A Novel Fuzzy-Based Thresholding Approach for Blood Vessel Segmentation from Fundus Image

Farha Fatina Wahid [1], Raju G. [2], Shijo M. Joseph [3], Debabrata Swain [4], Om Prakash Das [5], and Biswaranjan Acharya [6, *]

[1] Department of Information Technology, Kannur University, Kerala, India; Email: farhawahid@gmail.com (F.F.W.)
[2] CHRIST University, Bengaluru, India; Email: raju.g@christuniversity.in (R.G.)
[3] Mahatma Gandhi College, Iritty, Kannur, Kerala, India; Email: shijomjose71@gmail.com (S.M.J.)
[4] Department of Computer Science and Engineering, Pandit Deendayal Energy University, Gandhinagar, India; Email: debabrata.swain7@yahoo.com (D.D.)
[5] GSK India Global Services Private Limited, Bangalore, India; Email: ompdas@gmail.com (O.P.D.)
[6] Department of Computer Engineering-AI & BD, Marwadi University, Rajkot, India
*Correspondence: biswaacharya@ieee.org (B.A.)

***Abstract*—Retinal vessel segmentation is a vital part of pathological analysis in Fundus imaging. The automatic detection of blood vessels resolves several issues in the manual segmentation process. Most unsupervised segmentation methods depend on conventional thresholding techniques for final vessel extraction. It may lead to the loss of some vessel pixels, leading to inaccurate analysis of retinal diseases. In this work, we incorporate fuzzy concepts into two threshold-based vessel detection methods, namely "mean-c thresholding" and "Iso-Data thresholding," which results in a mask consisting of membership values rather than binary values. The two fuzzy-based thresholding algorithms are applied independently on each image, and the resultant membership image (mask) is fused to get a single membership mask. The fusion is performed using fuzzy union operation. Experiments are carried out with Fundus images from DRIVE, STARE and CHASE_DB1 databases.ses. The proposed fusion framework gives a 3%, 6%, and 5% increase in sensitivity compared to traditional thresholding methods when applied to the DRIVE, STARE, and CHASE_DB1 databases, respectively. The accuracy obtained for the datasets is 96.02%, 94.57%, and 94.34%, respectively.**

***Keywords*—fundus images, blood vessel segmentation, thresholding techniques, fuzzy thresholding, mean-c, IsoData**

I. Introduction

Retinal blood vessel segmentation is an active area of research in clinical pathology. The automatic extraction of retinal vessels is crucial in identifying several ophthalmic diseases, such as diabetic retinopathy, retinal artery occlusion, atherosclerosis, arteriolar narrowing, etc. [1]. Most ophthalmic diseases are caused due to abnormalities in the vascular system. Length, width, branching pattern, tortuosity, and angles are the attributes of retinal blood vessels that contribute more to the diagnostic procedure [2]. The abnormalities in the vessel attribute may lead to difficulties and challenges in blood vessel segmentation. Some challenges for retinal vessel segmentation are an extensive range of widths and tortuosity, relatively lower contrast of thin retinal vessels, the presence of brighter optic disc and fovea, and blood vessel shape variations [3].

Manual segmentation of retinal vessels by an expert is time-consuming and complex and needs repetitive analysis of the segmentation results. Automatic vessel segmentation, on the other hand, helps clinicians by providing accurate and speedy identification of blood vessels [1]. Several algorithms have been reported to precisely segment vessels from fundus images [4–6]. The broad categorization of retinal vessel segmentation falls into supervised and unsupervised algorithms. The supervised algorithms require prior training samples to learn the extraction of vessels. Most publically available databases provide manually segmented vessels for each input image in the database, known as gold standard images. These manually segmented vessels are used for training. Unsupervised algorithms, on the other hand, do not require prior training. It depends on techniques like matched filtering, morphological operations, thresholding techniques, multi-scale operations, etc. [1, 2]. As prior models are not required, unsupervised algorithms are easier to implement and widely used for retinal vessel segmentation.

Among the unsupervised algorithms, the thresholding technique is widely used as it helps to distinguish vessel and non-vessel pixels into two categories [1, 2]. Generally, thresholding techniques result in a binary mask with pixels classified as vessels or non-vessels based on a crisp decision. In vessel segmentation, the boundary between vessel and non-vessel is fuzzy rather than crisp. When a crisp decision is made, the thresholding techniques may fail to identify vessel pixels near the threshold value. In this paper, a fuzzy-based thresholding scheme for retinal blood vessel

Manuscript received October 31, 2022; revised November 28, 2022; accepted December 20, 2022; published March 8, 2023.

segmentation is proposed to address this issue. The work aims to develop a framework to fuzzify existing thresholding algorithms and produce a new efficient vessel segmentation algorithm by applying fusion rule on the fuzzified algorithms. In certain circumstances, when a crisp decision is made, the thresholding techniques may fail to identify vessel pixels near the threshold value. To address this issue, in this paper, a fuzzy-based thresholding scheme for retinal blood vessel segmentation is proposed. The objective of the work is to develop a framework to fuzzify existing thresholding algorithms, and produce new efficient vessel segmentation algorithm by applying fusion rule on the fuzzified algorithms.

A fuzzy membership is designed to quantify the degree to which each pixel in a fundus image can be a vessel pixel. The final segmented vessels are obtained by defuzzification of these membership weights. Two existing thresholding techniques, namely mean-c thresholding and IsoData thresholding, are chosen for the study. The two algorithms are modified by introducing a Fuzzification step using a Fuzzy membership function, resulting in a membership mask compared to a conventional binary mask. Fuzzy union operation is applied on the membership mask obtained from both the algorithms, and finally, defuzzification is applied to the resultant Fuzzy image. Retinal blood vessels are then segmented from the fundus image to the input fundus image using this mask.

