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Optic Disc Localization Methodologies in Retinal Images: A Review

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Abstract: Diabetic retinopathy is an eye-disease that is very common among people who are suffering from diabetes. Glaucoma is also an eye disease that damages the optic nerve head and leads to vision loss. Optic disc localization is important for the early detection of Glaucoma and clinical features of diabetic retinopathy such as microaneurysms, hard exudates, soft exudates, hemorrhages, neovascularization and macular edema. This study examines the optic disc localization methodologies in two dimensional retinal images acquired from a fundus camera. The aim of this study is to review and categorize the optic disc localization techniques and methodologies. Researchers intend to give the reader a frame work for the existing research and discuss the current trends and future direction. The performance of various methods is compared and analyzed on publicly available DIARETDB0, DIARETDB1, DRIVE, STARE and MESSIDOR databases.

Key words: Retinal image analysis, diabetic retinopathy, optic disc localization, glaucoma detection, soft exudates

INTRODUCTION

Diabetes mellitus is a life-threatening disease that occurs when the pancreas does not secrete enough insulin or the body is unable to process the insulin properly. This condition results in an abnormal increase in blood glucose levels. Over time this high level of glucose causes damage to blood vessels. This damage affects the eyes and the nervous system as well as heart, kidneys and other organs (Alberti and Zimmet, 1998). The World Health Organization expects that the number of people with diabetes will increase from 130-350 million over the next 25 years (WHO, 1998). Diabetic Retinopathy (DR) is a common complication of diabetes and occurs when the increased blood glucose levels damages the capillaries which nourish the retina. As a result of this damage, the capillaries leak blood and fluid on the retina (Frank, 1995). The stage of DR is typically judged by ophthalmologists based on features such as blood vessel area, exudates, hemorrhages, microaneurysms and texture (Faust *et al.*, 2012). Optic Disc (OD) localization is the prerequisite for segmenting all of these features.

In normal retinal images, the OD generally appears bright, yellowish, circular/slightly oval in shape and roughly one-sixth the width of the image diameter (Hoover and Goldbaum, 2003) (Fig. 1). It is located

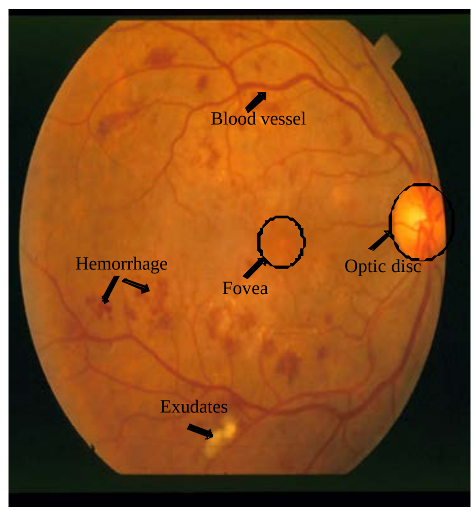

Fig. 1: Retinal image with anatomical structures

roughly 2.5 times of the OD diameters from the temporal edge of the OD (Sinthanayothin *et al.*, 1999). Any change in the structure of the OD is a sign of various retinopathies especially glaucoma (Li and Chutatape, 2004). OD localization is important for detecting clinical features of DR such as microaneurysms, hard exudates, soft exudates or cotton wool spots, hemorrhages, neovascularization and macular edema. The detection of

