

## Detection of the Presence of Micro Aneurysms in Retinal Images using FCM

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**Key words:** Fuzzy c-means clustering, medical decision-making, spatial information, anisotropic diffusion filter, fund us image, image classification, biomedical image processing, pattern recognition, non-local methodologies

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Page No.: 181-185

Volume: 19, Issue 9, 2020

ISSN: 1682-3915

Asian Journal of Information Technology

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**Abstract:** In diabetes retinopathy, identification of Micro aneurysms is an important phase for treatment of diabetic patients. The clustering technique which we are going to present identifies micro aneurysms from optic disk in the retinal fundus pictures. Constrained Spectral Clustering (CSC) has shown great deal with images to identify MA in medical retinal images with increasing accuracy in image segmentation. CSC performs by integrating sparse based coding to construct efficient frames based on clustering in image segmentation to identify MAs in retinal images for better image segmentation in pixel calculation in large image data sets present in application processing. So in this study, we extend CSC with Fuzzy C-Means (FCM) Clustering. FCM is used to cluster the data in which the dataset is grouped into n clusters. Every data point of the dataset belongs to every cluster to a certain degree. In FCM, we perform efficient clustering with spatial pixel evaluation in retinal images with diabetic retinal images to divide spectral coding in medical decision analysis with preferable operations.

## INTRODUCTION

The treatment of anguish from diabetes macular hydrous has advanced after some time with restorative and therapeutic medications progressively being respected and connected, besides to customary retinal laser gadget photocoagulation. The disease Diabetic Retinopathy (DR) is one of the issues of diabetes that produces in a large portion of the sufferers with a longstanding disease and a top reason for loss of sight in some nations. Productive treatments for diabetic retinopathy are accessible, however there is a need for starting investigation and ceaseless observing of diabetic patients. Suitable diabetic retinopathy is directed by an assessment of retinal pictures. Control rating of retinal pictures to make sense of the level of Diabetic Retinopathy is somewhat asset requesting<sup>[1]</sup>. Presence of Micro Aneurysms (MAs) on the

retina is a major indication of this disease. The issue of electronic retinal micro aneurysms distinguishing proof, is a prescribed method for this methodology that turned out to be to a great degree forceful with a large portion of the best in class ones in view of the results of a begin online contenders. The recognizable proof of micro aneurysms is critical in the method of diabetic retinopathy rating because it writes the explanations behind figuring out if a photo of patient's eye ought to be respected more beneficial or not. In this manner, it's not astounding that this abstract deals with the components of making a Computer Aided Design (CAD) framework for distinguishing proof of Diabetic Retinopathy and someother eye important ailments is somewhat thorough and examination of retina pictures is an extremely dazzling territory for the electronic picture taking care of group. Fuzzy c-means clustering is a technique in which

a piece of data can exist in two or more clusters. A traditional CSC does not consolidate the spatial subtle elements which makes it sensitive to aggravation and other picture relics though fuzzy c-implies grouping criteria highlight the spatial data into the record work for bunching. The customized fuzzy c-means grouping technique is utilized to recognize glaucoma which exists in the retina with different spatial blends.

**CSC clustering to MA's in retinal images:** Based on the above description<sup>[2]</sup>, we can identify that identification of MA's in retinal images using sparse coding technique is more complex. Constrained spectral clustering is an algorithm which identifies MA's in retinal images with preferable pixel representation. The procedure of identifying MA's in retinal images using CSC is described as follows Algorithm 1:

