optical disc or do not contai optical disc. Then, a conversion matrix is created with random initial values. These two matrices are processed in artificial bee colony algorithm. Finally, an optimized conversion matrix is applied to the original fundus image moving to a new color space and applied a threshold to obtain OD localization. On the other hand, in [8] was reported challenges associated with the variety of tones and color intensities in their experiments, specifically in Messidor. They noted that some images in this set have almost non-existent OD regions, which compromises the effectiveness of their methodology.

This article presents an approach to optical disc localization using classic digital image processing techniques. An optimized conversion method to move from the RGB color space to an adaptive grayscale color was presented to overcome brightness variance in retinal fundus images. A discrete cosine transform, median filtering, contrast adjustment and the circular Hough transform to identify circular shapes were also used to localization of optical disc.

II. Materials and methods

A. Dataset

A public de-identified dataset of retinal fundus images for glaucoma analysis (RIGA[1]) [9] was used. Six experienced ophthalmologists individually marked the optic disc and optic cup of these images. Annotations of the six ophthalmologists were analysed to detect any outliers between them for subsequent elimination from dataset, i.e. filtering out most reliable annotations.

RIGA dataset was derived from 3 different sources: 1) Messidor dataset, which contains 460 retinal images and 460 markings from each specialist, generating a total of 3.220 images; 2) Bin Rushed dataset, which contains 195 retinal images and 195 markings from each specialist, generating a total of 1.395 images; 3) Magrabi Eye dataset, which contains 94 retinal images and 94 markings from each specialist, generating a total of 658 images [10]. Fig. 2 shows three examples of original retinal fundus image from RIGA dataset, an image for each RIGA data source .

A total of 749 retinal images are available, along with 4.494 manual annotations. Image format is JPG or TIFF with 3 colour channels (Red, Green, Blue). Table I shows the data from RIGA dataset, including images resolutions.

TABLE I: Dataset RIGA

Datasets	Images	Masks	Resolutions
Messidor	460	2760	2.240 x 1.488
Magrabia	94	564	2.746 x 1.936
Bin-Rushed	195	1.170	2.376 x 1.584
Total	749	4.494	-

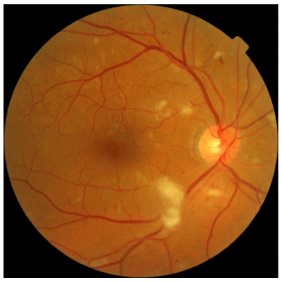
An image from Magrabia has been removed because it has no original retina fundus image, only its manual annotations.

B. Proposed approach

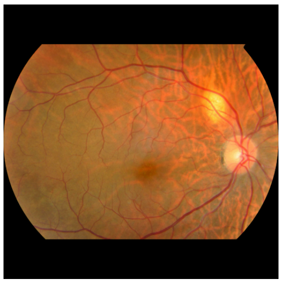
The approach developed is divided into three main stages: grey-scale image adaptation, noise reduction and circular object detection, as shown in flow diagram in Fig. 3.

a) Adaptive Grayscale: The contrast variation in different colour channels of RGB images makes it difficult to locate Optic disc in both diseased and healthy retinas [11]. This occurs in RIGA dataset, as shown in Figure 4, which shows two retinal images where this contrast variation occurs in R and G channels.

[1]https://deepblue.lib.umich.edu/data/concern/data_sets/3b591905z



(a) Messidor dataset image.

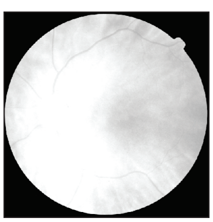


(b) Magrabia dataset image.

(c) Bin-Rushed dataset image.

Fig. 2: Three examples of retinal fundus images from RIGA dataset.

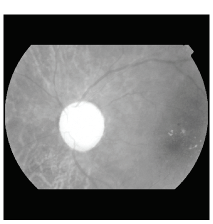
(a)



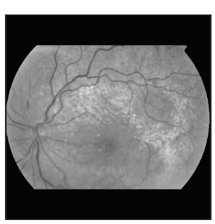
(b)

(c)

(d)



(e)



(f)

Fig. 4: Retinal fundus images with variations in brightness in the Red and Green channels. (a and d) Examples of retinal image (RGB). (b and e) Red channel. (c and f) Green channel.

Therefore, images were then converted from RGB to greyscale. In [12] was proposed a method for converting RGB space color to greyscale, which aligns with human perception and does not suffer significant loss of image characteristics. The proposed method is defined in (1).

$$G_{\text{Luminance}}(R, G, B) = 0.3 \times R + 0.59 \times G + 0.11 \times B \quad (1)$$

This method assigns a weighting coefficient to each colour channel (RGB). However, according to [13], only Red and Green channels are relevant for locating optical disc. Therefore, an adaptation was made to convert images from RGB standard to greyscale, which only considers Red and Green colour channels.