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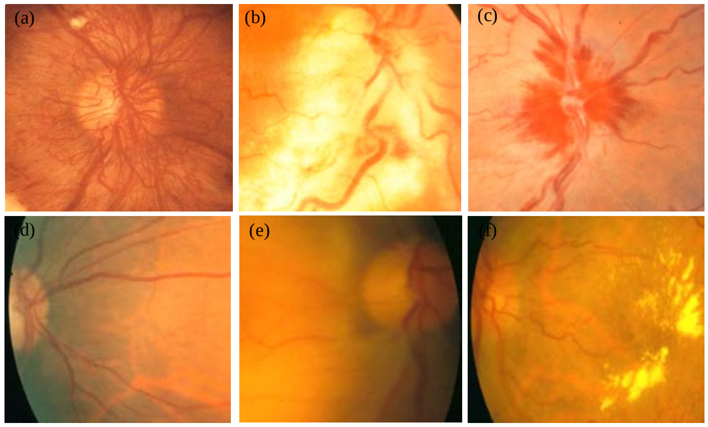

Fig. 2: Abnormal OD; a) vessel occlusions; b) imprecise OD boundary; c) affected OD; d) blurring; e) uneven illumination and f) abnormal lesions

central macula (fovea) is used for grading the severity of lesions such us diabetic macula edema (Sinthanayothin *et al*., 1999) which can be approximately located based on the geometric relationship between the OD location and the vascular structure. The accurate identification of OD refines the segmentation of the exudates regions (Osareh *et al*., 2003) and is used for diagnosing hypertension retinopathies (Qureshi *et al*., 2012) and diabetes (Abdel-Ghafar and Morris, 2007). The detection of OD is occasionally used to segment the blood vessel of retinal images and compute the central retinal artery and vein equivalent (Lowell *et al*., 2004). The segmented OD also acts as a control point for retinal image registration.

Manual OD detection can be time consuming and tedious when the image quality is poor. Therefore, extensive research efforts have been devoted to automating this process. Computer-aided OD detection is also a difficult or time consuming task for several reasons: the presence of strong distracters such as vessel occlusions, imprecise boundaries, affected OD, blurring effect, uneven illumination and abnormal lesions such as exudates and peripapillary atrophy (Lowell *et al*., 2004; Goldbaum *et al*., 1996) (Fig. 2).

Faust *et al*. (2012), Haleem *et al*. (2013) and Mendonca *et al*. (2013) review the OD localization methods in different directions. This study conducts a comprehensive review of the existing methods for the automatic detection of OD from retinal fundus image. This review categorizes and discusses the existing methods in detail and provides insights for future directions related to the automatic detection of ODs.

MATERIALS AND METHODS

Usually the publicly available ImageRet (Kauppi *et al*., 2007), DRIVE (), STARE (Hoover and Goldbaum, 2003) and MESSIDOR (Messidor, 2004) databases are used for evaluating the performance of OD localization. Occasionally the researchers use local databases for evaluating their methods that are labeled as ‘other’ in this research. Table 1 presents the details of publicly available retinal image databases.

Table 1: Publicly available retinal image databases

Database	Total images	Normal images	Resolution	FOV
DIARETDB0	130	20	1500×1152	50°
DIARETDB1	89	5	1500×1152	50°
DRIVE	40	33	565×584	45°
STARE	81	31	605×700	35°
MESSIDOR	1200	546	1440×960 (or) 2240×1488 (or) 2304×1536	45°

The ImageRet database was made publicly available in 2008 and is subdivided into two sub-databases, DIARETDB0 (Standard Diabetic Retinopathy Database-Calibration Level 0) and DIARETDB1(Standard Diabetic Retinopathy Database-Calibration Level 1). The images are marked by four experts for the presence of microaneurysms, hemorrhages and hard and soft exudates.

The DRIVE (Digital Retinal Images for Vessel Extraction) database photographs were obtained from a diabetic retinopathy screening program in Netherlands. The screening population consisted of 453 subjects between 31 and 86 years of age. Each image has been JPEG compressed. The 7 pathological images contain pathology, namely exudates, hemorrhages and pigment epithelium changes. The images were acquired using a Canon CR5 non-mydriatic camera.