**Algorithm 1; Scalable constrained spectral clustering to define image segmentation in retinal images:**

- 1: Input is a dataset  $X \in \mathbb{R}^{d \times n}$ ,  $p$  is the base vector number, an imperative lattice of  $n$  by  $n$ , and  $k$  the group number
- 2: Then choose a  $p$  vector information from the info dataset irregularly and stack them in segments grid wise  $U \in \mathbb{R}^{d \times n}$
- 3: Calculate  $Z \in \mathbb{R}^{d \times n}$  utilizing and then perform  $Z = D^{-1/2}U$  where  $D$  is an inclining grid with components  $D_{ij} = \sum_j Z_{ij}$
- 4: Then compute  $\hat{S} = \hat{Z}\hat{Z}^T$  then do  $\hat{Q} = \hat{Z}\hat{Q}\hat{Z}^T$
- 5: Now find the biggest eigen value  $\gamma_{\max}$  among the summed up Eigen system  $\hat{Q}X = \gamma\hat{S}X$
- 6: If  $\beta \geq \gamma_{\max}$ , then return  $\{v^*\} = \emptyset$  something else, Then discover all the eigenvectors  $\{U_i\}$  by comprehending the summed up Eigen-framework where  $u_i$  signifies the  $i$ th eigenvector  $1 \leq i \leq p$
- 7: Now among  $\{U_i\}$  the eigenvectors find  $\{U_i\}^+$  related with positive Eigenvalues
- 8: Normalize each  $u_i \in \{u_i\}^+$  by increasing a variable by performing  $\frac{1}{\sqrt{u_i^T \hat{S} u_i}}$
- 9: Now remove the eigenvectors from  $\{u_i\}^+$  that are not orthogonal to the vector  $1^T \wedge S$
- 10: Among  $\{u_i\}^+$  find the  $m$  eigenvectors that prompt to the littlest estimations of  $u_i^T$ , where  $m = \min \{k-1, |\{u_i\}^+|\}$ , then stack them up in sections of framework  $V$
- 11: Calculate  $V^{(r)} = \hat{Z}^T V (I - V^T A V)$
- 12: Now normalize  $V^{(r)}$  lines to have a unit length and then nourish it to the  $k$ -implies calculation
- 13: Output is the gathering pointer

It says that the information parameter  $b$  is tunable, that makes the calculation adaptable to the side data. Here, the value of  $b$  is larger that means more side data is considered. The usage of sparse code generation for preferable pixel representation in large images is shown in next part.

## MATERIALS AND METHODS

**Proposed approach:** This photo which is acquired from the photo assets will be transformed into dim scale picture, so that, it has the capacity to explore the photo in

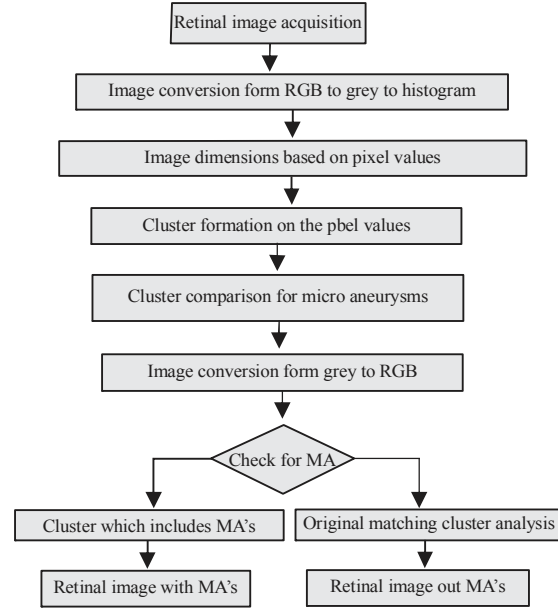


Fig. 1: Proposed approach

a more proficient way. The fuzzy variables are focused on variable necessities such as assortment of gatherings, assortment of cycle and picture estimating (Fig. 1).

The measuring of the information picture is analyzed in light of the fact that the customized spatial fuzzy c-means grouping is connected on 2-3D pictures. The info picture is handed over different points of view to perceive the ideal centroid over different data places. The advantages of spatial turning are to find out the resemblance activities for identifying miniaturized scale aneurysms in retinal pictures. The fuzzy components, such as, account work; target capacity and centroid are utilized to find a gathering in a proficient approach to get a considerable grouping sum. The separation of the data spots are perceived relying upon the fuzzy components i.e., the range assess over the information elements are measured. The gatherings are shaped in light of the spatial fuzzy components and furthermore contrasted and consistent container with the same position of turning. As of no chance that two gathering data over spatial fuzzy are same then the eye is not experiencing smaller scale aneurysms. Generally, the eye is influenced by the miniaturized scale aneurysms (Fig. 2).

The generated histogram of the given input picture is evaluated based on various shifts. After shifting various groups are formed because of the different forms of spinning. If there is any angular distinction then the distance from the centroid also differs as a result the histogram provides a complete research on spatial factors.

