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Optic Disk Localization by a Robust Fusion Method

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ABSTRACT

The optic disk localization plays an important role in developing computer-aided diagnosis (CAD) systems for ocular diseases such as glaucoma, diabetic retinopathy and age-related macula degeneration. In this paper, we propose an intelligent fusion of methods for the localization of the optic disk in retinal fundus images. Three different approaches are developed to detect the location of the optic disk separately. The first method is the maximum vessel crossing method, which finds the region with the most number of blood vessel crossing points. The second one is the multi-channel thresholding method, targeting the area with the highest intensity. The final method searches the vertical and horizontal region-of-interest separately on the basis of blood vessel structure and neighborhood entropy profile. Finally, these three methods are combined using an intelligent fusion method to improve the overall accuracy. The proposed algorithm was tested on the STARE database and the ORIGA^{light} database, each consisting of images with various pathologies. The preliminary result on the STARE database can achieve 81.5%, while a higher result of 99% can be obtained for the ORIGA^{light} database. The proposed method outperforms each individual approach and state-of-the-art method which utilizes an intensity-based approach. The result demonstrates a high potential for this method to be used in retinal CAD systems.

Keywords: optic disk, retinal fundus image, computer-aided diagnosis

1. INTRODUCTION

The optic nerve head, or optic disk (OD), is the location where the optic nerve connects to the retina[1]. In a typical retinal fundus image, the OD is an elliptic region which is brighter than surrounding regions. OD is an important feature in the fundus image for analyzing ophthalmologic pathologies. OD size and cup-to-disk ratio are important indicators of glaucoma. OD is also an important landmark for locating the macula, which is critical for diagnosis of diabetic retinopathy and age-related macula degeneration. In addition, the localization of the OD is also closely related to the localization of the peripapillary atrophy, which is an indicator for pathological myopia. Thus, correct localization of the OD plays an important role in computer-aided diagnosis of ocular diseases.

The OD localization is not straightforward as it faces many difficulties. Firstly, ODs can vary significantly in appearance. Although most ODs appear to be very bright compared to its surroundings, many ODs have relatively flat texture within the OD and low contrast compared to other retinal structures. Secondly, the sizes of ODs vary from image to image. This situation is made even more complicated if images are of different fields as only a portion of the OD is visible for many macula centered (Field 2) images. Moreover, existence of retinal pathologies is the biggest challenge for OD localization. Peripapillary atrophy and large bright lesions are among the most disturbing pathologies for OD localization. In addition, poor image quality, caused either by cataract or poor image capture, makes it even more difficult.

There are many efforts spent on the localization of the OD, utilizing different characteristics of the OD. The OD can be detected by identifying the brightest area in the fundus image. Zhang et al.[2] located the OD as the center of the window that contains the most number of bright pixels. A fringe removal was used to remove bright artifacts in the border of the image. Subsequently, a p-tile thresholding method was utilized to select the top 0.5% of the brightest pixels. Finally, the window that contains the maximum number of bright pixels is considered to be the region-of-interest. Similarly, Walter and Klein[3] approximated the OD location as the centroid of the largest connected component in the binary image

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obtained through intensity thresholding. Instead of finding the brightest spot, Sinthanayothin et al.[4] proposed a method to locate the area with the largest intensity variation. The images were preprocessed to enhance the local contrast, followed by finding a disk-sized window that has the highest average variation. Hough Transform is also commonly used to locate the OD. Abdel-Ghafar et al.[5] used a Circular Hough Transform method to detect the OD in the green channel of the fundus image. A morphological closing operation was performed to remove the blood vessels in the preprocessing step. Then the Circular Hough Transform was applied to the edge map of the image obtained by the Sobel operator. Lastly, the largest circle found was used to approximate the location of the OD. Another important feature that can be analyzed for OD localization is the retinal vasculature. Hoover and Goldbaum[6] proposed the fuzzy convergence method, which utilizes a voting algorithm to determine the convergence point of the retinal vasculature.

In this paper, we introduce an automatic OD localization method based on an intelligent fusion of three different approaches and prior knowledge. Initially, three methods of OD detection that employs different image properties will be described in detail respectively. Then the fusion scheme is discussed. Finally, the last part presents evaluation of the algorithm on various databases and comparison with existing methods.