The STARE (Structural Analysis of Retina) database was composed with the intention to create a difficult database. Only 31 images of healthy retinas are contained in this database. The other fifty retinal images exhibit a

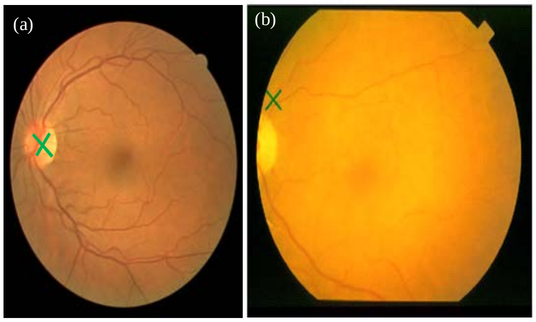

Fig. 3: Successful and unsuccessful OD localization; a) successful and b) unsuccessful

wide variety of lesions and other symptoms of diseases. The images were acquired using a TopCon TRV-50 fundus camera.

The MESSIDOR (Methodes Evaluation Systemes Segmentation Indexation Dediees Ophtalmologie Retinienne) database is the largest database of 1200 retinal images currently available on the internet and is provided courtesy of the Messidor program partners. The 800 of these images were captured with pupil dilation and 400 without dilation using a Topcon TRC NW6 non-mydriatic retinograph. The images were acquired at three different ophthalmology departments with different resolution and are stored in TIFF format.

Measures: Success rate (accuracy) and computation time are the most commonly used measures for evaluating OD localization methods. Once the detected OD center is within the circumference of the OD in the reference standard, it is then considered to be a successful detection. Figure 3 shows the successful and unsuccessful detection of OD.

RESULTS

Classification of optic disc localization approaches: OD localization methods are broadly categorized into four groups: brightness-based, template matching, based on Hough transform and binary vasculature.

Method based on brightness: In normal retinal images, the OD generally appears as a large bright object. Brightness-based algorithms are designed according to this assumption. To localize the OD from the intensity image, a certain threshold must be set. The selected threshold is used to create the binary image (Fig. 4). The results obtained by brightness-based methods are shown in Table 2.

Sinthanayothin *et al.* (1999) assumed 80×80 pixels as the size of the OD and intensity variations of the

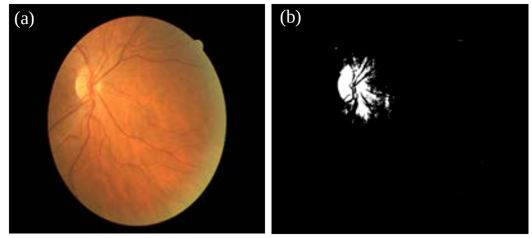

Fig. 4: Thresholding of largest connected object; a) original and b) binary image with highest 2% intensity

Table 2: Obtained results by brightness based methods

Methods	Database	Accuracy (%)
Sinthanayothin *et al.* (1999)	DRIVE	60.00
	STARE	50.00
	Other	99.10
Walter and Klein (2001)	DIARETDB1	92.13
	DRIVE	77.50
	STARE	58.00
	Other	100.0
Hsiao *et al.* (2012)	DRIVE	93.00
	STARE	89.00
Godse and Bormane (2013)	DIARETDB0	96.92
	DIARETDB1	96.62
	DRIVE	100.0
	Other	100.0
Haar (2005)	STARE	58.00

neighboring pixels were used to localize the OD. The point with the highest pixel variance was treated as the OD center.

Walter and Klein (2001) developed an algorithm to identify the OD using pixel brightness, discrete distance function and watershed transform in Hue Saturation Luminance (HSL) color space.

Hsiao *et al.* (2012) corrected the uneven illumination of the fundus image using an illumination correction operator. Then, the OD was localized as the brightest large area in the fundus image.

Godse and Bormane (2013) identified OD candidate regions using a threshold value. The threshold value was obtained using a histogram. Then, the ratio of number of pixels occupied by the clusters (candidate region) to the number of pixels occupied by a rectangle surrounding the cluster <40% was discarded. Finally, the centroid of the cluster was determined using calculus. Haar (2005) searched for a large connected group of bright pixels with a pixel value above a certain threshold.