To calculate a new channel weighting coefficients for each image, the average luminosity of R and G channels is calculated plus the coefficients 0.3 and 0.59, respectively, according to (2) and (3).

$$\overline{R} = \frac{1}{n} \sum_{i,j} R(i, j) + 0.3 \quad (2)$$

$$\overline{G} = \frac{1}{n} \sum_{i,j} G(i, j) + 0.59 \quad (3)$$

Then, coefficients are normalised in the interval $(0, 1)$ by softmax function σ, defined in (4).

$$\sigma(x_i) = \frac{\exp(x_i)}{\sum_j \exp(x_j)} \quad (4)$$

Where, x_i is given by input vector $[\overline{R}, \overline{G}]$ and denominator is a sum of exponentials of all elements in the vector. With this, the adapted greyscale image is defined in (5).

$$AG_{\text{Luminance}} = \sigma(x_1) \times R + \sigma(x_2) \times G \quad (5)$$

Fig. 5 shows the difference between classic method for converting RGB colour space to greyscale proposed in [12] and proposed adaptive grayscale method. Fig. 5a is a retinal fundus image. In Red channel has significant characteristics for optical disc localization, but irrelevant information in Green channel. Fig. 5b shows the result of classic method for converting RGB colour space to greyscale presented in [12]. Fig. 5c shows proposed adaptive grayscale method. When retinal fundus image has significant OD information in Red channel, the proposed method will assign a higher weighting coefficient to this channel. On the other hand, when retinal fundus image has no relevant OD information in Red channel, the proposed conversion method will assign a weighting coefficient lower than weighting coefficient for Green channel. Thus, information relevant to OD localization is preserved.

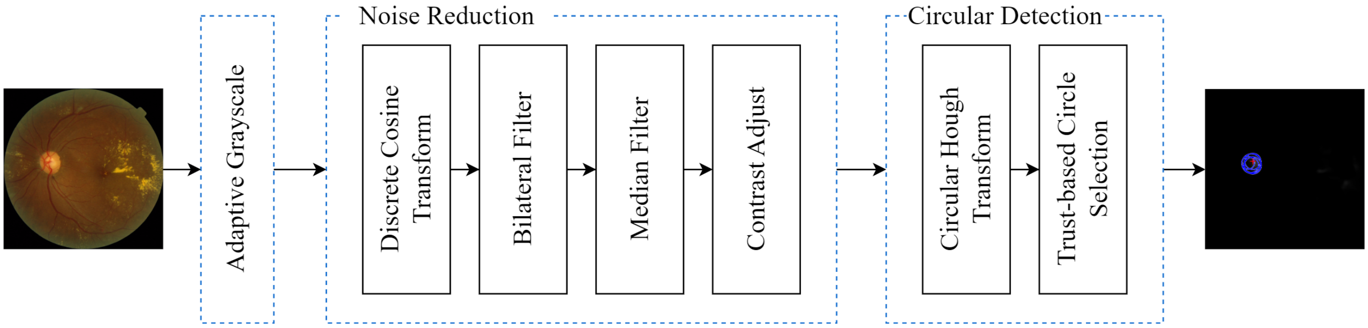


Fig. 3: Flow chart of the proposed approach.

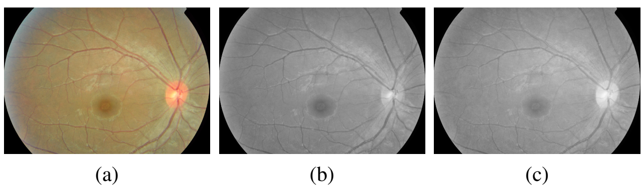


Fig. 5: Conversion RGB colour space to greyscale methods for retinal fundus image. (a) Example of retinal image (RGB). (b) Image generated using classic method proposed in [12]. (c) Image generated using proposed adaptive grayscale method.

b) Noise Reduction: To reduce image noise, a method based on discrete cosine transform (DCT) was implemented. This method converts from spatial domain to frequency domain, facilitating the selective removal of noise [14], [15].

DCT is applied to adapted grayscale images, generating a frequency spectrum for each image, where relevant information and noise are represented as frequency components. Next, an ideal low-pass filter was applied to capture relevant characteristics of image in the frequency domain and suppress unwanted frequency components. This filter was modelled according to a sinusoid function (sinusoid is defined in (6)), preserving lower frequency region and excluding most of high frequencies, which are generally associated with noise in the image. Then, inverse discrete cosine transform (IDCT) was applied to filtered frequency spectrum, returning the image to spatial domain. On resulting image, now with significantly reduced noise, Bilateral Filtering, Median Filter and Contrast Adjustment techniques were applied. In this way, the combination of DCT, filtering and adjustments produces final images highlighting optic disc and with minimal interference from noise.

$$y(x) = r(1 - \cos(x)) \tag{6}$$

Where, r is a constant representing the curvature, x is a set of linearly spaced values in the interval $(-\pi, 0)$. $y(x)$ is limited to a length equal to one fifth of image width.