2. PROPOSED METHOD

Intensity-based methods are the most stable way to detect the OD location given an image of good quality. However, those methods usually fail if large PPA or lesions exist. In such cases, retinal vasculature based methods often give better results. Vessel-based methods also have their limitations as they rely heavily on the vessel detection algorithm. If the retinal vasculature is not well detected or invisible due to poor image quality, it is very likely that these methods fail to detect the correct location of the OD. In order to design a robust OD detection method, we can utilize both intensity feature and retinal vasculature feature so that their respective limitations can be eliminated. In our proposed method, we combine a vessel-based method, an intensity-based method, a mixture-feature method as well as prior knowledge of possible OD locations.

2.1 Maximum Vessel Crossing Method

This approach is based on the idea that all major blood vessels converge at the OD, and thus this region should have the maximum number of crossing points of blood vessels. The method comprises three steps. Initially, the retinal vasculature is detected and post-processed to obtain the vessel skeleton. Then the blood vessel crossing points are detected through a corner detection method. Finally, a sliding window is used to find the area with the largest number of crossing points, which represents the location of the OD.

We use the well-known Frangi filter[7] to extract the blood vessels in the OD. The filter is defined as follows:

$$F(x) = \left(1 - e^{-\frac{A(x)^2}{2\alpha^2}}\right) e^{-\frac{B(x)^2}{2\beta^2}} \left(1 - e^{-\frac{S(x)^2}{2\gamma^2}}\right) \quad (1)$$

where A discriminates plate-like from line-like structures; B discriminates blob-like structures and the second-order-like structure S eliminates background noise. α, β and γ are constants that control the sensitivity for A, B and S. To eliminate the effect of noise, we filter the vessel map to remove small white regions. Subsequently, we perform a morphological thinning to get the skeleton of the vessels. The skeleton is then pruned to remove small branches at endpoints.

In order to detect the vessel crossings, a corner detection method[8] is implemented. The curvature is computed at a fixed low scale and local maxima of the curvature function are treated as the corner candidates. Then, an adaptive thresholding method is applied to remove round corners, which are most likely noises. In addition, end points are identified and removed from the list of candidate corners as vessel bendings occurs only in the middle of the vessel. Finally, we constrain the angle of the corner to be within the range $[\phi_{min}, \phi_{max}]$, where ϕ_{min} and ϕ_{max} are set to 100° and 260° respectively.

To determine the area with the largest number of blood vessel crossings, we define a sliding window that has a similar size as the OD. The number of crossing points in each window is then computed. The window that contains the OD is decided according to the following equation:

$$P = \arg_{(i,j)} \max \left((I_c)_w(i,j) \right) \tag{2}$$

where $(I_c)_w$ is the number of vessel crossing points within a window W centered on a pixel (i,j). The center of the window is used to approximate the location of the OD center. This method is illustrated in Figure 1.