The main contributions of our work are as follows.

- Framework to fuzzify thresholding algorithms.
- Retinal vessel segmentation algorithm that combines multiple fuzzified thresholding algorithms using max fusion rule.

The paper is organized as follows: Section II describes the literature review and the proposed methodology in Section III. Experimental results and discussion are provided in Section IV. Section V concludes the paper.

II. Literature Review

A summary of the state-of-the-art vessel segmentation algorithms is given below:

Zhu *et al.* (2016) [7] carried out vessel segmentation using an ensemble method. Classification and Regression Tree (CART) was used to train a weak classifier with a 36-dimensional feature vector extracted from the image. Finally, an AdaBoost classifier was constructed for vessel segmentation based on iterative training. Experiments were carried out on the DRIVE database, and an accuracy of 0.9535 was obtained. Zhu *et al.* (2016) [8] used Extreme Learning Machine (ELM) for vessel segmentation. The authors used a 39-dimensional discriminative feature vector, along with manual labels, to construct a matrix for pixels in the training set. On the DRIVE database, 0.9607 accuracies were reported. Orlando *et al.* (2016) [9] reported retinal vessel segmentation using a discriminatively trained fully connected random field model. A structured output support vector machine was used to automatically learn the parameters of the model. Based on the F1 score, the authors obtained 0.7857, 0.7332, 0.7644, and 0.7158 when experimenting with DRIVE, CHASE, STARE, and HRF image databases. Jin *et al.* (2019) [10] proposed a Convolutional Neural Network (CNN) based vessel segmentation mode. A set of convolutional layers were inserted into deep architectures to adapt different resolutions. The authors reported 0.9628 and 0.9690 accuracies on DRIVE and STARE databases.

An automatic technique for retinal vessel segmentation, which included the design of a bank of 180 Gabor filters, was proposed by Farokhian *et al.* (2017) [11]. The authors used an imperialism competitive algorithm for the automatic parameter selection. An accuracy of 0.9392 was reported on images from the DRIVE database. Mean-c thresholding for vessel segmentation was adopted by Dash and Bhoi (2017) [12]. The authors extracted the green channel of the image and enhanced it with the CLAHE algorithm. On the enhanced image, denoising was carried out before segmentation. Experiments were carried out on DRIVE and CHASE databases and reported accuracy of 0.955 and 0.954, respectively. Wang *et al.* (2018) [13] adopted a two-step process for blood vessel segmentation. Initially, vessels were enhanced using Hessian-based vessel filtering, and the enhanced images were segmented using fuzzy entropic thresholding. Based on precision, 87.70% was reported for images in the DRIVE database.

Grey level hit-or-miss transform (GHMT) for blood vessel segmentation was used by Pal *et al.* (2019) [14]. The input images were pre-processed using a novel approach of CLA-HE algorithm, footed on morphological gradient operation supported by 2D wavelet transform. The enhanced image was then segmented using GHMT. The iterative rotation of structural elements was the key idea of the algorithm. A hysteresis thresholding scheme was used to obtain the final segmented vessels. Experiments were conducted on the DRIVE database, and an accuracy of 94.37% was obtained. Sigursson EM *et al.* (2014) [15] proposed extracting vessel features based on adaptive morphological directional filters. The features relied on the linear connectivity and contrast of vessel structure. The features were used to carry out a data fusion task using fuzzy set theory. An average accuracy of 0.9515 was obtained for images in the DRIVE database.

Zhou *et al.* (2020) [16] proposed a vessel segmentation algorithm that dealt with complexities like false vein detection and loss of thin vessels. A line detection algorithm followed by the Hidden-Markow model was used to retrieve the blood vessels. On the DRIVE database, an accuracy of 0.9475 was obtained. DBSCAN algorithm, along with morphological reconstruction (MR), was used for vessel segmentation by Mardani and Maghooli (2021) [17]. The input images were divided into smaller rectangular blocks. The patterns of blood vessels were obtained using DBSCAN clustering parameters. Noise removal was performed using a median, logical AND operator, and MR filter. The vessels were segmented by setting the parameters R, ε, Z, and K. Thin vessels obtained using combinations of Z and K modes were joined to form thick vessels. An average accuracy of 0.9519 was obtained for images from the DRIVE database. Zhou *et al.* (2020) [16] proposed a vessel segmentation algorithm which dealt with complexities like false vein detection and loss of thin vessels. A line detection algorithm followed by the Hidden-Markow model was used to retrieve the blood vessels. On the DRIVE database, an accuracy of 0.9475 was obtained. DBSCAN algorithm along with morphological reconstruction (MR) was used for vessel segmentation by Mardani and Maghooli (2021) [17]. The input images were divided into smaller rectangular blocks. The patterns of blood vessels were obtained using DBSCAN clustering parameters. Noise removal was carried out using a median, logical AND operator and MR filter. The vessels were segmented by setting the parameters R, ε, Z and K. Thin vessels obtained using different combinations of Z and K modes were joined to form thick vessels. An average accuracy of 0.9519 was obtained for images from the DRIVE database.

