Comparative Analysis of Improved of FCM Algorithms in the Segmentation of Retinal Blood Vessels

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Research Article

Keywords: Fuzzy c-means clustering, Retinal fundus images, Vessels segmentation, Comparison, Analysis.

Posted Date: January 5th, 2022

DOI: <https://doi.org/10.21203/rs.3.rs-886041/v1>

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Comparative analysis of improved of FCM algorithms in the segmentation of retinal blood vessels

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Abstract

The main purpose of identifying and locating the vessels of the retina is to specify the various tissues from the vascular structure of the retina (which could be differentiated between wide or tight) of the background of the fundus image. There exist several segmentation techniques that are spreading to divide the retinal vessels, depending on the issues and complexity of the retinal images. Fuzzy c-means is one of the most often used algorithms for retinal image segmentation due to its effectiveness and speed. This paper analyzes the performance of improved FCM algorithms for retinal image segmentation in terms of their ability and capability in segmenting and isolating blood vessels. The process we followed in our paper consists of two phases. Firstly, the pre-processing phase, where the green channel is taken for the color image of the retina. Contrast enhancement is performed through CLAHE, proceeded by applying bottom-hat filtering to bottom-hat filtering is applied with the purpose to define the region of interest. Secondly, in the segmentation phase the obtained image is segmented using FCM algorithms. The algorithms chosen for this study are: FCM, EnFCM, SFCM, FGFCM, FRFCM, DSFCM_N, FCM_SICM and, SSFCM performed on DRIVE and STARE databases. Experiments accomplished on DRIVE and STARE databases demonstrate that the DSFCM_N algorithm achieves better results on the DRIVE database, whereas the FGFCM algorithm provides better results on the STARE database in term of accuracy. Concerning time consumption. The FRFCM algorithm requires less time than other algorithms in the segmentation of retinal images.

Keywords: Fuzzy c-means clustering, Retinal fundus images, Vessels segmentation, Comparison, Analysis.

1 Introduction

The segmentation of the blood vessels is a high priority for interpreting medical images because

the analysis of vessels is crucial for examination, treatment planning, execution, and evaluation of clinical outcomes in various fields, including neurosurgery, laryngology, and ophthalmology.

Generally, in the field of ophthalmology, the segmentation of vessel structures from the fundus images is often done manually, which is tedious, time-consuming, and error-prone, especially for large population screening. Also, the rating of the majority of pixels is often apparent to an ophthalmologist, except for those of vessels of near pathology, and those of small vessels which are difficult to distinguish easily [Almotiri et al. \(2018\)](#), [Niemeijer et al. \(2004\)](#), [Srinidhi et al. \(2017\)](#). Therefore, automatic segmentation is needed, as it can reduce manual fundus photography while increasing speed and accuracy. However, there are many challenges related to the classification of vessels in the image of the retina, which comprise the low contrast accompanying the fundus image, the inhomogeneity of the background lighting, and noise. The inhomogeneity and noise occur as a result of the process of imaging, The noise can alter the intensity of a pixel and results in an uncertain classification. While the low contrast that accompanies the image is due to the variation between the background and the contrast of the different blood vessels. As a result, the difference between thicker and thinner vessels is higher. Another challenge depends on color variations that occur in the retina of different subjects, which are rooted in biological characteristics. In addition, the fundus image contains noise that can alter the intensity of a pixel and affect its classification certainty [Abdulsahib et al. \(2021\)](#). Inevitably, there are various methods and techniques available for vessel segmentation of retinal images. In such a manner, clustering is a popular method for image segmentation, and diverse algorithms have been proposed and used medically. Clustering is an unsupervised classification approach that seeks to divide data into numerous disjoint subsets based on data characteristics. clustering technology generally classifies the image pixels in c-clusters in order that members of the same cluster are more associated with one another than those of other cluster, where the number, c-of clusters is generally predefined or fixed by a validity criterion or according to priori knowledge. The clustering algorithms of image segmentation involve k-means [Macqueen \(1967\)](#), k-medoids [Bezdek et al. \(1984\)](#), mean-shift [Comaniciu and Meer \(2002\)](#), fuzzy c-means (FCM) [Bezdek et al. \(1984\)](#), etc. Therefore, FCM based algorithms have been popularly used in the segmentation of

