International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 06 Issue: 03 | Mar 2019 www.irjet.net p-ISSN: 2395-0072

RETINAL STRUCTURE SEGMENTATION USING ADAPTIVE FUZZY THRESHOLDING

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Abstract- Examining the eye could be as efficacious as physical one in determining health concerns. Screening the retina is the initial step to detect the hidden health issues which even includes pre-diabetes and diabetes. By clinical diagnosis and prognosis, ophthalmologists depend highly on the binary segmented version of retina fundus image, where the accuracy of segmented vessels, optic disc and abnormal lesions extremely affects the diagnosis accuracy which in turn affects the subsequent clinical treatment steps. This paper proposes an automated retinal fundus image segmentation system which consists of three segmentation subsystems and follows same core segmentation algorithm. Despite of broad difference in features and characteristics; retinal vessels, optic disc and exudate lesions are extracted by each subsystem without the need for texture analysis or synthesis. In order to obtain complete clinical insight and avoid complexity with the existing techniques, our proposed system can detect these anatomical structures using one session with great accuracy even in pathological retina images. The proposed system uses a robust hybrid segmentation algorithm that combines adaptive fuzzy thresholding and mathematical morphology. The system is justified by using four benchmark datasets which are DRIVE and STARE (vessels), DRISHTI-GS (optic disc), and DIARETDB1 (exudates lesions). By adopting these algorithms competitive segmentation performance is achieved out by performing a variety of up-to-date systems and demonstrating the capacity to deal with other heterogeneous anatomical structures.

Index Terms— Retina screening, retinopathy, retinal vessels segmentation, optic disc segmentation, retinal exudate segmentation, fuzzy systems, fuzzy C-means, adaptive local thresholding, morphological operations.

I. INTRODUCTION

Though the retina is located in the peripheral location, but it is also a part of the central nervous system, which represents the neural portion of the eye. The biological changes in the retinal physical structure has a very great diagnostic value as they possess important information used to detect and diagnosis a variety of retinal diseases such as Diabetic Retinopathy (DR), glaucoma, hypertension, Age- related Macular Degeneration (AMD), and Retinopathy of Prematurity (RoP) . The major disease that can disturb overall health condition of a person in general is the diabetes. The most common cause for the vision loss during working age is diabetic retinopathy. When a person is suffering from diabetes the chances for him to go through various abnormalities like diabetic retinopathy if it affects retina, nephropathy if affect kidneys and diabetic neuropathy if it affects the nervous system are high and diabetes is considered as a critical risk factor when it comes to heart and blood vessels. More than half of the blindness cases can be prevented by early diagnosis and regular retinal examining. Diabetes are the leading sources for retina associated vision loss and blindness in the USA. Retinal screening is the way used to detect the diabetic retinopathy in initial stages itself before any changes to one's vision are noticed.

It is true that in the early stages of the diabetic retinopathy, no radical symptoms are noticed but eventually many symptoms starts to occur and the severity increases slowly with the time. In the beginning the diabetic retinopathy starts with a small change in the blood vessel of the retina, so the initial abnormality can be detected by identifying the existence of the microaneuryms. Then, diabetes affects the nerve head of the optic which is called as optic disc which leads to changes in the shape of the optic disc. Further the complications due to the diabetes is noticed in the increased size of the vessels, walls permeability of the retina which allows the leaking of the lipid formations by the weak wall of the blood vessels which leads to the hardening of the exudates. Overall these if the retinopathy is detected in the early stages itself with the help of treatment it can cease it getting worse, otherwise the symptoms become sensible along with the time, which could be even more difficult to treat.

Retinal screening which is performed by the imaging instruments such as fundus camera, scanning laser ophthalmoscope (SLO), where the ophthalmologists uses both the 2D retinal yielded image and the segmented version of it in the process of diagnosis of pre-diabetes, diabetic retinopathy, and other health concerns that can be

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decreased. All these drawbacks have inspired us to develop a system which can extract different retinal structures all at one session with more accuracy and without any need for the synthesis or the texture analysis. This paper explores and combines the mathematical morphology theories, fuzzy sets and their ability to perform fast and accurate segmentation system. The general framework with prism of the proposed system of multi object soft thresholding segmentation system is shown in Fig. 1.