Retinal vessel segmentation using a hierarchical mating tool was proposed by Swathi *et al*. (2021) [18]. In this work, a tri-map was created based on vein area highlights. Vessel components were separated using various level picture strangling strategies. An accuracy of 0.9600 was reported for images on the DRIVE database. An encoder-decoder structure-based vessel segmentation algorithm was proposed by Zhai *et al.* (2022) [19]. The inception module and multiple pyramid pooling models were used in the encoding and decoding phases, respectively. Finally, multi-scale and multi-local area feature fusion was adopted to improve segmentation results. For the DRIVE database, an accuracy of 0.9571 was reported. Yugander *et al.* (2022) [20] proposed a vessel segmentation algorithm based on maximum principal curvature and adaptive histogram equalization. The algorithm was divided into three stages. In the first stage, maximum principal curvatures were identified using a second-order Hessian derivative, followed by vessel separation from the background using the ISODATA algorithm. In the third stage, unwanted isolated vessels segmented were removed using morphological open operation. An average accuracy of 0.9418 was obtained for experiments on images from DRIVE and STARE databases. Chakour *et al.* (2022) [21] proposed a retinal vessel segmentation algorithm that integrated the enhancement stage with dynamic preprocessing, improving the segmentation accuracy. An accuracy of 0.9323 was obtained from images from the DRIVE database.

Based on the review, it is observed that most of the works used the DRIVE database for their experimentation. Different supervised algorithms such as Classification and Regression Tree (CART), Extreme Learning, Randomfield model, and CNN, as well as unsupervised algorithms like Gabor Filter, Mean-c thresholding, Adaptive morphological directional filters, GHMT, HMM, DBSCAN, Adaptive Histogram Equalization, are used for the segmentation of blood vessels from fundus images. Most of the method relies on binary crisp thresholding for distinguishing vessels and non-vessels. But, in real-time, the boundary between vessels and non-vessels is fuzzy. So, our focus is to develop an algorithm for vessel segmentation using a fuzzy-based thresholding technique. Based on the review carried out, it is observed that majority of the works used DRIVE database for their experimentation. Different supervised algorithms such as Classification and Regression Tree (CART), extreme learning, random field model, CNN as well as unsupervised algorithms like Gabor Filter, mean-c thresholding, adaptive morphological directional filters, GHMT, HMM, DBSCAN, adaptive histogram equalization, etc. are used for the segmentation of blood vessels from fundus images. Majority of the method relies on binary crisp thresholding for distinguishing vessels and non-vessels. But, in real time, the boundary between vessels and non-vessels is fuzzy. So, our focus is to develop an algorithm for vessel segmentation using fuzzy based thresholding technique.

III. Proposed Methodology

In this section, a novel retinal vessel segmentation algorithm is presented. Most state-of-the-art vessel segmentation algorithms enhance vessels before the segmentation process. Then a hard or crisp threshold is applied to distinguish vessel pixels from their surrounding non-vessel pixels, followed by a post-processing stage that eliminates unwanted isolated pixels from the extracted blood vessel pixels [12, 14, 22]. In this work, instead of using a crisp binary threshold for segmenting the blood vessels, Fuzzy based approaches are introduced. In hard thresholding, based on the threshold, a pixel is identified as a vessel pixel or not. A binary mask is created based on this concept. In the proposed scheme, a fuzzy membership calculated using a given threshold is assigned to each pixel which signifies the degree to which that pixel belongs to the group of vessel pixels. A mask is created with these membership values – a Fuzzy mask instead of a binary mask. These membership masks describe the membership weights for a pixel to be a vessel pixel.

Two popular thresholding algorithms, Mean-c thresholding, and IsoData thresholding, are chosen for the present study. Separate membership masks are created corresponding to the two approaches. The membership functions of the two thresholding techniques are then fused using the max fusion rule to obtain the final membership weights for each pixel in the input image. Finally, a defuzzification is performed to obtain crisp results on whether a pixel belongs to a vessel or non-vessel group. The block diagram of the proposed algorithm is depicted in Fig. 1.

A. Preprocessing

A preprocessing step is an essential pre-requisite for any segmentation algorithm to be effective. Here, preprocessing is carried out by enhancing the input fundus images, thereby providing better visibility of vessels. As an initial step for enhancement, the green channel of the input fundus image in the RGB color model is extracted. The Green channel is chosen due to its high contrast visibility in it. The Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm is applied to this green channel image. The enhanced retinal image is further denoised by using a median filter.

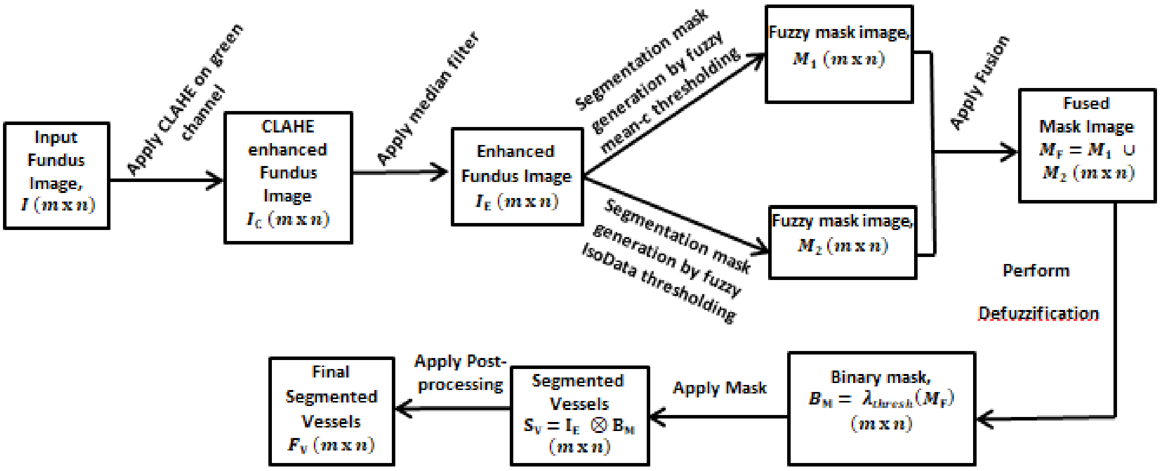

Figure 1. Block diagram of the proposed approach.