medical images. Such success mainly attributes to the introduction of fuzziness for the belongingness of all image pixels. This allows the clustering methods to preserve more information from the original image than the hard segmentation methods. In order to increase the performance of FCM for remove noise, some techniques has proposed. Bias correction fuzzy c-means (BCFCM) are a type of fuzzy c-means in which a bias field is added to the objective function, according to [Ahmed et al. \(2002\)](#). Despite the fact that the bias field can repair pixels distorted by noise, it has low efficiency for many types of noisy images due to the bias field's sparsity. Based on this research, [Zhang et al. \(2018\)](#) proposed a deviation sparse FCM (DSFCM) that employs regularization with sparsity constraint to ease the occurrence of a BCFCM defect. DSFCM produces accurate clustering centers, however it is susceptible to regularization parameters and so has a low robustness. In the same work, [Zhang et al. \(2018\)](#) take the deviations between measured values and theoretical values into account. In [Szilagyi et al. \(2003\)](#) suggested an enhanced FCM (EnFCM) by incorporating a histogram into the goal function and applying local linear-weight filtering to each pixel. The EnFCM achieves good computational performance in image segmentation because the number of gray levels is usually significantly fewer than the pixels in a grayscale image. On the basis of this work, [Cai et al. \(2007\)](#) proposed the fast generalized FCM (FGFCM) by incorporating a bilateral filter into the objective function. In the work [Chuang et al. \(2006\)](#) the spatial information was incorporated into conventional FCM for better segmenting images. Recently, Using morphological reconstruction and membership filtering, [Lei et al. \(2018\)](#) suggested a fast and robust fuzzy c-means (FRFCM). FRFCM obtains acceptable segmentation results and needs a short accomplishment time for various kinds of images. In the same context, [Wang et al. \(2020\)](#) proposed a robust fuzzy clustering algorithm based on membership linking and filtering for the segmentation of noise images. [Jia et al. \(2020\)](#) suggested an approach (SSFCA) related to a regularization under Gaussian metric that is inserted in the objective function of fuzzy clustering algorithms to acquire fuzzy membership with sparsity, which decreases the proportion of noisy features and enhances clustering results.

Following the work cited above, the purpose of this study is to compare the effectiveness of improving FCM algorithms in blood vessel segmentation, which have a publicly available implementation, to push researchers to develop and suggest algorithms that are compatible with the complexities of eye retina images, based on the theory of fuzzy. Eight variants of the FCM algorithm were studied. Their performance was evaluated using two publicly available databases (DRIVE, STARE) with the ground truth of vessel segmentation. In order to keep the experimental conditions consistent, the image preprocessing portions of the methods were separated and applied to all algorithms. The choice fell on: FCM, EnFCM, SFCM, FGFCM, FRFCM, DSFCM_N, FCM.SICM, SSFCM.

The remainder of this work is arranged in the following manner. In Section II, we present the background for our research. In Section III, we explain in detail the methodology used. The experimental results on DRIVER and STARE databases are described in Section IV. Finally, we present the conclusion in Section V.

2 Background

Clustering is an unsupervised segmentation where the image is segmented in several groups or regions. It is applied generally in various decision-making obstacles and chiefly in medical image studies. Fuzzy set theory suggested by Zadeh (1965) provides a mighty tool for such soft partitioning. Fuzzy clustering is hence an efficient tool in segmenting medical images. Dunn (1973) developed fuzzy c-means clustering (FCM) based on fuzzy set theory, which Bezdek et al. (1984) improved for image segmentation. For the purpose of solve some of the problems it encounters in image segmentation, there are various extensions of the FCM algorithms available for image segmentation. The performance of these algorithms depends on the type of the images, and on the targeted area. In this section, we present FCM and some extension FCM algorithms that we study in point of view, efficiency, in retinal segmentation

2.1 FCM

An image I with P pixels. Since each image pixel often implies a set of attributes (variables), I

can be formulated as $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_P\} \subset \mathbb{R}^P$. The FCM algorithm divides X into several clusters C by minimizing the following objective function:

$$J_{FCM} = \sum_{i=1}^C \sum_{j=1}^P u_{ij}^m \|\mathbf{x}_j - \mathbf{v}_i\|^2 \quad (1)$$

Subject to

$$\sum_{i=1}^C u_{ij} = 1, \text{ for } j \in \{1, 2, \dots, P\}, \text{ with } 0 \leq u_{ij} \leq 1 \quad (2)$$

where,

u_{ij} : is the degree of membership of x_j in the cluster C_i .

m : is the fuzzification exponent ($m > 1$) .

x_j : is the i th of d -dimensional measured data.

v_i : is the d -dimension center of the cluster.

$\|\cdot\|$: is the Euclidean distance.

The minimization of (1) can be realized by iteratively updating the partition matrix and the cluster centers:

$$u_{ij}^m = \frac{1}{\sum_{q=1}^C \left(\frac{\|\mathbf{x}_j - \mathbf{v}_i\|}{\|\mathbf{x}_j - \mathbf{v}_q\|} \right)^{\frac{2}{m-1}}} \text{ and } \mathbf{v}_i = \frac{\sum_{j=1}^n u_{ij}^m \cdot \mathbf{x}_j}{\sum_{j=1}^n u_{ij}^m} \quad (3)$$

By presetting a nonnegative threshold ε , (FCM)¹ iterates until $\max_{ij} \left\{ \left\| u_{ij}^{(t+1)} - u_{ij}^{(t)} \right\| \right\} < (\varepsilon)$ has been met. Here, t is an iteration index. This procedure converges to a local minimum or a saddle point of J_{FCM} .