Brightness-based algorithms are fast, simple and reasonably robust for normal images. But these algorithms may fail when the OD is obscured by blood vessels (Fig. 2a) and distracters such as exudates (Fig. 2f), soft exudates and bright artifacts (Haleem *et al.*, 2013).

Method based on template matching: The template matching method assumes the optic disc to be

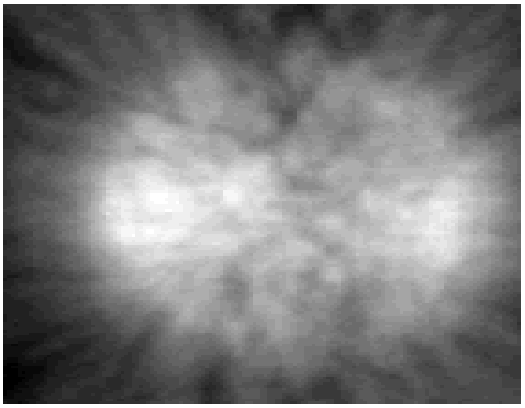

Fig. 5: Grayscale template

Table 3: Obtained results by template based methods

Methods	Database	Accuracy (%)
Li and Chutatape (2004)	Other	99.00
Osareh *et al.* (2003)	STARE	58.00
Lowell *et al.* (2004)	Other	99.00
Haar (2005)	STARE	58.00
Dehghani *et al.* (2012)	DRIVE	100.0
	STARE	91.36
Ramakanth and Babu (2014)	DIARETDB0	98.56
	DIARETDB1	98.88
	DRIVE	100.0
	STARE	93.83
	MESSIDOR	99.42
Yu *et al.* (2012)	MESSIDOR	99.10
Lalonde *et al.* (2001)	DIARETDB0	89.52
	DIARETDB1	89.99
	DRIVE	80.55
Sopharak *et al.* (2008)	DIARETDB0	95.29
	DIARETDB1	93.70
	DRIVE	98.61

approximately circular and consisting of bright pixels; based on these assumptions, the templates are created (Fig. 5). Then, a running window with the size N×N is applied to the intensity plane of the image and for each new position of the running window, the correlation between the running window and the template is calculated. The pixel with the highest correlation is selected as the location of the OD center. The results obtained by template-based methods are shown in Table 3.

Osareh *et al.* (2003) proposed a template-based approach to approximately locate the OD. Initially, the images were normalized by applying histogram specifications and the OD region from 25 color normalized images was averaged to produce a gray-level template (Fig. 5). The normalized correlation coefficient was then used to find the most perfect match between the template and the candidate pixels in the given image.

Lowell *et al.* (2004) used a specialized correlation filter that matches the key elements of the optic disc structure. The correlation peak gives the approximate center of the OD. The OD consists of a significant vertically oriented, roughly centrally located band of low intensity blood vessels; therefore, a template consisting of a Laplacian of Gaussian with a vertical channel in the middle to correspond to the major vessel band is created and matched to the patches of the test image.

Haar (2005) created a template using the OD appearances of 25 images. Then, the template was matched to patches of the test image.

Instead of creating an image as a template, Dehghani *et al.* (2012) constructed three histograms as a template, each corresponding to one color component. In the first step, they applied an average filter with a size of 6×6 pixels to reduce the noise. Then, a window the typical size of the OD (80×80 pixels) was used to extract the OD of each retinal image. In the next step, the color components (red, blue and green) of each optic disc were separated to obtain the histogram of each color component. Finally, the mean histogram of each color component for all retinal image samples was calculated as a template and matched to the given test image. The Approximate Nearest Neighbor Field (ANNF) technique was proposed by Ramakanth and Babu (2014).

They used a single OD image as a reference dictionary. To reduce the computation cost, the template features and sub-image pixels of the test image were extracted and matched.