B. Segmentation Mask Generation

In conventional vessel detection using hard thresholding, a threshold is used to classify a set of pixels into two groups—vessel pixels and non-vessel pixels—by generating a binary mask. i.e., if the pixel value is greater than or equal to a predefined constant (threshold), say, then the pixel is classified as a vessel pixel. The binary mask image is obtained using Eq. (1).

$$BM = \{1,\ I(x,y) \geq \quad 0,\ \text{otherwise} \qquad (1)$$

The main issue with this binary mask image is that it may lead to the loss of some vessel pixels from being identified. Even if these pixels are very close to the threshold, due to the crisp thresholding, they cannot be considered vessel pixels (the reverse is also true). To overcome this issue, a novel fuzzy-based thresholding scheme for retinal vessel segmentation is proposed. The existing definition of threshold function is modified such that memberships are assigned to each pixel in the input image, which indicates the degree to which the pixel can belong to the group of vessel pixels, i.e., instead of generating a binary mask image, a fuzzy membership mask is generated. The membership function for fuzzifying the threshold function is given as follows.

$$\mu(x,y) = \begin{cases} 1,\ I(x,y) \geq \theta_U \\ \frac{I(x,y)-\theta_L}{\theta_U-\theta_L}, \quad \theta_L < I(x,y) < \theta_U \\ 0,\ I(x,y) \leq \theta_L \end{cases} \qquad (2)$$

where θ is the hard threshold, $\theta_U = \theta$ and $\theta_L = \beta \times \theta$, $1 > \beta \geq 0$.

The membership function in Eq. (2) can be adapted for any hard thresholding approach.

1) Fuzzy mean-c thresholding

In mean-c thresholding, the original input image is convolved using a mean filter with the neighborhood of size N×N. A difference image is obtained by subtracting the original image from the convolved image. Thresholding is carried out on this difference image using a constant c [12]. In the fuzzy-based mean-c thresholding, instead of generating a binary mask image, a membership mask image is returned based on the membership function defined in Eq. (2).

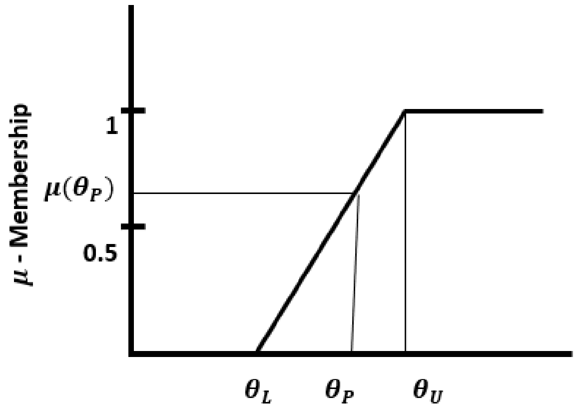

Figure 2. Membership function.

2) Fuzzy IsoData thresholding

IsoData thresholding is an iterative thresholding technique. The initial threshold is set to the mean value of the input image. The image is divided into two portions based on the threshold value, and the mean value of the two portions is calculated – MAT (Mean Above Threshold) and MBT (Mean Below Threshold). The new threshold value is set as the average of these two values. This process continues iteratively until the difference between two consecutive threshold values becomes less than a constant, say. Finally, the threshold value is normalized and set as the threshold for obtaining the binary mask image [22]. In the fuzzy-based IsoData thresholding, instead of taking the threshold as such, it is fuzzified using Eq. (2), and the application of this fuzzy-based thresholding returns a membership mask image corresponding to the input image.

C. Fusion of Membership Mask Images

In the proposed algorithm, the membership mask images returned by the Fuzzy mean-c thresholding and Fuzzy IsoData thresholding are fused using the fuzzy union (max) rule to obtain a fused membership mask image.

Let M1 and M2 be the membership mask images returned using fuzzy-based mean-c thresholding and IsoData thresholding algorithms. Then, the fused membership mask image MF is obtained as

$$MF = M1 \cup M2 \tag{3}$$

D. Defuzzification

The final binary mask image for vessel segmentation is obtained from the fused membership mask image by transforming the fuzzy memberships to crisp value with the help of defuzzification using λ-cut operation. It is given as

$$B_M = \lambda_{thresh}(M_F) \tag{4}$$

E. Vessel Extraction

The defuzzified binary mask image is applied to the enhanced green channel image to obtain the segmented blood vessels.

$$S_v = IE \otimes BM \tag{5}$$

where IE denotes the enhanced green channel image.

F. Post Processing

The segmented vessels obtained using Eq. (5) undergo post-processing with the help of morphological cleaning operations to remove isolated pixels from the segmented image.

IV. Experimental Results and Discussion

Experiments are carried out with images obtained from publically available fundus image databases like Digital Retinal Images for Vessel Extraction (DRIVE), Structured Analysis of Retina (STARE), and Child Heart and Health Study in England (CHASE_DB1) databases.