2.2 EnFCM

Enhanced fuzzy c means (EnFCM)² algorithm was proposed by Szilagyi et al. (2003) based on FCM.S Ahmed et al. (2002) algorithm research. It executes clustering based on gray-level histograms (l) rather than pixels of a summed image, which lessens the computational complexity. A linearly-weighted sum image (ξ) is formed in advance from the original image and its local neighbor average

¹<https://fr.mathworks.com/help/fuzzy/fcm.html>

²<https://github.com/marearth/fcm-m>

image in terms of:

$$\xi_l = \frac{1}{\alpha + 1} \left(x_l + \frac{\alpha}{N_R} \sum_{j \in N_l} x_j \right) \quad (4)$$

where,

ξ_l : is gray value of the l th pixel of the image (ξ) .

x_j : is the neighbors of x_l .

α : is control the effect of the neighbors term.

N_l : is stands for the set of neighbors x_j falling into a window around x_l .

Next, the clustering process is running on the gray level histogram of the newly formed image (ξ).

As a result, the objective function, in this case is represented as :

$$J_{EnFCM} = \sum_{i=1}^c \sum_{l=1}^q \gamma_l u_{il}^m (\xi_l - v_i)^2 \quad (5)$$

Subject to

$$\sum_{l=1}^q \gamma_l = N \text{ and } \sum_{i=1}^c u_{il} = 1 \quad (6)$$

where,

v_i : is the prototype of the i th cluster.

u_{il} : is the fuzzy membership of gray value l with respect to cluster i .

q : is the number of gray levels of the addressed image which, usually much less N .

γ_l : is the total number of pixels with a gray value of l .

The J_{EnFCM} is minimized, employing the following equations for calculating the membership partition matrix and the cluster centers:

$$u_{il} = \left[\sum_{j=1}^c \left(\frac{\xi_l - v_i}{\xi_l - v_j} \right)^{\frac{2}{m-1}} \right]^{-1} \quad (7)$$

$$v_i = \frac{\sum_{l=1}^q \gamma_l u_{il}^m \xi_l}{\sum_{l=1}^q \gamma_l u_{il}^m} \quad (8)$$

The iterative process of the EnFCM algorithm is similar to the FCM algorithm, but it is implemented to the new image (4) by using (7) and (8).

2.3 SFCM

Chuang et al. (2006) suggested a spatial fuzzy c-means (SFCM)³ algorithm in which spatial information can be integrated into fuzzy membership functions directly using

$$h_{ij} = \sum_{k \in N_b} u_{ik} \quad (9)$$

where,

N_b : is local window centered around the image pixel n .

h_{ij} : is the probability that pixel x_j belongs to i th cluster.

The memberships u_{ij} is updated using the following relationships:

$$u_{ij} = \frac{u_{ij}^p h_{ij}^q}{\sum_{k=1}^c u_{kj}^p h_{kj}^q} \quad (10)$$

where,

p, q : two parameters controlling the respective contribution. The weighted u_{ij} and the centroid v_i are updated as usual according to Equation 3.

2.4 FGFCM

Cai et al. (2007) proposed the fast generalized fuzzy c-means clustering (FGFCM)⁴ that included a new factor S_{ij} as a local similarity measure trying to ensure both detail preservation and noise-immunity for image segmentation. Simultaneously, it eliminates the empirically-adjusted parameter α that EnFCM requires, and it ultimately achieves gray-level histogram clustering. Its definition is given as follows:

$$S_{ij} = \begin{cases} \exp\{-\max(|p_i - p_j|, |q_i - q_j|)/\lambda_s - \|x_i - x_j\|^2/\lambda_g \sigma_i^2\} & i \neq j, \\ 0 & i = j. \end{cases} \quad (11)$$

where,

i th : is the center of the local window.

j th : is the set of the neighbors falling into the window around the i th pixel.

p_i, q_i : is the coordinates of pixel i .

x_i : is the gray level the value i .

λ_s, λ_g : two scale factors playing a role similar to factor α in EnFCM.