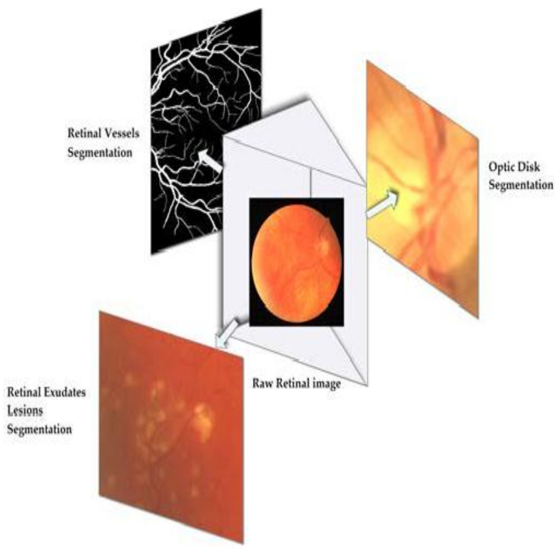

Fig. 1 General framework with prism of the proposed system.

The thresholding is one of the most well- known, accurate technique used for image segmentation tasks in general and particularly in medical image segmentation tasks.
Thresholding techniques searches for a global value which maximizes the separation between different classes that is different tissues in the image, Thresholding at a level is effective if the objects in the image under examination have well defined areas and also if the gray levels are with minimum interference clustered around values. Objects in medical images like organs and tissues are different as objects in natural scenes. So different tissues and organs are represented by different gray levels using the thresholding segmentation techniques. When soft transition between different gray levels are exhibited by the images, uneven illumination or noise distortions, principal segmentation errors arise due to the pixel-wise approach adopted by global thresholding. The pixels with same gray levels are segmented into the same object which is considered as a issue in global thresholding with one hard value. As retinal images are a great examples of this kind of situations, in order to avoid such situations a region based thresholding technique is used in this work. We use a combination of both rule based and machine learning techniques, in which the
adaptive local fuzzy thresholding represents the hard segmentation phase of proposed system and morphological operations represent the soft segmentation. To the best of our knowledge only very few number of existing system have thought about extracting multiple anatomical structures with more accuracy but there is no record in the history of using hybrid model which combines adaptive fuzzy and morphology mathematical techniques to solve these kind of problems. In short , in this paper we developed a compact segmentation system which can localize, identify and extract multiple biological structures that has highly different features in a one segmentation with comparably high segmentation accuracy.

I. PROPOSED SYSTEM

In this work we came up with a system that combines two different algorithms called adaptive fuzzy thresholding and mathematical morphology. The general flowchart of the proposed system is shown below in the Fig.2. The morphological operators are used in pre and post processing phase of the system and adaptive fuzzy thresholding is used in processing phase as this represents the core of the segmentation algorithm, morphological operators are considered in complement steps. Our proposed system has three major phases they are: Region of Interest (ROI) extraction, coarse segmentation and soft segmentation. In the first phase the target region is extracted out of the raw retina image to enhance the segmentation accuracy of the target retinal biological structure such as vessels, exudate lesions or optic disc and lower the computational cost, the /ROI image undergoes few pre-processing steps which involves some major morphological operations that leads to initial identification of the target region. Though this stage is a initial one but it has high effect in the final segmenting accuracy of the fuzzy processing phase. The ROI forms the input for local adaptive fuzzy thresholding, which gives the hard segmented image and another set of morphological operations are applied in the soft segmentation stage and is followed by the binarization and convex-hull transform smoothing steps produces the final segmented images like *vessels, optic Discor exudates* depending on the target retinal anatomical structure. The common phases involved in our proposed system are graphically illustrated in Fig. 3.

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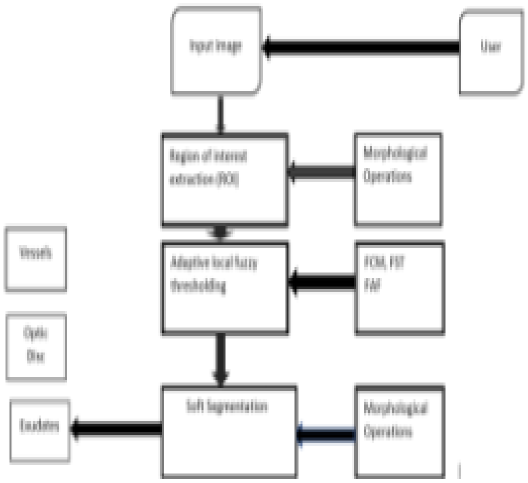

Fig. 2. General flowchart of the proposed hybrid system.