DRIVE database contains a total of 40 images which are divided into training and testing sets. The images in the database are obtained from a diabetic retinopathy screening programme conducted in the Netherlands. The 40 images in the database are randomly selected from those obtained from 400 subjects. Among the images chosen, only 7 had slight signs of diabetic retinopathy, and the remaining are healthy eye fundus. For both the training and testing sets, along with the images, corresponding manual segmented data and field-of-view masks are provided [23]. The STARE database consists of 400 raw images and includes a list of diagnoses and diagnosis codes for each image. There are separate sets of images for optic nerve identification, blood vessel segmentation, etc. For vessel segmentation, 20 sample images with manually segmented results from two experts are provided [24]. In the CHASE_DB1 database, there are 28 images obtained from 14 patients' right and left eyes. It also contains gold-standard data from two experts in the field [25].

For the implementation of mean-c thresholding, the window size is fixed to 13×13, and the constant c is fixed to 0.042. For the fuzzification of mean-c thresholding and IsoData thresholding, the value is fixed at 0.9. For defuzzification, the value is set to 0.85 empirically.

Generally, vessel segmentation algorithms are validated by comparing the results obtained using the automated method with the ground truth data available. The efficacy of the proposed algorithm is evaluated using performance metrics like sensitivity, specificity, and accuracy [26].

$$Sensitivity = \frac{truepositive}{truepositive + falsenegative} \tag{6}$$

$$Specificity = \frac{truenegative}{truenegative + falsepositive} \tag{7}$$

$$Accuracy = \frac{truepos + trueneg}{truepos + trueneg + falsepos + falseneg} \tag{8}$$

Based on the performance evaluation metrics, the results obtained using the two thresholding schemes (without incorporating the Fuzzy concept) and the proposed fusion-based fuzzy thresholding technique on images from DRIVE, STARE, and CHASE_DB1 databases are given in Tables I–III respectively.

Results obtained for all three algorithms from sample images from DRIVE, STARE, and CHASE_DB1 databases are depicted in Figs. 3–5.

TABLE I. Average Performance of The Algorithms Based on Performance Evaluation Metrics -DRIVE Database

	Sensitivity	Specificity	Accuracy
IsoData	0.6490	0.9853	0.9497
Mean-c	0.7376	0.9851	0.9593
Fusion	0.7691	0.9766	0.9602

TABLE II. Average Performance of The Algorithms Based on Performance Evaluation Metrics -STARE Database

	Sensitivity	Specificity	Accuracy
IsoData	0.6031	0.9609	0.9165
Mean-c	0.6326	0.9551	0.9354
Fusion	0.6948	0.9435	0.9457

TABLE III. Average Performance of The Algorithms Based on Performance Evaluation Metrics –CHASE_DB1 Database

	Sensitivity	Specificity	Accuracy
IsoData	0.6050	0.9568	0.9239
Mean-c	0.6917	0.9720	0.9401
Fusion	0.7435	0.9635	0.9434

A. DRIVE Dataset

Table I shows an average improvement of 3% in sensitivity measures obtained for the proposed fusion-based approach. The proposed method offers a slightly better value from an accuracy point of view. This work mainly focuses on fine-tuning the parameters to suit the DRIVE dataset. The computation time and accuracies obtained for sample images are given in Table IV. The computation time given is only an indication of the relative complexity. The increase in execution time compared to the base algorithms is minimal. The accuracy obtained is compared with a few selected methods (Table V). The proposal is giving a comparable or better performance.

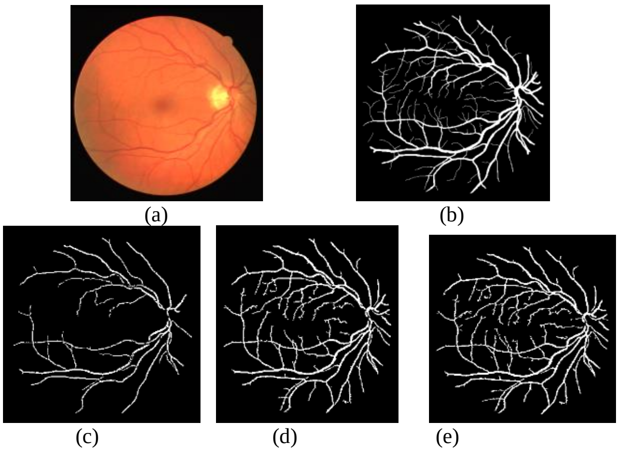

Figure 3. Segmented Vessels obtained for image *01_test* from DRIVE database (a) Original Image (b) Manually Segmented Vessels (c) IsoData thresholding (d) mean-c thresholding (e) Proposed fuzzy-based fusion approach.

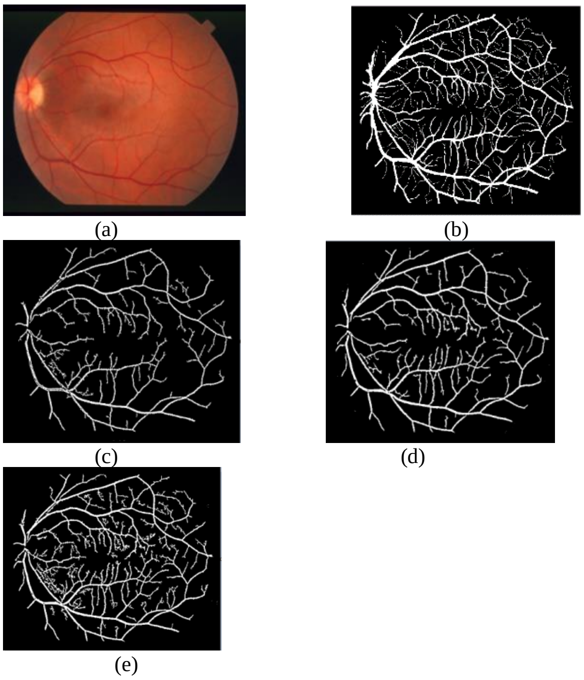

Figure 4. Segmented Vessels obtained for image *im0255* from STARE database (a) Original Image (b) Manually Segmented Vessels (c) IsoData thresholding (d) mean-c thresholding (e) Proposed fuzzy-based fusion approach.