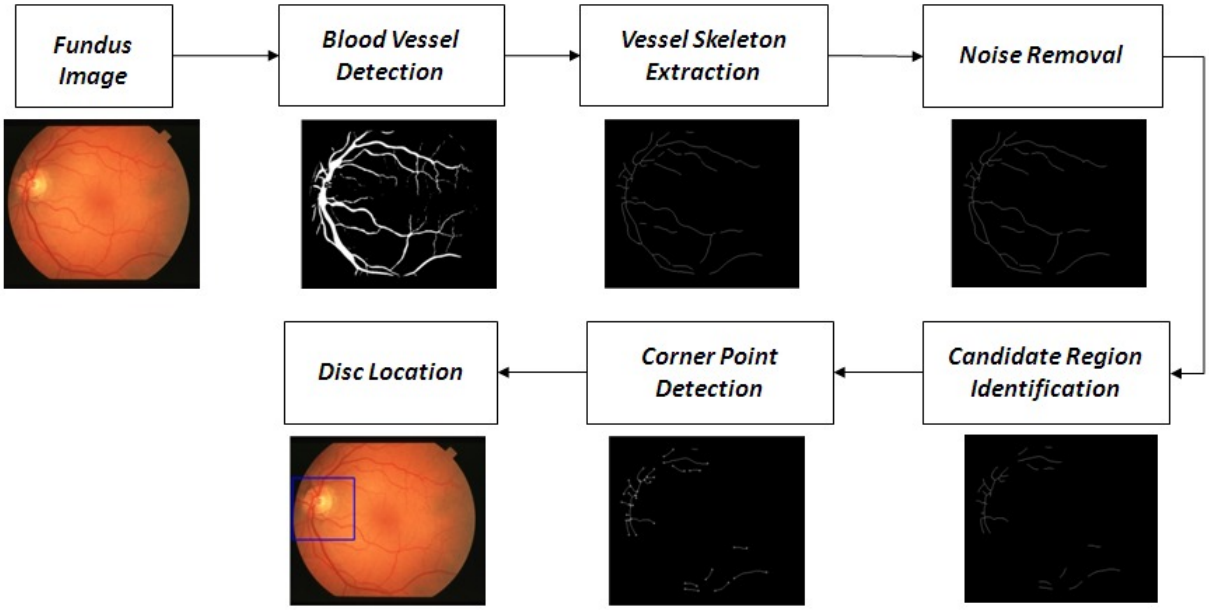

Figure 1. Flowchart of vessel crossing based method for OD localization

2.2 Multi-channel Thresholding Method

As the OD usually has higher color intensity than other areas of the retinal image, the OD location can be approximated by finding the region with the highest intensity value. However, single-channel thresholding method is not robust as it can be easily influenced by noise. Therefore, we employ a multi-channel thresholding method to determine the region with the highest brightness. The red, green channel and the grayscale images are chosen to be the inputs for our method. Red channel image is often referred to be the best channel for OD localization. But it loses this usefulness if the image suffers from over-exposure. Green channel has the best contrast for different structures of the retina. Grayscale image is the most consistent image to process as it contains the information from all channels. However, it loses some of the unique features from each channel due to the averaging effect. The multi-channel approach is superior to the single-channel approach as the former utilizes two more channels to confirm the result.

In this method, each channel experiences a p-tile thresholding process, where the top 0.5% of the brightest pixels are extracted. Prior to the thresholding, a fringe removal is used to remove bright edges of the image. To remove the effect of artifacts and pathologies that may have higher intensity, a morphological operation is performed to smooth the peaks. To further reduce noises, binary components that have a major axis longer than a certain length will not be considered as candidates for the OD. The OD location for each channel is selected to be the centroid of the largest binary component. As a result of this step, three different disk locations will be obtained. The center point of the two nearest locations will be considered as the final OD location.

Figure 2 illustrates the OD detection process through multi-channel thresholding method.

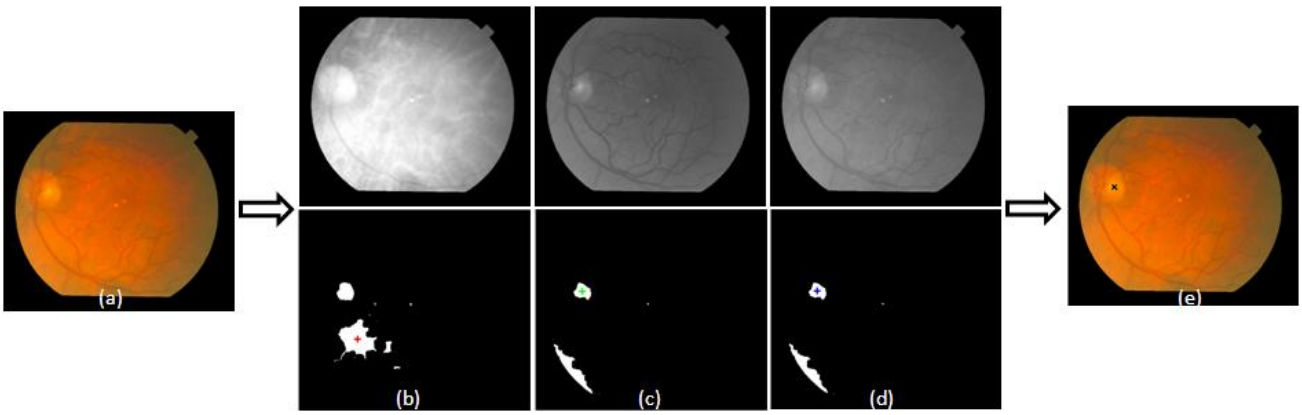

Figure 2. OD localization by multi-channel thresholding method. (a) Original Image. (b) Red channel image and thresholding result. (c) Green channel image and thresholding result. (d) Grayscale image and thresholding result. (e) Final result.