An adaptive binary template was created by Yu *et al.* (2012) to locate the OD candidates. Then, a two-dimensional Matched Filter (MF) kernel was convolved with all OD candidates to estimate the main vessel's orientation inside the OD. The candidate with maximum correlation to the MF Kernel was considered as the actual OD.

Principal Component Analysis (PCA) was used to extract different features present in the fundus image including OD and vessels (Sanchez *et al.*, 2004). Li and Chutatape (2004) created the template using Principal Component Analysis (PCA). The sub-images of the test images were matched with the template and the Euclidean distance from the PCA Model was calculated for each sub-image. The sub-image with the OD at the center will have the least Euclidean distance from the PCA Model.

Lalonde *et al.* (2001) created a five-level resolution pyramid using the Haar wavelet transform. At this level, the small bright pixels belonging to exudates had disappeared and the pixels belonging to the optic disc were still visible. Each candidate pixel in the image at the fifth level of the pyramid corresponded to a region of many pixels in the original image. To pinpoint one pixel within such a region as an OD-center candidate, the original image was smoothed and the brightest pixel within the region was selected as a candidate.

Entropy filtering-based OD localization was proposed by Sopharak *et al.* (2008). After necessary preprocessing, the binarization was done with Otsu's algorithm and then the largest connected region with an approximately circular shape was marked as a candidate for the OD.

The results of template-based methods are quite accurate compared to brightness-based methods but the computation cost is high. Eventually, the computation time is reduced using effective algorithm techniques (Ramakanth and Babu, 2014; Lalonde *et al.*, 2001). However, the shape model (template) may not be suitable for detecting the various disc shapes from many pathological changes.

Method based on the Hough transform: The Hough transform is capable of finding geometric shapes in an image. The OD has an approximately circular shape; therefore, the Hough transform can be used to detect the OD. To detect the edges of all possible orientations at each pixel, various edge detection kernels such as Sobel, Canny, Prewitt, Roberts and Log edge were used. On this edge map of the retinal surface, a single threshold was applied to obtain a binary edge map. Finally, the Hough transform is applied on an edge map at different orientations. The circle with the highest magnitude of evidence is chosen as the optic disc (Treigys *et al.*, 2008). The results obtained by Hough transform-based methods are shown in Table 4.

Unlike the conventional Hough transform, Haar (2005) sum the intensity differences at edges instead of using an equal weight for all edges. If the boundary of the optic disc is fuzzy then the Hough transform prefers fitting the circle on the vessel retina's edges. These edges often have a higher weight within the OD than outside of the OD because of the brightness within the OD.

Lu (2011) designed a circular Hough transform to capture both the circle shape of the OD and the image variation across the OD boundary simultaneously. To reduce the computation cost, the retinal image can be down sampled to 0.3 of its original size.

Fleming *et al.* (2007) detected a temporal arcade using vessel properties such as the intensity gradient of the vessel wall and the vessel width. Then, the semi-ellipse Hough transforms was applied on the temporal arcade to localize the OD.

Ravishankar *et al.* (2009) tried to track the OD by combining the convergence of the thicker blood vessel, initiating it and the high disc intensity properties in a cost function. The segments of the thicker blood vessel's skeleton were modeled as lines found by the Hough transform.

Table 4: Obtained results by hough transform based methods

Methods	Database	Accuracy (%)
Haar (2005)	STARE	66.70
Lu (2011)	STARE	98.77
	MESSIDOR	99.75
Fleming *et al.* (2007)	Other	98.40
Ravishankar *et al.* (2009)	DIARETDB0	80.12
	DIARETDB1	76.41
	DRIVE	86.10
Zhu *et al.* (2010)	DRIVE	90.44
	STARE	44.40
Lu and Lim (2011)	DIARETDB0	99.20
	DIARETDB1	98.90
	DRIVE	97.50
	STARE	96.30