B. STARE and CHASE Datasets

6% and 5% improvements in sensitivity measures are obtained for images in the STARE and CHASE_DB1 databases. Regarding accuracy measures, the proposed fuzzy-based fusion approach gives comparable results to the original thresholding techniques. This improvement in sensitivity measure is obtained with a slight decrease in specificity, which can be neglected.

TABLE IV. COMPUTATION TIME VS ACCURACY OF SAMPLE IMAGES

Image	Method	Time (in seconds)	Accuracy
01_test (DRIVE)	IsoData	0.3231	0.9207
	Mean-c	0.2661	0.9621
	Fusion	0.3531	0.9679
im0255 (STARE)	IsoData	0.4294	0.9237
	Mean-c	0.2296	0.9138
	Fusion	0.4550	0.9333
Image_05L (CHASE_DB1)	IsoData	0.8628	0.9427
	Mean-c	0.1830	0.9385
	Fusion	0.8961	0.9501

TABLE V. PERFORMANCE (ACCURACY) OF DIFFERENT ALGORITHMS BASED DRIVE DATABASE

Sl No.	Algorithm	Accuracy
1	Farokhian F *et al.* (2017) [11]	93.9
2	Dash and Bhoi (2017) [12]	95.5
3	Sigursson EM *et al.* (2014) [15]	95.2
4	Zhou *et al.* (2020) [16]	94.6
5	Mardani and Maghooli(2021) [17]	95.2
6	Swathi *et al.* (2021) [18]	96.0
7	Zhai *et al.* (2022) [19]	95.7
8	Yugander *et al.* (2022) [20]	94.2
9	Chakour *et al.* (2022) [21]	93.2
10	Proposed Method	96.02

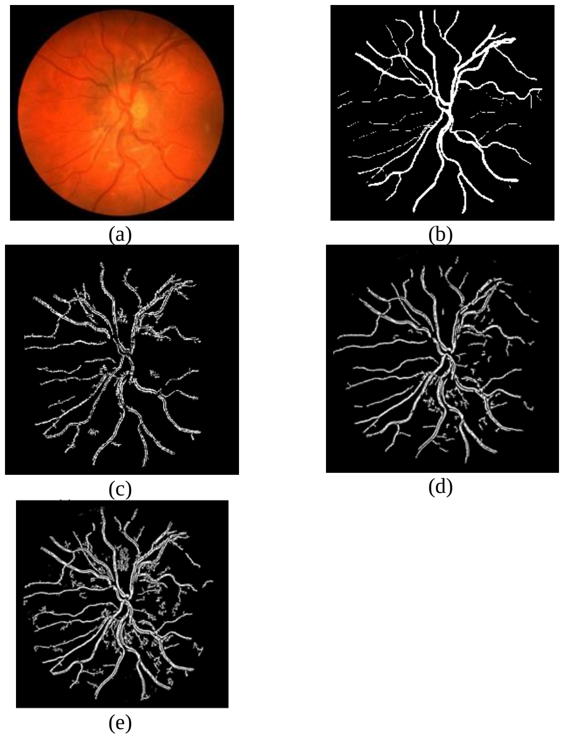

Figure 5. Segmented Vessels obtained for image *Image_05L* from CHASE_DB1 database (a) Original Image (b) Manually Segmented Vessels (c) IsoData thresholding (d) mean-c thresholding (e) Proposed fuzzy-based fusion approach.

Based on the experimentation carried out on DRIVE, STARE, and CHASE databases, it is observed that the proposed framework can identify more true positive pixels, leading to an increased sensitivity value. Also, the accuracy of the proposed fuzzy-based fusion framework is comparable with other state-of-the-art methods used for comparative study.

The framework is purely a classical segmentation algorithm using a fuzzy approach that does not involve learning. Learning-based methods give better accuracy with appropriate model parameters and fine-tuning [28]. But, it requires a complex learning process and sophisticated computing resources. The concept introduced can be incorporated into learning-based models also. One possible way to improve the algorithm is by learning optimal parameters using deep architecture.

The proposal opens up several possible research directions. Some of them are presented below:

- Preprocessing – several novel algorithms are available for Fundus enhancement. Their effectiveness in vessel segmentation is linked to the segmentation algorithm and vice versa. In this work, basic CLAHE is used. An extensive study may be carried out with other enhancement algorithms.
- Different Fuzzy implications shall be considered for aggregation or defuzzification.
- Values of performance indicators depend on the ground truth provided by the data sets. Hence experiments need to be carried out with more samples and data sets.
- Analysis of the key parameters and the possibility of relating the parameters with image statistics.
- The proposed framework is developed using two methods. It is extendable to other methods also.