2.3 Vessel Structure and Neighborhood Entropy Method

In the vessel structure of a typical disk centered (Field 1) fundus image, the OD location usually has the most blood vessels vertically and least horizontally. However, locating the OD based only on this characteristic may not be robust. To improve the robustness, we incorporate the neighborhood entropy information, as the OD region usually has the highest entropy both vertically and horizontally. To implement this method, the blood vessel map (or vessel edge map) and the neighborhood entropy map are required. The vessel edge map can be obtained by the Canny edge detection method. The entropy map is obtained by calculating the entropy value for a window that is centered at each pixel of the image. Denoting the vessel edge map as I_e and the entropy map as E, the horizontal position of the OD can be found by:

$$P_h = \arg_j \max \{ a \times \mathrm{F}(I_{e,r,j}) + b \times \mathrm{H}(E_{r,j}) \} \tag{3}$$

where $\mathrm{F}(I_{e,r,j})$ is the normalized number of edge points in the j^{th} column, $\mathrm{H}(E_{r,j})$ is the normalized entropy in the j^{th} column, a and b are positive coefficients which add up to one.

The vertical position of the OD can be obtained by:

$$P_v = \arg_k \min \{ c \times \mathrm{F}(I_{e,k,c}) - d \times (E_{k,c}) \} \tag{4}$$

where c and d are positive coefficients.

The final position of the OD is then determined as pixel (k, j). Figure 3 illustrates how the vertical and horizontal positions of the OD are determined.

2.4 Intelligent Fusion

To determine the final OD position, we use an intelligent fusion of these three approaches as well as prior knowledge. The fusion is achieved in a few steps. Initially, the centroid of the three candidate locations is calculated. Subsequently, a voting scheme is used to determine the OD position based on the relative position of these four points. If all candidate points are within one fifth of the disk diameter (DD) to the centroid, the final OD position is determined as the centroid point. If only two candidate points are within one fifth of the DD to the centroid, the OD position is the average point of these two candidate points. Otherwise, the OD location will be determined by prior knowledge. As shown in Figure 4, OD falls in regions of A, B and C for more than 90% of Field 1 and Field 2 fundus images. Thus, we can approximate the OD location based on this knowledge if it's inconclusive using the previous steps. Finally, the OD locates in the

center of the trust region which is closest to the centroid, provided all conditions in the previous steps are not fulfilled. Figure 5 shows an example of locating the OD using the fusion method.

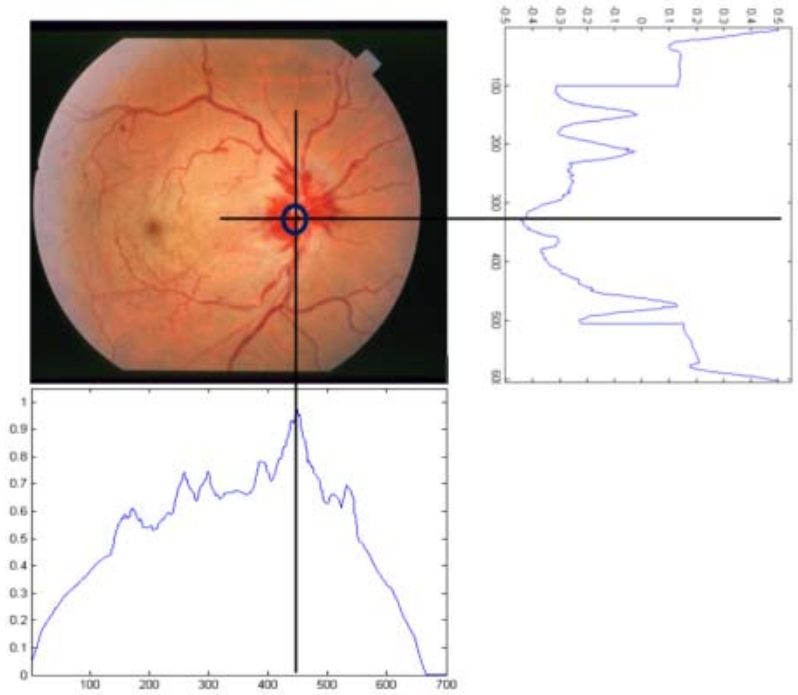

Figure 3. Example of OD localization using vessel structure method (a, b, c, d are set to be 0.5)