σ_i is a function of the local density surrounding the

³<https://fr.mathworks.com/matlabcentral/fileexchange/31068-spatial-fuzzy-clustering-and-level-set-segmentation>

⁴<https://github.com/marearth/fcm.m>

central pixel, and its value indicates the local window's gray value homogeneity degree. σ_i is defined as:

$$\sigma_i = \sqrt{\frac{\sum_{j \in N_i} \|x_i - x_j\|^2}{N_R}} \quad (12)$$

FGFCM algorithm integrates local and gray level information (11) inside its objective function producing in advance a new image (ξ_i) as follows:

$$\xi_i = \frac{\sum_{j \in N_i} S_{ij} x_j}{\sum_{j \in N_i} S_{ij}} \quad (13)$$

where,

ξ_i : is the gray level value of the i th pixel of the image ξ .

x_i : is the gray level value of the neighbors of window center.

N_i : is the set of neighbors falling in the local window.

S_{ij} : is the local similarity measure between the i th and the j th pixel.

2.5 FRFCM

Lei et al. (2018) suggested a fast and robust fuzzy c-means clustering algorithm (FRFCM)⁵, which is based on morphological reconstruction and membership filtering. They could be considered as preprocessing and post-processing, respectively. FRFCM is done on gray level histogram similar to EnFCM. For the data point ($x_j = RC(x)$) and its membership value (u_{ij}), the objective function is minimized using the Lagrange function, where ($RC(x)$) is the morphological closing reconstruction of original image (x). The objective function is written as follows:

$$J_{FRFCM} = \sum_{j=1}^N \sum_{i=1}^c \gamma_j u_{ij}^m \|x_j - y_i\| - \lambda \left(\sum_{i=1}^c u_{ij} - 1 \right) \quad (14)$$

where,

γ_l : is the number of the pixels having the gray value equal to l .

u_{il} : is the fuzzy membership of gray value l .

x_j : is the gray level of an image that has been reconstructed using MR ($RC(x)$).

λ : is a Lagrange multiplier.

Instead of using the distance vector (between the pixel values and cluster centers), a faster membership filtering is used. The following relationships are used to update the memberships filtering:

$$u_{ij} = \|x_j - y_i\|^{-2/(m-1)} / \sum_{r=1}^c \|x_j - y_r\|^{-2/(m-1)} \quad (15)$$

The cluster centers (y_i) is updated using the following relationships:

$$y_i = \sum_{j=1}^N \gamma_j u_{ij}^m x_j / \sum_{j=1}^N \gamma_j u_{ij}^m \quad (16)$$

2.6 DSFCM_N

In deviation-sparse fuzzy c-means with neighbor information (DSFCM_N)⁶ algorithm, Zhang et al. (2018) take into account the deviations e_k between measured values x_k and theoretical values $x_{\Delta k}$. In a different wording, instead of employing the measured values for clustering directly, the theoretical values calculated from measured values are involved in clustering. In this state, the accuracy of the calculated deviations would have a great influence on the clustering results. To distinguish noise from outliers, Zhang et al. (2018) imposed sparsity constraint on the deviations between measured and theoretical values. Moreover, this sparsity could also ensure that the deviations would not diverge. The objective function is denoted as:

$$J_{DSFCM-N} = \sum_{i=1}^c \sum_{j=1}^N u_{ij}^m \left(\sum_{k \in N_j} \frac{1}{1 + d_{kj}} \|x_k - e_k - y_i\|_2^2 \right) + \sum_{t=1}^l \lambda_t \sum_{k \in N_j} \frac{\sum_{j=1}^N \|e_{jt}\|^p}{1 + d_{kj}} \quad (17)$$

where,

k : is the neighbor of pixel j in the local window N_j .

N_j : is the local window centralized in j .

N_k : is the neighbor pixels including j .

d_{kj} : is the Euclidean distance between k and j .

e_k : is the deviation vector of pixel k .

l : is the dimension of the data.

λ : is a regulating vector of length l .

⁵<https://github.com/jiaxhsust/Significantly-Fast-and-Robust-FCM-Based-on-Morphological-Reconstruction-and-Membership-Filtering>

⁶https://github.com/zhangyuxuan1996/DSFCM_N

The deviation matrix (e_{jt}) is updated using the following relationships:

$$e_{jt} = \frac{\text{soft} \left(\frac{\sum_{i=1}^c \sum_{k \in N_j} \left(\frac{(u_{ik})^m (x_{jt} - v_{iq})}{1 + d_{kj}} \right)}{\sum_{i=1}^c \sum_{k \in N_j} \frac{1}{1 + d_{kj}} (u_{ik})^m} \right)}{\sum_{i=1}^c \sum_{k \in N_j} \frac{1}{1 + d_{kj}} (u_{ik})^m} \quad (18)$$

The memberships (u_{ij}) is updated using the following relationships:

$$u_{ij} = \left(\frac{\sum_{r=1}^c \left(\sum_{k \in N_j} \frac{1}{1 + d_{kj}} \|x_k - e_k - y_i\|^2 / \sum_{k \in N_j} \frac{1}{1 + d_{kj}} \|x_k - e_k - y_r\|^2 \right)^{1/m-1}}{\sum_{k \in N_j} \frac{1}{1 + d_{kj}} \|x_k - e_k - y_i\|^2} \right)^{-1} \quad (19)$$