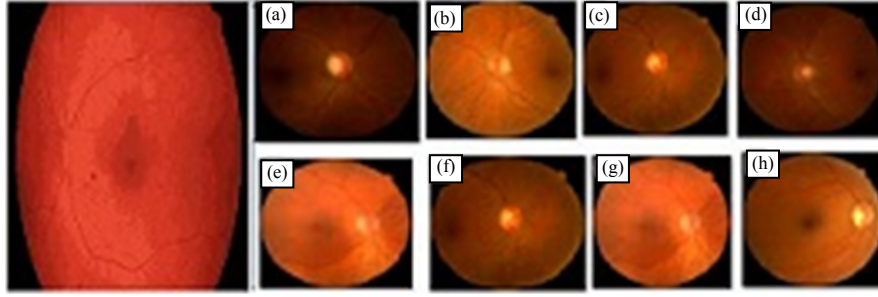


Fig. 2(a-h): Original retinal images using these retinal images we generate average histogram image (a-h)

**Procedure for implementation of FCM:** Among the most generally used fuzzy procedures, fuzzy grouping is one of the best one in picture division especially the retinal images. FCM is a redundant criteria which means it can be used to create bunches where the class records of  $p$  can be considered as a level of having the place of the pixel to the gatherings.

Let  $A = \{x_1, x_2, x_3, \dots, x_n\}$  is the set representing the  $p$  of the given image,  $n$  corresponds to a wide range of  $p$ .  $B = \{v_1, v_2, v_3, \dots, v_c\}$  represents the set of the corresponding fuzzy team features where  $c$  represents the number of categories. Our main aim is to lessen the reason function  $J(U, V)$ .  $(U, V)$  is a squared error clustering specification which is described here:

$$J(U, V) = \sum_{i=1}^n \sum_{j=1}^c \mu_{ij}^m \|x_i - v_j\|^2$$

Here  $\|x_i - v_j\|^2$  is Euclidean range between  $x_{ij}$  and  $v_j$ .  $\mu_{ij}$  is consideration stage of pixel  $x_i$  to the group middle  $v_j$  and  $i_{ij}$  has to match the following conditions:

$$\mu_{ij} \in [0, 1], \forall i = 1, \dots, n, \forall j = 1, \dots, c$$

$$\sum_{j=1}^c \mu_{ij} = 1, \forall i = 1, \dots, n$$

$U = (\mu)_{i \times c}$  represents a fuzzy partition matrix. The parameter  $m$  represents the fuzziness index which is commonly used to control the fuzziness of each and every pixel.  $m$  is a weighting factor and its value should be in the range, its value must be  $>1$  and it should control the stage of fuzziness in the resulting functions. As  $m$  value nears the unity, features become clear and the also the binary technique feature. As  $m$  value increases, the consideration feature gradually becomes fuzzy.

**The algorithm for FCM is as follows:** Initialise the centres of the clusters  $V = \{v_1, v_2, \dots, v_c\}$  or initialise the membership matrix function  $\mu_{ij}$  with a random value, so

that, it satisfies the conditions shown above. Now using the below formula compute the fuzzy membership  $\mu_{ij}$ :

$$\mu_{ij} = \frac{1}{\sum_{k=1}^c \left( \frac{d_{ij}}{d_{ik}} \right)^{\frac{2}{m-1}}}$$

and then calculate the fuzzy centres  $v_j$  using:

$$v_j = \frac{\sum_{i=1}^n (\mu_{ij})^m x_i}{\sum_{i=1}^n (\mu_{ij})^m}$$

This is the process of the fuzzy c-means in modern data environment and in picture confirmation procedures. Now, develop the process discussed in part III for clustering confirmation of related activities.

## RESULTS AND DISCUSSION

**Performance evaluation:** The recommended strategy focuses on obtaining information from factors like centroid and mean values by rotating images in some position which are established by the variety.

Calculated after rotating the image. The optic cup sizing reviews the given image by determining its variation from regular to prolonged sizing. This spatial rotation of the image is to identify the centroid so that we can identify the glaucoma (Fig. 3).

The following retinal image is given as input to the constrained spectral clustering Fig. 4. This input image is converted as following for analysis Fig. 5. After the conversion of the given image to gray scale output is obtained (Fig. 6).