V. Conclusion

This paper proposes a novel approach for blood vessel segmentation using a fuzzy-based thresholding technique. Instead of conventional thresholding techniques for blood vessel segmentation, a thresholding technique based on a fuzzy membership mask is introduced. Membership mask images using fuzzy-based mean-c thresholding and IsoData thresholding techniques are generated and fused using the fuzzy union rule. The fused membership mask image is defuzzified using a-a cut operation to obtain the final binary mask image for vessel extraction. The experimental analysis based on sensitivity, specificity, and accuracy measures shows improved performance compared to individual thresholding techniques. The proposal is a new framework that can be extended in different directions to design better approaches for vessel segmentation from fundus images.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

The basic idea of the work is prepared by Raju G. and Farha Fatina Wahid. Shijo M. Joseph and Debabrata Swain evaluated the proposal. The proposal is translated into a flow diagram by Farha Fatina Wahid and Raju G., which is refined by taking contributions from all authors. The algorithm is implemented and test with data by Farha Fatina Wahid. The programs were verified by Shijo M. Joseph and Debabrata Swain. Results are validated by Raju G., Biswaranjan Acharya and Om Prakash Das. Draft paper is prepared by Farha Fatina Wahid and is refined by Raju G., Biswaranjan Acharya and Om Prakash Das. The final version of the paper is read and approved by all authors.

References

[1] M. M. Fraz, P. Remagnino, A. Hoppe, *et al.*, “Blood vessel segmentation methodologies in retinal images — A survey,” *Comput Methods Programs Biomed*, 2012.

[2] K. B. Khan, A. A. Khaliq, A. Jalil, *et al.*, “A review of retinal blood vessels extraction techniques: Challenges, taxonomy, and future trends,” *Pattern Anal. Appl.*, 2018.

[3] J. Dash and N. Bhoi, “An unsupervised approach for extraction of blood vessels from fundus images,” *J. Digit. Imaging*, 2018.

[4] Z. Jiang, J. Yepez, S. An, and S. Ko, “Fast, accurate and robust retinal vessel segmentation system,” *Biocybern Biomed Eng*, 2017.

[5] D. Koukounis, C. Ttofis, A. Papadopoulos, *et al.*, “A high-performance hardware architecture for portable, low-power retinal vessel segmentation,” *Integr VLSI J.*, 2014.

[6] A. Oliveira, S. Pereira, and C. A. Silva, “Retinal vessel segmentation based on fully convolutional neural networks,” *Expert. Syst. Appl.*, 2018.

[7] C. Zhu, B. Zou, Y. Xiang, *et al*, “An ensemble retinal vessel segmentation based on supervised learning in fundus images,” *Chinese J. Electron*, 2016.

[8] C. Zhu C, Zou B, R. Zhao, *et al.*, “Retinal vessel segmentation in colour fundus images using Extreme Learning Machine,” *Comput. Med. Imaging Graph*, 2017.

[9] J. I. Orlando, E. Prokofyeva, and M. B. Blaschko, “A discriminatively trained fully connected conditional random field model for blood vessel segmentation in fundus images,” *IEEE Trans. Biomed Eng.*, 2017.

[10] Q. Jin, Q. Chen, Z. Meng, *et al.*, “Construction of retinal vessel segmentation models based on convolutional neural network,” *Neural Process Lett.*, 2019.

[11] F. Farokhian, C. Yang, H. Demirel, *et al.*, “Automatic parameters selection of Gabor filters with the imperialism competitive algorithm with application to retinal vessel segmentation,” *Biocybern Biomed Eng.*, 2017.

[12] J. Dash and N. Bhoi, “A thresholding based technique to extract retinal blood vessels from fundus images,” *Futur. Comput. Informatics J.*, 2017.

[13] H. Wang, Y. Jiang, X. Jiang, *et al.*, “Automatic vessel segmentation on fundus images using vessel filtering and fuzzy entropy,” *Soft Comput.*, 2018.

[14] S. Pal, S. Chatterjee, D. Dey, *et al.*, “Morphological operations with iterative rotation of structuring elements for segmentation of retinal vessel structures,” *Multidim Syst Sign Process*, 2019.

[15] E. M. Sigursson, S. Valero, J. A. Benediktsson, *et al.*, “Automatic retinal vessel extraction based on directional mathematical morphology and fuzzy classification,” *Pattern Recognit. Lett.*, 2014.

[16] C. Zhou, X. Zhang, and H. Chen, “A new robust method for blood vessel segmentation in retinal fundus images based on weighted line detector and hidden Markov model,” *Comput. Methods Programs Biomed*, 2020.

[17] K. Mardani and K. Maghooli, “Enhancing retinal blood vessel segmentation in medical images using combined segmentation modes extracted by DBSCAN and morphological reconstruction,” *Biomed Signal Process Control*, 2021.

[18] S. Swathi, S. Sushma, C. D. Supraja, *et al.*, “A hierarchical image matting model for blood vessel segmentation in retinal images,” *Int. J. Syst Assur. Eng. Manag.*, 2021.

[19] Z. L. Zhai, S. Feng, L. Yao, and P. Li, “Retinal vessel image segmentation algorithm based on encoder-decoder structure,” *Multimed. Tools Appl.*, 2022.