A. Phase I: Image Pre-Processing

The vital goal of shape is called ROI extraction which selects the retinal structure of interest to reduce the computational cost and to strengthen the overall performance ; in which window around the focused anatomical structure region of the raw image is pulled out, then the pre-processing steps are applied on it . These anatomical structures have its own properties and features, thus, some of the pre-processing steps may be different. Though, the pre-processing general frameworks kept unchanged. Hence these pre-processing steps are quite dependent on the challenges done by the nature of focused anatomical structure, a short explanation of each anatomical structure is presented and continued by the required pre-processing steps.

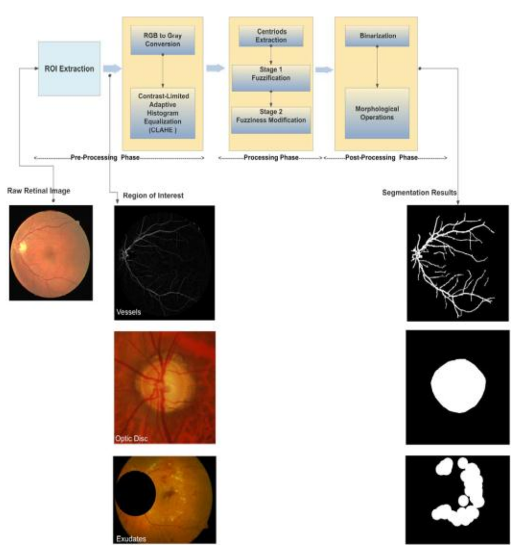

Fig. 3. System algorithm pipeline.

1) ROI Retinal Vessels Extraction

Vessel segmentation in retinal images involves a pull between exact vascular structure extraction and false responses near sites of the pathology or other nonvascular structures such as optic or macula. In this pressure arises from the low contrast nature of retinal vessels in differentiation to the fundus image background. On the other hand, retinal vasculature structure shows effective change in size and contrast and broad distributed branching on the whole surface of retinal fundus image. For example, the width of retinal vessels ranges broadly, from less than one pixel up to more than five pixels in a particular retinal image. In two stages retina vessels segmentation approach, they use morphological filters to highlight the linear structures in first stage. Secondary morphological operations and hysteresis thresholding is used to initiate the binary vessels image as a second stage.

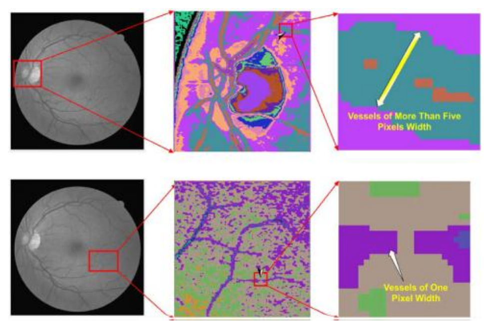

Fig. 4. . Difference in ranges between retinal vascular structures

2) Optic Disc of ROI

The optic nerve head is explained as the region of the retina where all retinal nerve fibers intersect to form the start of the optic nerve. The optic nerve head, or optic disc, is usually circular or approximately oval in shape and it contains a central brighter region called as Cup or Pallor. The tissue connecting between the cup and the disc margin is called neural rim or neuroretina.

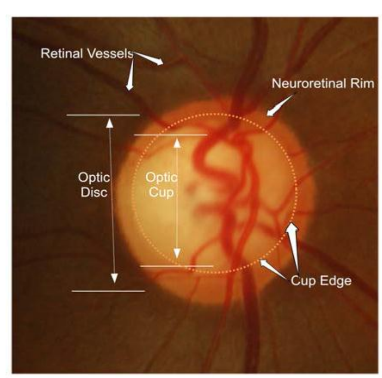

Fig. 5. Anatomical structure of optic disc.