The cluster centers (y_i) is updated using the following relationships:

$$y_i = \left(\sum_{j=1}^N u_{ij}^m \sum_{k \in N_j} \frac{1}{1 + d_{kj}} (x_k - e_k) \right) / \sum_{k \in N_j} \frac{1}{1 + d_{kj}} \sum_{j=1}^N u_{ij}^m \quad (20)$$

2.7 FCM_SICM

Robust fuzzy c-means clustering algorithm with adaptive spatial, constraint, and membership (FCM_SICM) ⁷ linking for noise image segmentation proposed by Wang et al. (2020). Firstly, the fast bilateral filter is applied to obtain local spatial and intensity information. Secondly, an absolute difference image between the original image and the bilateral filtered one is used, and the reciprocal of the different image whereas the different image itself constrain conventional FCM, as well as, the local spatial and intensity information, respectively. Finally, membership linking is reached by summing each membership degree calculated from the earlier iteration within every cluster in squared logarithmic form as the denominator of the objective function as follows:

$$J_{FCM_SICM}^{(t)} = \sum_{i=1}^K \frac{\sum_{j=1}^N \frac{1}{\Delta y_j} (u_{ij}^{(t)})^m \|y_j - c_i^{(t)}\|^2 + \sum_{j=1}^N \Delta y_j (u_{ij}^{(t)})^m \|\bar{y}_j - c_i^{(t)}\|^2}{\ln^2 \left(\sum_{e=1}^N u_{ie}^{(t-1)} + 1 \right)} \quad (21)$$

Subject to

$$\sum_{i=1}^K u_{ij}^{(t)} = 1 \quad (22)$$

The center (c_i) is updated using the following relationships:

$$c_i^{(t)} = \frac{\sum_{j=1}^N \left(\frac{1}{\Delta y_j} y_j + \Delta y_j \bar{y}_j \right) (u_{ij}^{(t)})^m}{\sum_{j=1}^N \left(\frac{1 + \Delta y_j^2}{\Delta y_j} \right) (u_{ij}^{(t)})^m} \quad (23)$$

The membership (u_{ij}) is updated using the following relationships:

$$u_{ij}^{(t)} = \frac{1}{\sum_{r=1}^K \left[\frac{\frac{\frac{1}{\Delta y_j} \|y_j - c_i^{(t)}\|^2 + \Delta y_j \|\bar{y}_j - c_i^{(t)}\|^2}{\ln^2 \left(\sum_{e=1}^N u_{ie}^{(t-1)} + 1 \right)}}{\frac{1}{\Delta y_j} \|y_j - c_r^{(t)}\|^2 + \Delta y_j \|\bar{y}_j - c_r^{(t)}\|^2 \ln^2 \left(\sum_{e=1}^N u_{re}^{(t-1)} + 1 \right)} \right]^{\frac{1}{m-1}}} \quad (24)$$

2.8 SSFCA

Self-Sparse Fuzzy algorithm (SSFCA) ⁸ was proposed by Jia et al. (2020). An algorithm based on a regularization under Gaussian metric that is integrated into the objective function of fuzzy clustering algorithm to obtain fuzzy membership with sparsity, which reduces a proportion of noisy features and improves clustering results. The final objective function is defined as :

$$J_{SSFCA} = \sum_{i=1}^c \sum_{j=1}^n u_{ij} \Phi'(\mathbf{x}_j | \mathbf{v}_i, \Sigma_i) + \gamma \sum_{i=1}^c \sum_{j=1}^n u_{ij}^2 \quad (25)$$

where,

γ : is a balance factor used for controlling the sparsity of memberships.

Σ_i : is covariance matrix.

$\Phi'(\mathbf{x}_j | \mathbf{v}_i, \Sigma_i)$: is the distance function between $\mathbf{x}_j$ and $\mathbf{v}_i$.

By setting the value of (γ), fuzzy memberships with varying degrees of sparsity can be obtained using the optimization approach suggested in

⁷https://github.com/wqshzmh/FCM_SICM-Algorithm

⁸<https://github.com/jiaxhsust/Robust-Self-Sparse-Fuzzy-Clustering-for-Image-Segmentation>

Huang et al. (2015) to be solved Equation 25. The memberships matrix can be written by

$$J_{SSFCA} = \min \|u_{ij} - h_{ij}\|^2 \quad (26)$$

Subject to,

$$h_{ij} = -\Phi'(\mathbf{x}_j | v_i, \Sigma_i) / 2\gamma \quad (27)$$

The cluster centers is updated using the following relationships:

$$\mathbf{v}_i = \frac{\sum_{j=1}^n u_{ij} \mathbf{x}_j}{\sum_{j=1}^n u_{ij}} \quad (28)$$