Ideal low-pass filter $H(u, v)$ is defined in (7).

$$H(u, v) = \begin{cases} 1 & \text{se } u \leq y(x_v)) \\ 0 & \text{se } u > y(x_v)) \end{cases} \tag{7}$$

Thus, filter mask is modelled to cover an area of image that includes lower frequencies. This approach allows frequencies that represent relevant features of image to be preserved, while higher frequencies, which generally correspond to noise, are removed.

c) Circular Object Detection: Circular Hough Transform (CHT) [11], an extension of Hough Transform (HT), is generally used to identify lines or circles in images. CHT is defined in (8).

$$(x_i - a)^2 + (y_i - b)^2 = r^2 \tag{8}$$

Where, a and b refer to coordinates that determine circle's center, while r represents the radius.

In order to minimise detection errors by Circular Hough Transform (CHT) function and optimise performance in identifying circles, different tests were carried out for degrees of sensitivity, with an experimentally selected radius range being established between 50 and 120 pixels. Higher confidence circle is detected ideal candidate for OD. Finally, center coordinates of the OD candidate circle that are within the mask provided by experts is successful detection; otherwise, it is considered a failure.

III. Results and Discussions

The proposed approach was evaluated using RIGA dataset with 749 human retinal images, which resulted in OD localization. In addition, a method of converting retinal images from RGB to grayscale was proposed. The advantage of this conversion is that it is easier to locate OD using classic digital image processing methods.

Fig. 6 shows the proposed approach applied to three retinal fundus images with different characteristics, healthy, diseased and with high luminance variation retinas. First row shows steps applied to a healthy retina. Second row shows steps applied to a diseased retina. Third row shows steps applied to a retina with high luminance variation. On the other hand, first column shows original fundus images. Second column shows