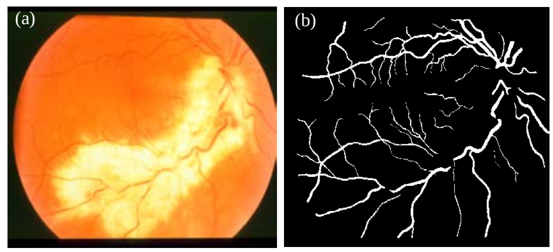

Fig. 6: Result of vascular segmentation; a) original and b) binary vessel map

Zhu *et al.* (2010) detected the edge map using Sobel or Ganny operators. Then, the OD center and radius were approximated using circular Hough transform.

Lu and Lim (2011) designed a line operator to detect circular regions that have similar brightness structures to the OD. For each image pixel, the line operator first determines the line segments of a specific length at multiple specific orientations that center at the image pixel. The orientation of the line segment with the minimum/maximum variation has a specific pattern that can be used to accurately locate the OD.

Method using binary vasculature: Normally, the eye's fundus image vessels tend to not be affected by diabetic signs and can be detected even when such signs exist in the image (Fig. 6). This method identifies the optic nerve as the focal point of the blood vessel network. To determine the focal point, the retinal vessel network must be detected. The determination of the convergence point of a vasculature structure is the most efficient way to localize the OD in terms of accuracy, robustness and computational time. The results obtained by binary vascular-based methods are shown in Table 5.

Hoover and Goldbaum (2003) developed an algorithm using fuzzy convergence to identify OD after

Table 5: Obtained results by binary vascular based methods

Methods	Database	Accuracy (%)
Hoover and Goldbaum (2003)	STARE	89.00
Haar (2005)	STARE	71.60
Youssif *et al.* (2008)	STARE	98.80
	Other	100.0
Foracchia *et al.* (2004)	STARE	97.50
Mendonca *et al.* (2013)	DRIVE	100.0
	STARE	98.80
	MESSIDOR	99.80
	Other	100.0
Tobin *et al.* (2007)	STARE	87.70
	Other	81.00
Niemeijer *et al.* (2009)	Other	99.99
Park *et al.* (2006)	DRIVE	90.25
Mahfouz and Fahmy (2010)	DIARETDB0	98.46
	DIARETDB1	97.75
	DRIVE	100.0
	STARE	92.59
Ying *et al.* (2007)	DRIVE	97.50
Welfer *et al.* (2010)	DIARETDB1	97.70
	DRIVE	100.0
Rangayyan *et al.* (2010)	DRIVE	100.0
	STARE	69.10

the application of illumination equalization. They extracted the vascular structure using matched filter then the Optic Nerve Head (ONH) was detected using fuzzy convergence.

Haar (2005) determined the potential OD locations using the segmented vasculature. The binary vascular structure was obtained using Niemeijer *et al.* (2009) Method. Then, the extracted vasculature is dilated with a squared 5×5 kernel to increase the amount of potential OD locations. Finally the Hough transform was applied to localize the OD.

Youssif *et al.* (2008) segmented the retinal vessels using a simple and standard 2D Gaussian matched filter. Consequently, vessels' direction map of the segmented retinal vessels was obtained using the same segmentation algorithm. Then, the segmented vessels were thinned and filtered using local intensity to represent the optic disc center candidates. The Gaussian matched filter was resized in four different sizes and the difference between the output of the matched filter and the vessels' directions was measured. The minimum difference provided an estimate of the optic disc-center coordinates

Foracchia *et al.* (2004) extracted the skeleton of vasculature to measure the diameter, centre point and direction of the vessel. Then, the main blood vessels were modeled using parabolas to identify the centre of the disc.

Mendonca *et al.* (2013) estimated the distribution and variability of vessels around each image pixel using the concept of entropy of vascular directions which associates high values of this measure with the occurrence of a large number of vessels with multiple orientations. This information was then combined with the highest image intensities for localize the OD.