The covariance matrix is updated using the following relationships:

$$\Sigma_i = \frac{\sum_{j=1}^n u_{ij} (\mathbf{x}_j - \mathbf{v}_i)^T (\mathbf{x}_j - \mathbf{v}_i)}{\sum_{j=1}^n u_{ij}} \quad (29)$$

3 Methodological

In this study, we compare the segmentation of improved FCM algorithms on the retina image to see their capacity in extracting blood vessels. The preprocessing stage aims to improve image quality. The preprocessing stage aims to improve image quality. One of the most crucial tasks in machine vision and image processing is contrast enhancement of the input image. This group of processes is merely for enhancing and increasing image clarity so that a better comprehension and segmentation of the images can be reached. Figure 1 describes a flowchart of the retinal image segmentation phases with the improved FCM algorithms. The flowchart consists of five parts: retina image from the database, extraction green channel, image enhancement, image segmentation, and vascular separation. In the image enhancement stage, some techniques such as CLAHE and bottom hat filter are implanted to improve the final segmentation result. In segmentation stage the improved FCM algorithms are applied to divide the image into 3 clusters, one of them is interesting area. In vascular separation the area of interest is extracted and validated with some indicators to see effectiveness of different FCM algorithms subject to experience.

3.1 Retinal image Components

It is well known that the image of the retina consists of three channels, green, red, and blue Figure 2 .. Among these channels, the red one is supersaturated, and the blue one is poorly lit to reveal the blood vessel. The green channel is considered for vascular detection due to the large contrast between the blood vessels and their background. For the reason being, the image analysis is continued on the green channel. Azzopardi et al. (2015).

3.2 Contrast limited adaptive histogram equalization

The improvement of image contrast is a process of increasing the quality of contrast of the intensity variations of the considered image. Contrast enhancement is beneficial in analyzing medical images. CLAHE is a method widely used in the processing of biomedical images and signals. Its main interest lies in increasing the visibility of the interesting portions of the image. CLAHE is an improved type of adaptive histogram equalization (AHE) Pizer et al. (1987) developed by K. Zuiderveld Zuiderveld (1994). CLAHE reduces the noise amplification problem by segmenting an image into small interrelated areas called tiles, followed by employing histogram equalization above any tile.

3.3 Bottom-hat filtering (BTH)

In digital image processing and mathematical morphology, bottom-hat (BTH) filtering is used for various tasks, such as background equalization, image enhancement, feature extraction, and others. It is used for the improvement of retina images, given its effective ability in enhancing the appearance of the retinal vessels of the eye that appears black in a background that is considered less black. Bottom-hat filtering (BTH) process is based upon subtracting the input image (I) from the result $\phi_S(I)$ of performing a morphological closing operation ($\cdot$) on the input image (I). The closure performs a dilation ($\oplus$) followed by Erosion ($\ominus$). The result is filling holes and connecting objects nearby. The equation of the bottom hat (BTH) filtering is given as follows:

$$BTH = \phi_S(I) - I \quad (30)$$

Fig. 1: Flowchart of the retinal image segmentation phases with FCM algorithms.

Fig. 2: The preprocessing for retinal image segmentation. (a) Color retinal image. (b) Green Channel. (c) Image generated after applied CLAHE. (d) Image generated after applied bottom-hat filtering.

In this study, the *BTH* filter is used immediately after the extraction of the green channel. Its role is to prepare and enhance the appearance of the image components, mainly the vessels. The filter settings are chosen after many experiments, and eventually, the value 11 is chosen for the structural element with the square shape as it gives satisfactory results [Bhabatosh et al. \(1977\)](#), [Gonzalez et al. \(2002\)](#).

In order to demonstrate the effectiveness and necessity for the processing of the retinal before the segmentation process image, we have segmented different FCM algorithms directly on retinal images prior to performing preprocessing, and then experimenting with their efficacy after each

processing phase. [Figure 3](#) illustrates this stage with all the studied algorithms. In some algorithms like FCM, EnFCM, SFCM and FGFCM do not divide the color image directly because it is prepared to segment the gray image. The images shown in [Figure 3](#) are the images of the division on the three channels in one image. Moreover, the images demonstrate the inability of the various FCM algorithms to segment retinal images and the need for pre-processing. The image also shows that the selected pre-processing contributed to obtaining the desired segmentation.

Fig. 3: The algorithms results from different preprocessing on the retinal image. (a) Results of algorithms on the color image of the retina. (b) Results of algorithms on the green channel image of the retina. (c) Results of algorithms after CLAHE process. (d) Results of algorithms after bottom-hat filtering process.