All optic nerve diseases lead to the constitutional changes in parapapillary and intrapapillary regions of the optic nerve head. These changes can be expressed quantitatively by many variables such as shapes, size of the optic disc, shape and size of pallor, the ratio of the cup and disc diameters, and the ratio of areas of the cup and disc. To explain these variables the foremost step is to extract the optic disc region from the raw retinal image.
These optic disc region of interest is nearly circular in shape; so, we use the Hough transform to select the center of neuroretinal rim of the optic disc, thereafter extract the square window around optic disc, which shows the optic disc region of interest that include the following steps:

a) Edge detection
Edge detection is often said as pre-processing step to Hough transform. Hence, the input image is given to Hough transform in which an edge map composed of a set of pixels partly describe the borderline of optic disc. The capability and fidelity of Hough transform in finding the midpoint of optic disc circle can be demonstrated by working faultless edge detection technique. Fuzzy c-means (FCM) clustering algorithm is applied for this purpose. In advance of applying FCM algorithm, retina image face a set of pre-processing steps in purpose of achieving accurate edge map as following.

Initially the red layer of retina image was extracted where it denotes as red layer extracting operator. In contrast to vessels extraction, red layer is the layer where the optic disc tissues have the higher contrast with other objects on fundus image. The enhanced image where I_{clahe} denotes the Contrast-Limited Adaptive Histogram Equalization (CLAHE) operator, normally it operates on small data regions of image rather than the entire area yields contrast-enhanced image. For further enhancement, we apply median filtering of 9×9-sized window and given as input to FCM algorithm.

b) Hough Transform
The basic idea behind Hough transform (point to curve transform) is that the perpendicular lines to edge point of a circle coincide in the center of the circle. Accordingly, if we draw perpendicular lines to every edge pixel of our map, then the regions of the circles center will appear as bright as 'hotspot' due to increase in perpendicular lines. Hough transform can be calculated using different methods: directional information (gradients), error compensation (smoothing) and voting in parameter space.
As we have only one optic disc each retina fundus image, our circle searching problem reduces fro many to one. Thus, we use this last method.
Parametric space voting method proceeds as follows: Optic disc can be explained as a circle-shaped object in the plane of fundus image.

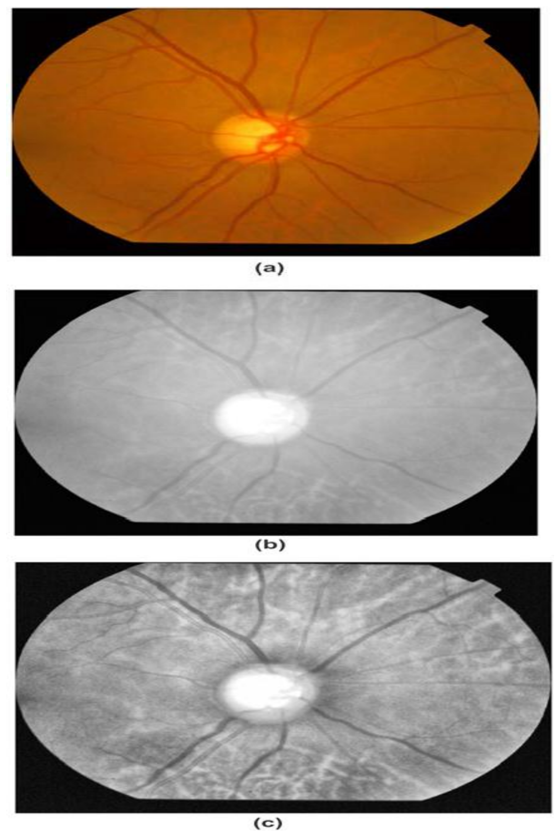

Fig. 6 (a) Raw retina image. (b) Corresponding red layer I^R .(c) CLAHE-enhanced image

c) OD ROI window
As much as Hough transform identifies the coordinates of optic disc circle, a flawless circle can be synthesized given a radius. Selecting the radius value depends on the verification of the data used; because each dataset that is produced via fundus camera of particular description in terms of image size and pixel resolution. Radius value is used in our system to establish the square windows, borders of optic disc region as it is equal to =2 pixels width. After that, we use MATLAB® image cropping function, finally image has been extracted.