The constrained spectral clustering has detected the presence of Micro aneurysms in the places that are circled black. The constrained spectral clustering has detected 46 Retinal Micro aneurysms with in approximately 303 sec. It is shown in Fig. 7:

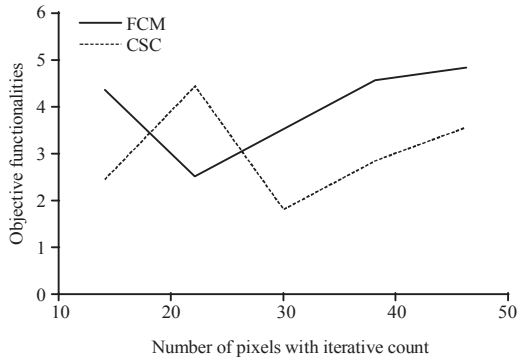


Fig. 3: Graph showing the variation of functionalities of FCM and CSC when number of pixels are increased

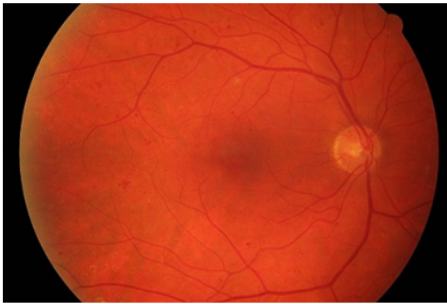


Fig. 4: Input given to constrained spectral clustering

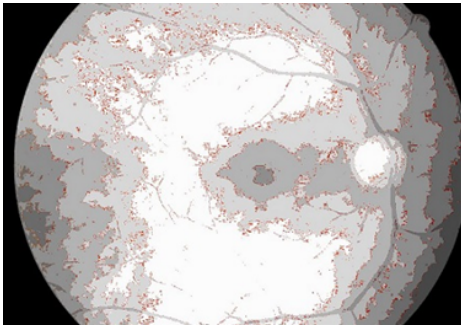


Fig. 5: Gray scale image of the input image

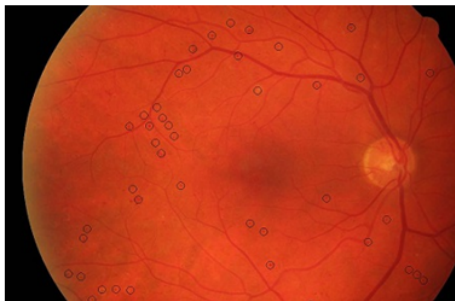


Fig. 6: Output of the given image with micro aneurysms detected

Proposed System Found : 46 Retinal MicroAneurysms  
ps operation took : 303.302607125 seconds

Fig. 7: Retinal micro aneurysms with in approximately 303 sec

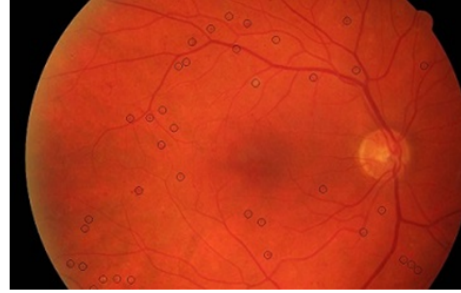


Fig. 8: Output image of fuzzy c-means clustering

Enhancement System Found : 41 Retinal MicroAneurysms  
xs operation took : 304.655071035 seconds

Fig. 9: Retinal micro aneurysms in approximately 304 sec

The same input retinal image is given as input to the Fuzzy C-Means (FCM) clustering technique. The FCM converts the given input image to histogram and analyses the results. The output of the FCM for the above given input is as follows Fig. 8. The above operation produced 41 retinal Micro aneurysms in approximately 304 sec. The performance is shown in Fig. 9.

The FCM produced just 41 retinal micro aneurysms which are less than the retinal micro aneurysms produced by the CSC but the time taken by the FCM is more than the CSC. The retinal Micro aneurysms detected by CSC are not completely accurate because the Micro aneurysms generated by rubbing of the eyes are also detected by the CSC which is not exactly the Micro aneurysms. But the FCM exactly distinguishes them from original Micro aneurysms and produces an exact result. So we can say that it is a betterment over CSC<sup>[3]</sup>.