4 Experiments

This section addresses the results obtained from experimental evaluations. Furthermore, an in-depth analysis of the achieved results obtained is also carried out. To evaluate the effectiveness and efficiency of the FCM algorithms, DRIVE and STARE databases are put to the test in our experiments. Eight extensions of FCM clustering algorithms: FCM, EnFCM, SFCM, FGFCM, FRFCM, DSFCM_N, FCM_SICM, and SSFCM are employed in these experiments. Different algorithms were employed, in which the retinal vessels are the region of interest that we aim to achieve, to segment the retinal image into 3 clusters, which represent the background, retinal vessels, and a cluster of the other ocular tissues. Where the retinal vessels are the region of interest that we require achieving. All parameters have been chosen based on many experiments in order to obtain the best results, and this was taken with all FCM algorithms.

In the following experiments, fuzzy exponent is $m = 2$, convergence threshold is $e = 10^{-5}$, and maximum iteration number is $T = 100$, and the other parameters for different FCM algorithms adopted for the comparison are shown in Table 1 below.

Table 1: Parameters used.

Methods	Parameters
EnFCM	$\alpha = 4.2$
SFCM	$w = 5, p = 1, q = 1$
FGFCM	$\alpha = 6.2$
FRFCM	$w = 1, se = 1, \text{shape} = \text{disk}$
DSFCM_N	$w = 3, \lambda = 10$
FCM_SICM	$\sigma_d = 0.5, \sigma_r = 2$
SSFCA	$\gamma = 3$

4.1 Database

There are many open public databases available for researchers, along with the ground truth images of blood vessel details, such as, IDRiD [Porwal et al. \(2018\)](#), CHASE_DB1 [Fraz et al. \(2012\)](#), DRIVE [Staal et al. \(2004\)](#) and, STARE [Hoover et al. \(2000\)](#), etc. Therefore, we chose the DRIVE and STARE databases. Table 2 demonstrates some of its characteristics.

4.2 Validation

The quality and effectiveness of each vascular segmentation methodology depend on its ability to accurately distinguish the vessels from background pixels. The performance assessment is

Table 2: Characteristics of databases.

Database	DRIVE	STARE
Number of image	40	20
Camera	Canon CR5	TopCon TRV-50
FoV	45°	35°
Spatial resolution	565 × 584	605 × 700
Format	JPEG	PPM
Ground truth	available	available

performed by comparing the achieved segmentation results with those made manually. This is done by calculating the following four parameters:

- *TP*: Number of pixels in the structures of interest (vessels) detected correctly.
- *TN*: Number of background pixels detected correctly.
- *FP*: Number of background pixels detected as the structures of interest pixels (vessels).
- *FN*: Number of pixels in the structures of interest (vessels) detected background pixels.

Using the above basic parameters, certain ratios are presented to determine and compare the performance of the proposed method under study with other segmentation methods as follows:

Precision

$$Pr = \frac{TP}{TP + FP} \quad (31)$$

Sensitivity

$$Sn = \frac{TP}{TP + FN} \quad (32)$$

Specificity

$$Sp = \frac{TN}{TN + FP} \quad (33)$$

Accuracy

$$Acc = \frac{TP + TN}{TP + TN + FN + FP} \quad (34)$$

4.3 Results on retinal images

In medical diagnostic support systems, image segmentation plays a critical role. Due to the complexity of medical images, dividing them is often difficult. For the sake of further illustration of the suggested method's effectiveness in retinal vascular segmentation, experimentations have been carried out on two well-know open access databases, DRIVE and STARE. The vascular

Table 3: Segmentation precision (Pr), sensitivity (Se), specificity (Sp), and accuracy (Ac) for the algorithms in the DRIVE database.

DRIVE				
Methods	Pr	Sp	Sn	Acc
FCM	0.8913	0.9939	0.4944	0.9504
EnFCM	0.8831	0.9935	0.4902	0.9497
SFCM	0.9331	0.9971	0.4012	0.9453
FGFCM	0.7748	0.9819	0.5979	0.9492
FRFCM	0.8803	0.9929	0.4996	0.9499
DSFCM_N	0.8762	0.9922	0.5354	0.9522
FCM_SICM	0.9231	0.9965	0.4165	0.9460
SSFCA	0.6516	0.9581	0.7289	0.9377

segmentation is assessed based on precision, sensitivity, specificity, and accuracy metrics as shown [Figure 7](#). The results obtained on the DRIVE database showed in [Table 5](#) display the effectiveness and accuracy of the DSFCM_N algorithm, The accuracy value is (Acc = 0.9522), which is the highest value compared to other algorithms, followed by the FCM algorithm with an accuracy value of (Acc = 0.9504), while the specificity value is (Sp = 0.9971) in the SFCM algorithm, and the highest sensitivity value is obtained by the SSFCA algorithm with a value of (Sn = 0.7289). [Figure 4](#) illustrates the comparison of segmentation results on DRIVE database. The results obtained on the STARE database [Table 4](#) showed the effectiveness of the FGFCM algorithm. The accuracy value is (Acc = 0.9517), which is a little higher comparing to the FRFCM algorithm where the value is (Acc = 0.9511), and the specificity value is (Pr = 0.9911) obtained by the SFCM algorithm. The highest precision value is obtained by the EnFCM algorithm, (Pr = 0.8831). [Figure 5](#) depicts the comparison of segmentation results on the STARE database.