3) ROI of Exudates Lesions.
One of the major signs in the presence of diabetic retinopathy is the existence of exudate regions. This shows a color of retinal fundus image for a patient that has different distributed exudate islands along with the level of observations made by expert ophthalmologists. These exudate lesions appear as either white or yellow soft

abnormal regions of different sizes, non-uniform shapes and fuzzy divergence on the surface of retinal fundus image. Although retina exudates follow neither uniform sizing nor a uniform intensity distribution, the optic nerve head and bight reflections within empty retinal vessels which exhibit similar appearence. These exudates lesions represent the most challenging type of retinal lesions to identify and extract the most challenging of all retinal anatomical structures to segment. The extraction of exudates in the region of interest follows the same method used in optic disc extraction. Moreover, the region of the optic disc is replaced with black region; thus, exudates islands cannot be misclassified as the optic disc region during segmentation phase.

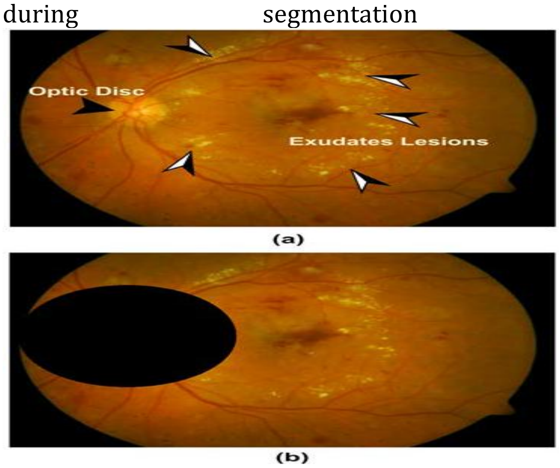

Fig. 7. (a) Raw retina image contains white spots represent hard exudates lesions. (b) Exudates ROI.

Phase II: Image Processing

This section elaborates the fuzzy theory-dependent coarse segmentation phase of our proposed hybrid system. This phase was inspired by a local fuzzy thresholding open methodology. This segmentation methodology combines two powerful thresholding techniques: adaptive local thresholding and spatial local information-based thresholding. This phase basically consists of three stages: *fuzzy modeling*, *fuzzy model aggregation* (fuzziness spatial filtering) and *binarization* as illustrated in the following subsections.

1) Stage I: Fuzzy Modeling

In this stage, the pixel values (intensities) of our retinal image are converted to fuzzy membership values based on properly defined membership functions. Our fuzzy model was built through four basic steps: image fuzzification, fuzzy sets composition, fuzzy relations (functions) composition and defuzzification.

a) Image fuzzification

One can look at image fuzzification as sort of image coding; where the input for this step is, that can be viewed as composed of fuzzy sets assemblage as an example for optic disc case. Each fuzzy set corresponds to a particular zone of. There is no loss of generality to anatomical parts, as can be shown in Fig. 6, the multiple intersected zones are there in the optic disc, many represent optic disc and the remaining others represent vessels exist in optic disc region and remaining part represents the background.

b) Fuzzy sets composition

Fuzzy model formulation is the process through discourse of universal which represents preprocessing phase which can be produced by the region or interest completely. From the fig 6, it contents of multiple overlapped zones and each zone defines a fuzzy set, it represents the target anatomical structure which specifies includes the image, exudates, vessel and optic disc shown where the zone represents the region of pixels those can be belong to either to fundus background or anatomical structure. Therefore, this model of our result can be specified mathematically.

c) Fuzzy relations (functions) composition

To perform the mathematical representation of membership functions, we can use fuzzy to represents algorithm for generation of core of representative membership functions through clustering into the clusters .then the centroid of the clusters will extract and used as first cores of the membership functions then the empirically determined by the support region.

2) Stage II: Fuzzy Model Aggregation

In this stage of processing, the values are assigned by the vector of fuzzy membership it is modified based on each fuzzy plane applied by the spatial filters. The foremost idea behind this process can be applied instead of spatial filters on pixel intensities (image space), we can even use the corresponding membership values (fuzzy membership space) as it can assigned mathematically.