#### Mathematical research of the microanyrism detection:

Fuzzy c-means clustering analyses two pictures which belong to the same group with account value in different perspectives of spinning. The representation of the image pixels is as follows:

$$I_1 = \begin{bmatrix} r11 & r12 & ..... & r1n \\ r21 & r22 & ..... & r2n \\ ..... & ..... & ..... & ..... \\ rm1 & rm2 & ..... & rmn \end{bmatrix}$$

The following is the representation of another retinal image:



$$I_2 = \begin{bmatrix} r11 & r12 & \dots & r1n \\ r21 & r22 & \dots & r2n \\ \dots & \dots & \dots & \dots \\ rml & rm2 & \dots & rmn \end{bmatrix}$$

The input pictures are turned out in various directions, so that, the outliers can be easily recognized from that of the feedback image. The input RGB image is then converted to gray scale image and processed further:

$$I_1 = X[\theta[I_1]]$$

$$I_2 = X[\theta[I_2]]$$

Now, we have to remove the noise using the filter for the efficient, image processing:

$$I_1 = \text{Filter}[X[\theta[I_1]]]$$

$$I_2 = \text{Filter}[X[\theta[I_2]]]$$

The image's center can be calculated according to the angle of rotation and the effective angle of rotation of the uploaded images is calculated as follows. The image comparison and final micro aneurysms can be detected as follows. Image comparison:

$$\begin{cases} \text{True} & \text{if } ((I_1 \cup MF \cup C \cup OF) \\ & \cap (I_2 \cup MF \cup C \cup OF)) = \phi \\ \text{false} & \text{otherwise} \end{cases}$$

Here I represents the number of iterations and MF the maximum false positive rate which processes each and every cluster according to the relevance of matching with the uploaded image. The results are as follows:

$$\begin{cases} \text{Image-Comparison} = \text{true, No Microanyrism} \\ \text{Image-Comparison} = \text{false, Microanyrism} \end{cases}$$

Using the above equation we compare and process pixels of clusters in fuzzy c-means of retinal images. The time taken by the proposed image processing is:

The fuzzy c-means algorithm converts the uploaded image into histogram for analysis. The uploaded image is rotated in different planes so that pixels related to same degree are attached to a similar cluster. Fuzzy c-means clustering algorithm reduces the false positive rate in the retinal images because it may include micro aneurysms as color in the input image.

Figure 10 that time taken by the fuzzy c-means clustering is greater than CSC because the computational logic of fuzzy c-means is more efficient than CSC. This paper gives the accurate information about the micro aneurysms of the uploaded image.

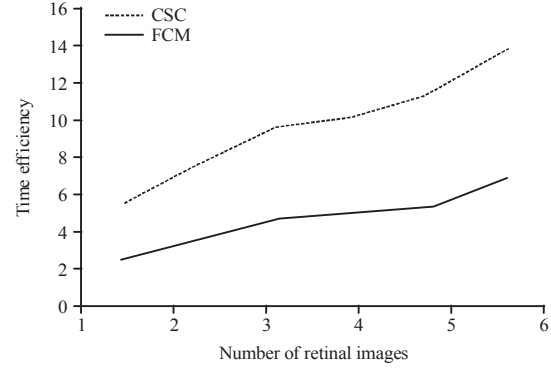


Fig. 10: The comparison between CSC and FCM in terms of time efficiency vs. number of retinal images

## CONCLUSION

We have proposed a way of identifying MA's on retinal images which is centered on the key factor of analysing candidate p cross-section details of the pre-processed image. In our proposed system the number of p to be shown are reduced significantly because we are considering only local maxima of the pre-processed image. We describe a set of concepts that best describes the size and apply that identification. The constrained spectral clustering is faster but complex and less accurate but the fuzzy c-means is slower compared to spectral clustering but more accurate than spectral clustering. The recommended procedure is the calculation of team centroid which calculates on the basis of the data aspects of the converted image and the process is repeated until no more detailed aspects are present in the image. The glaucoma disease can be identified by the team occurrence of more details aspects and this criterion is restricted to small data source centered on glaucoma. Later, the Personalized Spatial Unclear C indicates Clustering requirements can be prolonged to larger medical data source so that we can identify the glaucoma at the most.

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