4.4 Running Time

To evaluate the practicability of modified FCM algorithms, the execution times of various algorithms were compared. All experiments are executed on a workstation with an Intel® Core (TM) i5-2520, 2.5GHz CPU, and 2G memory using MATLAB. [Table 5](#) and [Table 6](#) show running times of different algorithms on DRIVER and STARE databases, respectively. The running time calculated using different algorithms was the average value obtained by executing each algorithm

Fig. 4: Comparison of segmentation results on DRIVE Database. (a) ground truth, (b) FCM result. (c) EnFCM result. (d) SFCM result. (e) FGFCM result. (f) FRFCM result. (g) DSFCM_N result. (h) FCM_SICM result. (i) SSFCA result.

Fig. 5: Comparison of segmentation results on STARE database. (a) ground truth, (b) FCM result. (c) EnFCM result. (d) SFCM result. (e) FGFCM result. (f) FRFCM result. (g) DSFCM_N result. (h) FCM_SICM result. (i) SSFCA result.

five times on DRIVE and STARE databases. From Figure 7, it is clear that SSFCM is very slow compared to other algorithms. This is due to the fact that SSFCA utilizes regularization under Gaussian metric that is integrated into the objective function of fuzzy clustering algorithms to obtain fuzzy membership with sparsity. SFCM, FGFCM, DSFCM_N, FCM_SICM are also slow compared to EnFCM and FRFCM. The incorporation of gray level, which is significantly less than the number of pixels in a image, makes EnFCM fast. FRFCM is very fast because FRFCM applies

morphological reconstruction and membership filtering. Furthermore, FRFCM employs the concept of the histogram. Therefore, the objective function of FRFCM converges rapidly. Given the experiments mentioned above, we can see that FRFCM requires very small computational time.

5 Conclusion

In this paper, a comparative analysis of different FCM algorithms for the segmentation of retinal

(a) Graph of the results obtained with various FCM algorithms on DRIVE database.

(b) Graph of the results obtained with various FCM algorithms on STARE database.

Fig. 6: Comparison of validation indicators on different FCM algorithms on DRIVE and STARE databases.

Table 4: Segmentation precision (Pr), sensitivity (Se), specificity (Sp), and accuracy (Ac) for the algorithms in the STARE database.

STARE				
Methods	Pr	Sp	Sn	Acc
FCM	0.7322	0.9788	0.5727	0.9474
EnFCM	0.8831	0.9802	0.5654	0.9482
SFCM	0.8146	0.9911	0.4632	0.9509
FGFCM	0.7804	0.9854	0.5464	0.9517
FRFCM	0.7525	0.9815	0.5870	0.9511
DSFCM_N	0.7264	0.9742	0.6059	0.9455
FCM_SICM	0.7749	0.9847	0.5026	0.9475
SSFCA	0.4872	0.9194	0.7919	0.9089

images has been made to assess the effectiveness and quality of these algorithms in the segmentation process. The algorithms are analyzed according to various indicators like precision, sensitivity, specificity, and accuracy. DSFCM_N is able delivers superior segmentation results in the DRIVE database, while FGFCM provides better results on the accuracy indicator in the STARE database, according to experimental results. On the other hand, the FRFCM algorithm requires less time than other improved FCM algorithms for retina segmentation on both DRIVE and STARE databases. Based on this study, the improved FCM algorithms in dividing the retinal vessels have major challenges and problems to be addressed and solved.

Declarations

Funding There is no funding for this study.

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent Informed consent was obtained from all individual participants included in the original study.

Fig. 7: Comparison of performance (in seconds) of improve FCM algorithms on DRIVE and STARE databases.

Table 5: Comparison of execution times (in seconds) of test image on DRIVE database.

Methods	FCM	EnFCM	SFCM	FGFCM	FRFCM	DSFCM_N	FCM_SICM	SSFCA
Average time	8.15	5.79	22.03	17.29	0.32	10.96	10.93	165.73

Table 6: Comparison of performance times (in seconds) of test image on STARE database.

Methods	FCM	EnFCM	SFCM	FGFCM	FRFCM	DSFCM_N	FCM_SICM	SSFCA
Average time	11,73	7,29	31,15	21,80	0,40	13,78	14,05	243,31

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