[20] P. Yugander, K. Abhishek, P. S. Reddy, *et al.*, "Extraction of blood vessels from retinal Fundus Images using maximum principal curvatures and adaptive histogram equalization," in *Proc. 2022 1st Int. Conf. Electr. Electron. Inf. Commun. Technol.*, 2022.
[21] E. Chakour, Y. Mrad, A. Mansouri, *et al.,* "Blood vessel segmentation of retinal fundus images using dynamic preprocessing and mathematical morphology," in *Proc. 8th Int. Conf. Control Decis. Inf. Technol.*, 2022.
[22] T. Coye, "A novel retinal blood vessel segmentation algorithm for fundus images," *MATLAB Cent. File Exch.*, 2015.
[23] J. Staal, M. D. Abràmoff, M. Niemeijer, *et al.*, "Ridge-based vessel segmentation in colour images of the retina," *IEEE Trans Med Imaging*, 2004.
[24] A. Hoover, "Locating blood vessels in retinal images by piecewise threshold probing of a matched filter response," *IEEE Trans Med. Imaging*, 2000.
[25] C. G. Owen, A. R. Rudnicka, R. Mullen, *et al.*, "Measuring retinal vessel tortuosity in 10-year-old children: Validation of the computer-assisted image analysis of the retina (caiar) program," I*nvestig. Ophthalmol. Vis. Sci.*, 2009.
[26] Sensitivity and Specificity. [Online]. Available: http://www.med.emory.edu/EMAC/curriculum/diagnosis/sensand.htm
[27] T. Shyamalee and D. Meedeniya, "Glaucoma detection with retinal fundus images using segmentation and classification," *Mach. Intell. Res.*, 2022.

Farha Fatina Wahid was born in Abu Dhabi, the United Arab Emirates on July 12, 1988. She obtained her B.Sc. degree in computer science in 2009, master of computer applications in 2012, and PhD in computer science in 2021 from Kannur University, Kerala, India.
She is currently an assistant professor in the Department of Information Technology, at Kannur University, Kerala, India. Before this, she was a senior research fellow under the UGC MANF scheme from 2014 to 2019 and a Guest Lecturer from 2012 to 2014 at the Department of Information Technology, Kannur University, Kerala, India. Her research interests include computer vision, machine learning and image processing. She published seven journal papers, five book chapters, and six articles in conference proceedings in the area of medical image processing and human gait recognition.
Dr. Wahid received the best paper award at ICTUS Conference held in Dubai, UAE in 2017. She also received UGC's Maulana Azad National Fellowship for pursuing PhD in 2014.

Raju G. is a native of Kollam, Kerala, India. He obtained an M. Sc. in physics (1986), a master's in computer applications (1992), and a PhD in computer science (2003) from the University of Kerala, India. He also completed his M.Tech. in computer and information technology from Manonmaniam Sundaranar University (2011), Tamil Nadu, Kerala.
He is currently working as a professor in computer science at CHRIST University, Bengaluru, India. He was a dean, academic council member and professor at Kannur University Kerala. His research interests include image processing, computer vision, data science, machine learning and deep learning.
Prof. Raju is a senior member of IEEE. He has published more than 125 research articles in journals, book chapters and conference proceedings.

Shijo M Joseph was born in Thodupuzha, Kerala, India on May 05, 1970. He obtained his degree in B.Sc. CMS (computer science mathematics & statistics) in 1993, master of computer science in 1996, and PhD in Computer Science from Kannur University Kerala, India.
He is currently an associate professor in the Department of Computer Science at Mahatma Gandhi College, Kerala, India. Before this, he was a lecturer at Mary Matha College Manathavady, Wayanad, Kerala, from 1996 to 2001. His research interests include Signal Processing, Speech processing, image processing, and Coding.
Dr. Shijo published seven journal papers, one book, one book chapter, ten articles in international conference proceedings, and three articles in national conference proceedings all papers are related signal processing.

Debabrata Swain was born in Odisha, India. He obtained his B.Tech degree in computer science and engineering from Bijupattnayak University of Technology, Odisha in 2008, and his M.Tech in computer science at Berhampur University, Odisha in2011. He was awarded his Ph. D. in computer engineering from KIIT University, India in 2020.
Now he is working as an assistant professor at Pandit Deendayal Petroleum University, Gandhi Nagar, India. Before he worked in different Univesity and engineering colleges like CHRIST Deemed to be University, Vishwakarma Institute of Technology, SRES College of Engineering Kopargaon, and Sharad Chandra Pawar College of Engineering at Pune, India.
Dr. Swain published more than 20 research articles in indexed journals. His research interest is Deep Learning and AI.

Om Prakash Das was born in Odisha, India. He obtained a bachelor's in engineering from Utkal University in 1999, MBA in information technology from Bharathidasan University in 2014 and an Executive Program in Business Analytics from IIM Kolkata. He is currently working for GSK as a senior manager in digital and technology. Before this, he worked as an analytic manager at Wells Fargo and as a Manager Consulting Expert in CGI.
He has extensive experience around 18 years in the information technology industry. His area of expertise is machine learning, data engineering and business intelligence.

Biswaranjan Acharya is a native of Odisha, India. He obtained his graduation in 2005 from Utkal University, Odisha, India. He received the MCA degree from IGNOU, New Delhi, India, in 2009, and the M.Tech. degree in computer science and engineering from the Biju Pattanaik University of Technology (BPUT), Rourkela, Odisha, India, in 2012.
He is currently pursuing a PhD degree in computer application with the Veer Surendra Sai University of Technology (VSSUT), Burla, Odisha, India. He is currently working as an Assistant Professor with the Department of Computer Engineering-AI, Marwadi University, Rajkot, Gujarat, India. He has a total of ten years of experience in academia at some reputed universities, such as Ravenshaw University and in the software development field.
He has published more than 40 research articles in reputed international journals and served as a reviewer for many peer-reviewed journals. He has more than 50 patents on his credit. His research interests include multiprocessor scheduling along with different fields, such as data analytics, computer vision, machine learning, and the IoT. He is also associated with various educational and research societies, such as IACSIT, CSI, IAENG, and ISC.