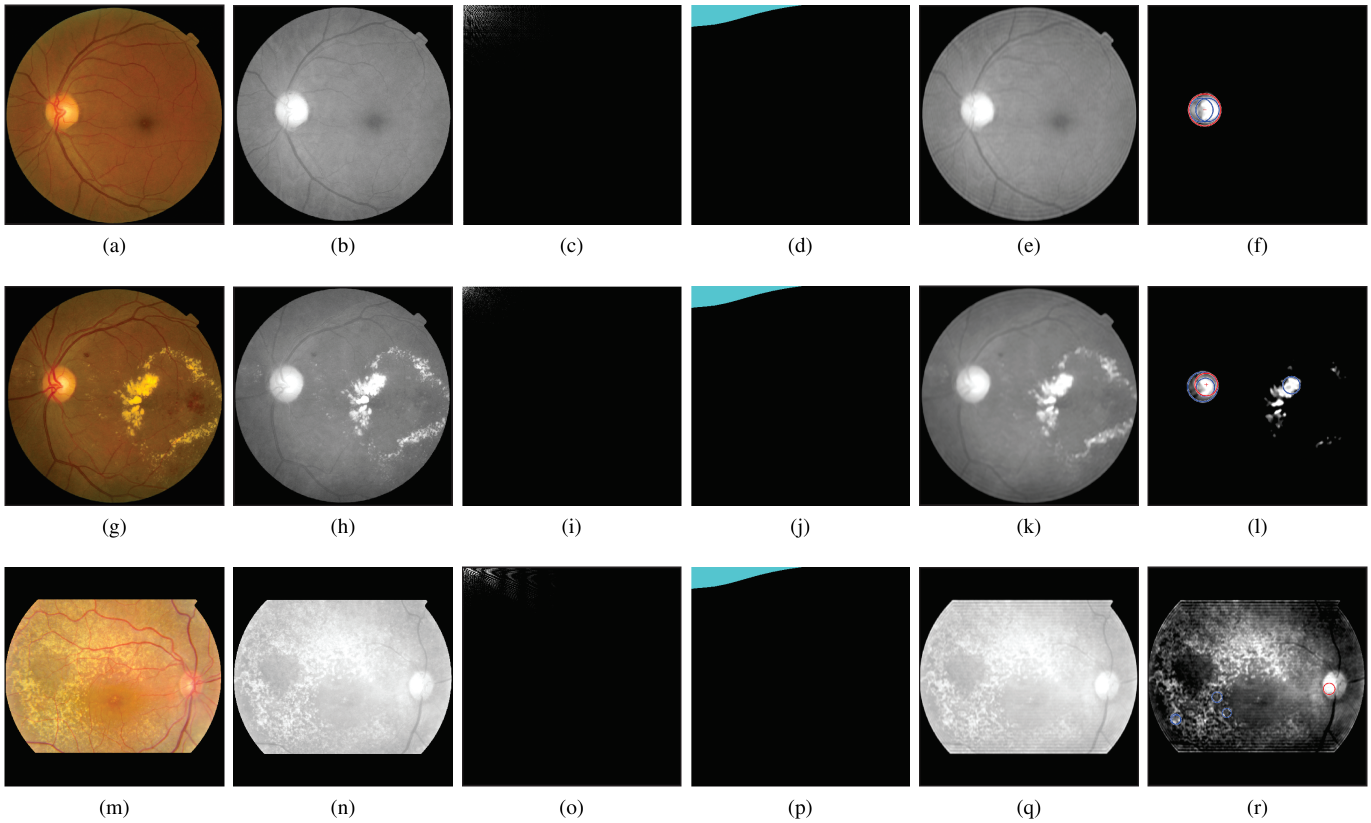


Fig. 6: Results of the steps in the proposed approach. (a, g and m) Input images with varying clinical conditions; (b, h and n) Adapted grayscale image; (c, i and o) Application of the discrete cosine transform; (d, j and p) Ideal low-pass filter; (e, k and q) Application of the inverse discrete cosine transform and (f, l and r) Localization of the optic disc.

a new adaptive greyscale images. Third column shows images after discrete cosine transformation. Fourth column shows ideal low-pass filter mask. Fifth column shows reconstructed images using inverse cosine transform. The OD localization using Hough transform is showned in the sixth column.

Table II shows a comparison of the proposed approach for OD localization with other state-of-the-art methods found to validate accuracy and robustness of this approach. In this Table, only OD localization is emphasized. The method's hit rate is measure for performance evaluation of the proposed approach.

Success rate obtained with the proposed approach for determining OD localization is 100% for Messidor, 97.87% for Magrabia and 98.46% for Bin-Rushed. There was no error in OD localization for Messidor. In Magrabia, for 94 retinal fundus images, OD was not localizated in two images. In Bin-Rushed, out of 195 retinal fundus images, OD was not localizated in only three retinal fundus images. In total, there were 5 images in which OD was not correctly localized, so the hit rate in RIGA dataset was 99.33% on average.

These results shows that the proposed approach works with variations in luminosity presented in RIGA dataset using a new adaptive grayscale. Therefore, unlike more advanced methods, retinal fundus images have been moved from RGB color space to facilitate OD localization. New adaptive grayscale can capture more relevant information between channels to make it easier to identify OD even if luminances varies from channel to channel and image to image. Overcoming not only the particularities in Messidor, but also a wide diversity and complexity present in RIGA dataset, which also incorporates Magrabia and BinRushed collections.

TABLE II: Comparison of performance.

Method	Dataset	Accuracy
Abdullah, M. et al. [11]	MESSIDOR	99.25
Almazroa, Ahmed et al. [9]	RIGA	96.40
Arunkumar, G. et al. [16]	MESSIDOR	78.00
Fan, Zhun et al. [17]	MESSIDOR	97.70
Guo, Fan et al. [5]	MESSIDOR	89.87
	ORIGA	91.31
Toman, H. et al. [19]	MESSIDOR	98.00
Toptas, B. et al. [8]	MESSIDOR	94.42
Zahoor, M. N. et al. [18]	MESSIDOR	99.18
Proposed method	MESSIDOR	**100.0**
	MAGRABIA	97.87
	BIN-RUSHED	98.46

IV. Conclusion

An approach for Optic Disc (OD) localization in retinal images has been proposed using RIGA dataset. This methodology was validated through manual markings by six different experts. Compared to other methods available in the literature, the approach stands out for being applicable to different types of retinal images, as well as healthy, diseased and luminance-variant images and retinas. The approach involves converting retinal images from RGB color to grayscale, in combination with discrete cosine and Hough transform. This combination proved to be robust, especially when handling variations in brightness and clinical conditions.

The evaluation process considers a successful OD localization case when OD candidate center is inside of the annotated area by experts. Experimental results showed that the proposed approach achieved a hit rate of 100% for Messidor, 97.87% for Magrabia and 98.46% for Bin-Rushed. Obtaining an average accuracy of 99.33% for OD localization in retinal fundus images for RIGA dataset. Results were achieved specifically using RIGA dataset, due to its availability.

When compared with results found in the literature that implement other methods, the proposed approach showed excellent results for Messidor, and for Magrabia and Bin-Rushed it achieves expressive results, but for latter two no studies were found in the literature for comparison.

For future work, techniques that implement deep learning for optic disc segmentation in retinal fundus images will be included.

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