Tobin *et al.* (2007) proposed a method based on spatial filtering and Bayesian classifiers to extract local features from the retinal vasculature, obtaining a confidence image map. The point with the highest confidence value in this confidence image map consider as OD center.

Niemeijer *et al.* (2009) determined a set of features based on vessel map and image intensity, like number of vessels, average width of vessels, standard deviation, orientation, maximum width, density and average image intensity. Then, the features are measured under and around a circular template to determine the location of the optic disc.

Park *et al.* (2006) extracted the vascular structure based on tensor voting. Tensor voting is the voting process of the expected candidates based on geometrical features. Then the OD was detected using mean shift procedure.

Mahfouz and Fahmy (2010) used image features such as retinal vessel orientation and the OD brightness for OD localization. They converted the 2-dimensional localization problem into to 1-dimensional problem by projecting the image features onto two orthogonal axes. Then, the resulting 1D signals were searched to determine horizontal and vertical co-ordinate of the OD.

Ying *et al.* (2007) differentiated the OD from other bright region, based on the fractal dimensions related to converging pattern of the blood vessels.

Welfer *et al.* (2010) segmented and pruned the vascular structure. Then, the OD was approximated using mathematical morphology.

Rangayyan *et al.* (2010) extracted the blood vessel using Gabor filter then the detection of peak in the node map was obtained via phase portrait analysis and an intensity based condition.

The success rates of vascular based methods are better compared to other methods because the vessels can be detected even when DR signs exist in the image. However, the accuracy of these methods is highly depends on the accuracy of vessel segmentation.

DISCUSSION

The quantitative results presented in the previous session are compared and shown in Fig. 7. The Brightness based algorithms are simple and fast compared with other methods. These methods provide better results only with healthy retina. The presence of strong destructors in DRIVE and STARE images low down the success rate of brightness based methods (Fig. 7).

The Hough transforms based methods yield better results when the OD boundary is well detected by edge detection operator. The methods may fail when the optic disc has a fuzzy boundary or the contrast between OD and background are not enough to detect the boundary edges.

The results of template based methods are comparatively accurate as compared to brightness based

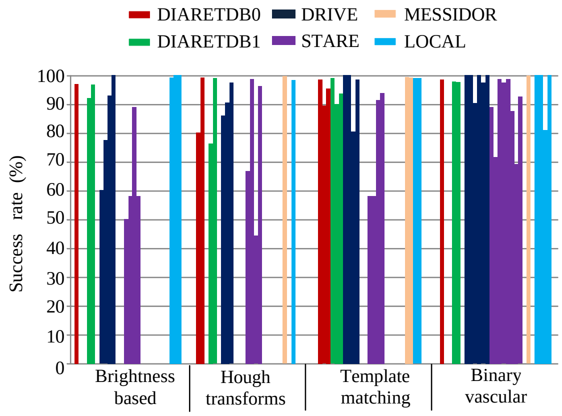

Fig. 7: Comparison of success rate in all the methods

and Hough transforms based methods but the computation cost is high. However, the template may not be suitable to detect the various disc shapes from many pathological changes.

Blood vessels in retinal images do not be affected by diabetic signs and can be detected even when such signs exist in the image. Therefore, the success rate of vascular based methods is better than all other methods (Fig. 7). However, the accuracy of these methods is highly depends on the accuracy of vascular segmentation.

CONCLUSION

The detection of OD in the retina has been a heavily researched area in recent years. The accurate detection of OD forms the backbone of many automated computer aided systems for screening and diagnosis of ophthalmologic diseases such as Glaucoma and diabetic retinopathy. In this study, researchers have provided a comprehensive review on OD localization using fundus photographs. Researchers have covered both early and recent literature focusing on OD localization techniques. The aim was to introduce the current localization techniques, give the reader a framework for the existing methods and discuss the current trends and future direction.

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