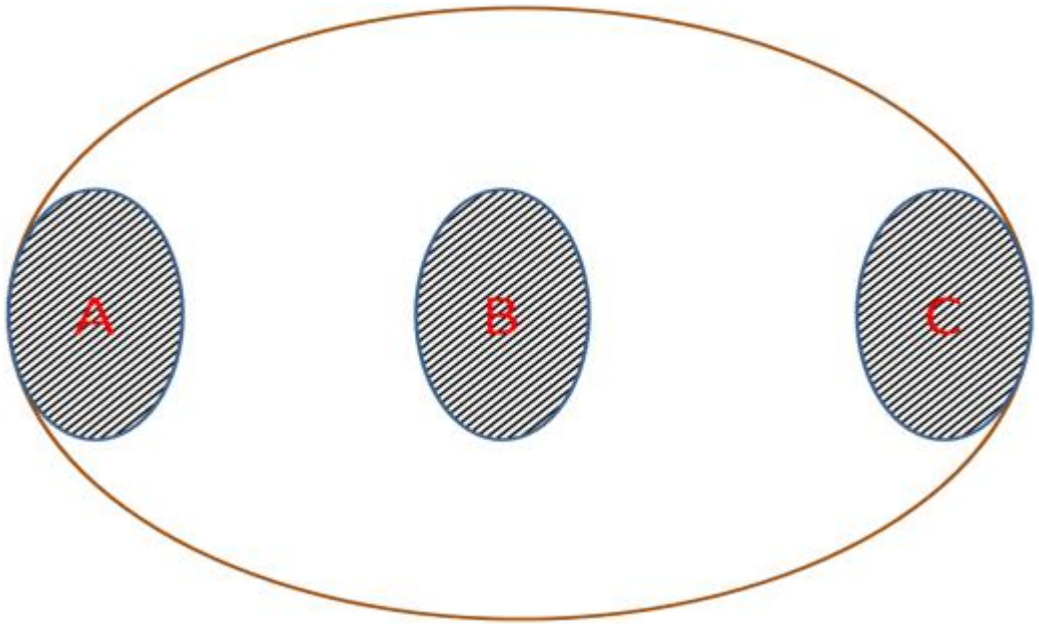

Figure 4. Trust regions for OD localizations

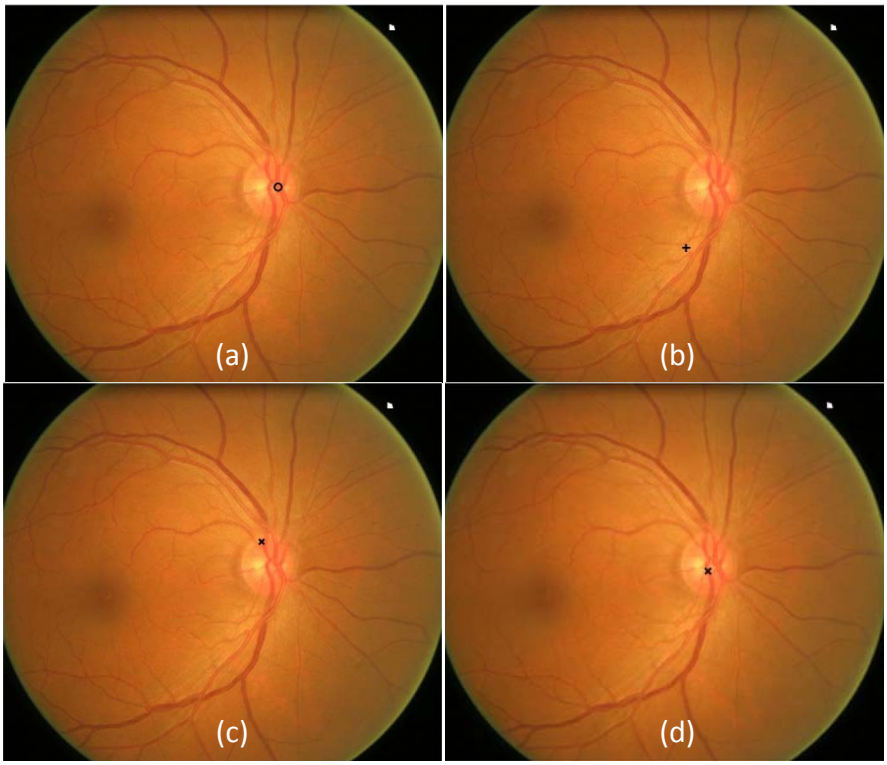

Figure 5. Illustration of OD localization by intelligent fusion method: OD location result by (a) Maximum vessel crossing method; (b) Multi-channel thresholding method; (c) Vessel structure and neighborhood entropy method; and (d) Fusion method.

3. EXPERIMENTAL RESULTS

The algorithm was evaluated on the STARE database[9] and the ORIGA^{light} database[10]. The STARE database contains 81 fundus images, in which 40 images are centered at the OD and 41 images are centered at the macula. In addition, 21 images in the database have OD seriously occluded or hardly visible. The ORIGA^{light} database consists of retinal fundus images from a population-based study and contains images with multiple pathologies. The database has two subsets, one with 650 Field 1 images and the other one with 650 Field 2 images.

To evaluate the performance of the proposed method, we define the criteria of successful detection. If the detected OD location is within the real OD area, it is considered to be accurate. To make a comparison, results for the three methods are recorded. We also implemented an intensity-based OD localization method by Zhang et al.[2]. The proposed method can achieve a detecting accuracy of 81.5% for the STARE database and 99% for the whole ORIGA^{light} database. The results are summarized in Table 1. Comparing the results of the proposed method with results by intensity-based methods and other three approaches, we can see that the proposed method improves significantly, especially for Field 2 images and images with low quality. Figure 6 shows sample results from different databases.

Table 1. OD localization results by maximum vessel crossing (MVC) method, multi-channel thresholding (MCT) method, vessel structure and neighbourhood entropy (VSNE) method, proposed method and intensity-based method

Database	MVC Method	MCT Method	VSNE Method	Intensity-based Method	Proposed Method
ORIGA^{light} Field 1	86.5%	99.4%	95.7%	98.8%	99.5%
ORIGA^{light} Field 2	95.4%	94.2%	97.7%	71.5%	98.5%
STARE	69.1%	71.6%	72.8%	44.4%	81.5%