C. Phase III: Image Post-Processing

The last stage of our proposed hybrid system is post processing or soft segmentation, which combines binarization, morphological post -processing and smoothing steps of the final phase. The finally segmented output of stage two will undergoes binarization through binary thresholding with the help of empirical thresholds according to target anatomical structure, we get the output semifinal accurately segmented structure .many isolated, and misclassified and artificial pixels are produced by binarization step.

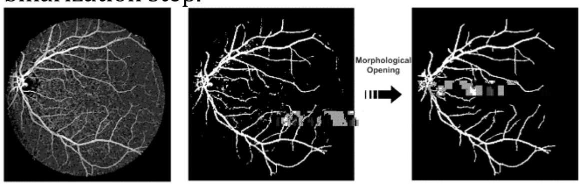

Fig. 8. Post-processing steps involved in retina vessels segmentation. (a) Output of processing stage. (b) Binarized output. (c) Morphological operations

In the case of exudate lesion extraction and optic disc, and In the case of vasculature structure are needed by using further steps: To obtain the smooth round shape of the optic disc and the clean, exudates islands by the smooth version are done by the morphological dilation operations are which is followed by convex hull transform, as shown in Fig. 9 and Fig. 10, respectively.

IV. RESULTS & DISCUSSION

The figure below shows the results after running the code/program.

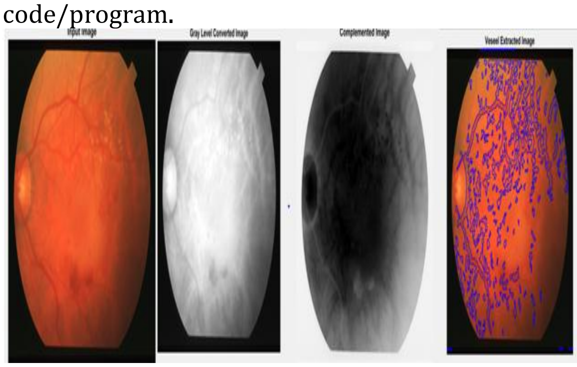

Fig:9 (a)*I*nput image (b)Gray level converted image, (c) Complemented image (d) Vessel extracted image. In the further step the vessel extracted image is converted to clahe enhanced image.

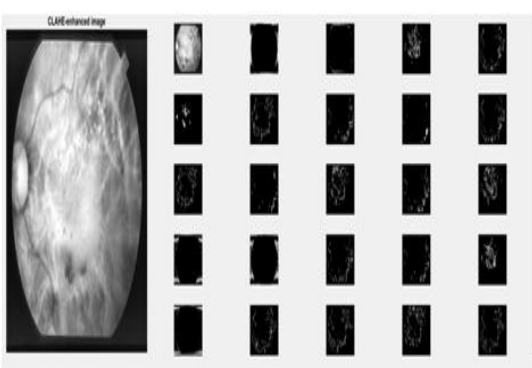

Fig:10 (a) Clahe-enhanced image (b) Cluster of exudates.

V. CONCLUSION

In this paper, we have proposed a automatic detection by generic system, localization and extraction of three retinal anatomical structures using morphological operations and hybrid of fuzzy set theory. From a clinical point of view, ophthalmic issues are obtained from development of computer-assisted diagnostic for the first step of design of retinal structures of extraction. The proposed subsystems outputs (vessels *detection subsystem, optic disc subsystem,* and *exudates lesions subsystem)* are obtained by the clinical information used integrated in a compact manner to capture that they contain.

From a research point of view, our paper makes two major contributions. First and the foremost proposed system eliminates the need for designing a separate system the retinal anatomical structure is detected by them; another one is to extract three different anatomical structures with various textures and features by the compact novel system. Depend upon this system, the performance detection and extraction tasks for another anatomical structures can be either inside of retina or outside of the retina or other organs can be developed by a hybrid framework.

Second, highly robust and accurate system is proposed has been shown for the performance of the state of -art on the public DRIVE, STARE, DRITSHTI-GS, and DiaRetDB1 retinal datasets. Therefore for the real -life diagnosis applications can be ideal by performing well at extracting vessels and optic disc from pathological retinal images.

From the same dataset Experimental results showed and used for the proposed system to achieve extract outputs in the terms of accuracy, sensitivity and specificity. This can be a clear idea of the powerful system that can be done by combining the hybrid manner with highly non-discriminative ones as fuzzy sets as morphological operations can be yielded when a highly discriminative operator can be done. The sort of trade-off between crisp world and the fuzzy one can be viewed by hybrid combination.

REFERENCES

[1] D. Purves, G. J. Augustine, D. Fitzpatrick, L. C. Katz, A.-S. LaMantia, J. O. McNamara, *et al.*, "Neuroscience," *Sunderland, MA: Sinauer Associates,* vol. 3, 2001.

[2] C. Wilkinson, F. L. Ferris, R. E. Klein, P. P. Lee, C. D. Agardh, M. Davis, *et al.*, "Proposed international clinical diabetic retinopathy and diabetic macular edema disease severity scales," *Ophthalmology,* vol. 110, pp. 1677-1682, 2003.

[3] J. B. Saaddine, A. A. Honeycutt, K. V. Narayan, X. Zhang, R. Klein, and J. P. Boyle, "Projection of diabetic retinopathy and other major eye diseases among people with diabetes mellitus: United States, 2005-2050," *Archives of ophthalmology,* vol. 126, pp. 1740-1747, 2008.

[4] P. H. Scanlon, C. Foy, R. Malhotra, and S. J. Aldington, "The influence of age, duration of diabetes, cataract, and pupil size on image quality in digital photographic retinal screening, "*Diabetes Care,* vol. 28, pp. 2448-2453, 2005.

[5] M. S. Haleem, L. Han, J. van Hemert, B. Li, and A. Fleming, "Retinal area detector from Scanning Laser Ophthalmoscope (SLO) images for diagnosing retinal diseases," *IEEE journal of biomedical and health informatics,* vol. 19, pp. 1472-1482, 2015.

[6] N. Solouma, A.-B. M. Youssef, Y. Badr, and Y. M. Kadah, "Real-time retinal tracking for laser treatment planning and administration," in *Medical Imaging 2001*, 2001, pp. 1311-1321.

[7] Y. Wang and S. C. Lee, "A fast method for automated detection of blood vessels in retinal images," in *Signals, Systems & Computers, 1997. Conference Record of the Thirty-First Asilomar Conference on*, 1997, pp. 1700-1704.

[8] A. Can, H. Shen, J. N. Turner, H. L. Tanenbaum, and B. Roysam, "Rapid automated tracing and feature extraction from retinal fundus images using direct exploratory algorithms," *IEEE Transactions on information Technology in Biomedicine,* vol. 3, pp. 125-138, 1999.

[9] H. Li and O. Chutatape, "Fundus image features extraction," in *Engineering in Medicine and Biology Society, 2000. Proceedings of the 22nd Annual International Conference of the IEEE*, 2000, pp. 3071-3073.

[10] S. Chaudhuri, S. Chatterjee, N. Katz, M. Nelson, and M. Goldbaum, "Detection of blood vessels in retinal images using two-dimensional matched filters," *IEEE Transactions on Medical Imaging,* vol. 8, pp. 263-269, 1989.

[11] N. P. Singh and R. Srivastava, "Retinal blood vessels segmentation by using Gumbel probability distribution function based matched filter," *Computer methods and programs in biomedicine,* vol. 129, pp. 40-50, 2016.

[12] B. Zhang, L. Zhang, L. Zhang, and F. Karray, "Retinal vessel extraction by matched filter with first-order derivative of Gaussian," *Computers in Biology and Medicine,* vol. 40, pp. 438-445, 4// 2010.

[13] Y. Zhang, W. Hsu, and M. L. Lee, "Detection of retinal blood vessels based on nonlinear projections," *Journal of Signal Processing Systems,* vol. 55, pp. 103-112, 2009.

[14] T. Zhu and G. Schaefer, "Retinal vessel extraction using a piecewise Gaussian scaled model," in *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2011, pp. 5008-5011.

[15] S. Bharkad, "Automatic segmentation of optic disk in retinal images," *Biomedical Signal Processing and Control,* vol. 31, pp. 483-498, 2017.

[16] K. Firdausy and K. W. Oktoeberza, "Segmentation of optic disc using dispersive phase stretch transform," in *Engineering Seminar (InAES), International Annual*, 2016, pp. 154-158.