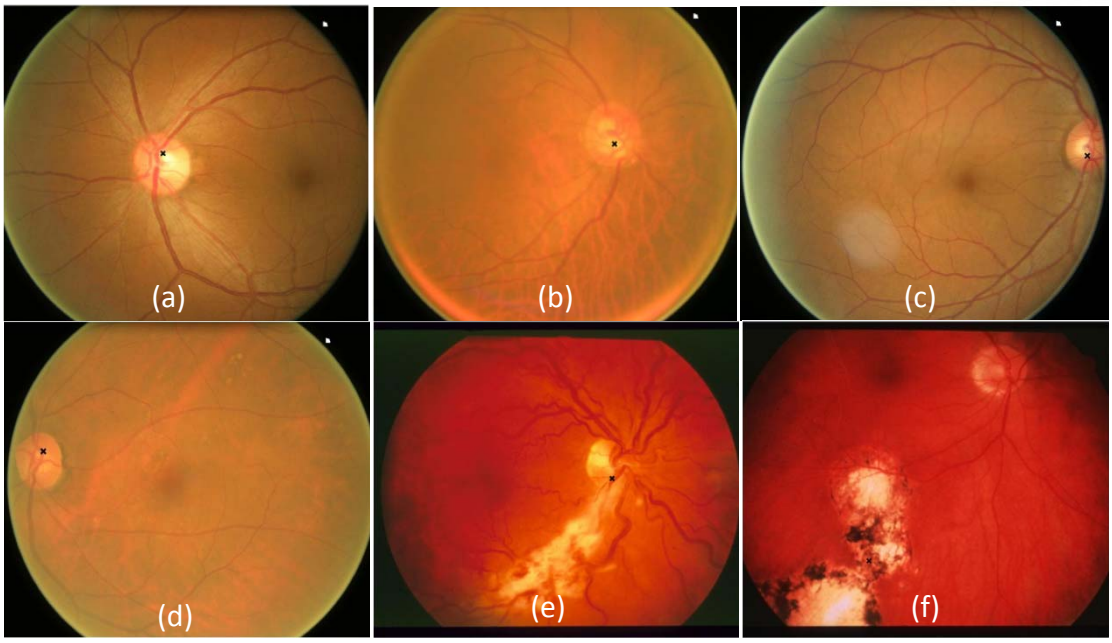

Figure 6. Sample OD localization results: (a)-(b) ORIGAlight Field 1 images; (c)-(d) ORIGAlight Field 2 images; (e)-(f) STARE images.

The reasons for inaccurate OD localization include existence of multiple pathologies which influences the quality of the images as well as the shape of the OD, large bright lesions that have similar appearance as the OD and poor illumination of the image. To further improve the results, pattern recognition or machine learning techniques can be used in combination with the proposed method to produce a confidence score or eliminate outliers.

4. CONCLUSIONS

In this paper, we have presented an automatic method to localize the optic disk from fundus images using an intelligent fusion method. The method combines a maximum vessel crossing method, a multi-channel thresholding method, a vessel structure and neighborhood entropy based method, as well as prior knowledge of OD location distribution. The method was tested on different databases for images with various quality, fields and pathologies. Results show that the accuracy can achieve 99% for the ORIGA^{light} database and 81.5% for the STARE database, indicating potential for our method to be used in retinal CAD systems.

REFERENCES

[1] Tasman, W. and Jaeger, E. A. , [Duane's Ophthalmology], Lippincott Williams & Wilkins, (2006)
[2] Zhang, Z., Lee, B.H., Liu, J., Wong, D.W.K., Tan, N.M., Lim, J.H.,Yin, F., Huang, W., Li, H., and Wong, T.Y., "Optic disc region of interest localization in fundus image for Glaucoma detection in ARGALI," in Proc. Of the 5th IEEE Conference on in Industrial Electronics and Applications (ICIEA), 2010, pp. 1686-1689.
[3] Walter, T. and Klein, J.-C, "Segmentation of color fundus images of the human retina: Detection of the optic disc and the vascular tree using morphological techniques," in Proc. 2nd Int. Symp. Med. Data Anal., 2001, pp. 282–287.

[4] Sinthanayothin, C., Boyce, J. F., Cook, H. L. and Williamson, T. H., “Automated localisation of the optic disk, fovea, and retinal blood vessels from digital colour fundus images,” Br. J. Ophthalmol., vol. 83, no. 8, pp. 902–910, 1999.
[5] Abdel-Ghafar, R. A., Morris, T., Ritchings, T. and Wood, I., “Detection and characterisation of the optic disk in glaucoma and diabetic retinopathy,” presented at the Med. Image Understand. Anal. Conf., London, U.K., Sep. 23–24, 2004.
[6] Hoover, A. and Goldbaum, M., “Locating the optic nerve in a retinal image using the fuzzy convergence of the blood vessels,” IEEE Trans. Med. Imag., vol. 22, no. 8, pp. 951–958, Aug. 2003.
[7] Frangi, A.F. et al., “Multiscale vessel enhancement filtering”, MICCAI Proceedings, Springer Verlag, 1998, pp. 130–137.
[8] He, X.C. and Yung, N.H.C., “Corner detector based on global and local curvature properties”, Optical Engineering, 47(5), pp: 057008, 2008.
[9] STARE project website, Clemson Univ. Clemson, SC [Online]. Available: http://www.ces.clemson.edu/~ahoover/stare
[10] Zhang, Z., Yin, F., Liu, J., Wong, D.W.K., Tan, N.M., Lee, B.H., Cheng, J. and Wong, T.Y., "ORIGA-light: An online retinal fundus image database for glaucoma analysis and research," in Conf Proc IEEE Eng Med Biol Soc.2010, 2010, pp. 3065-3068.