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Central Retinal Vein Occlusion: An Approach for the Detection and Extraction of Retinal Blood Vessels

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Abstract

It is very difficult but important to detect and segment the retinal blood vessels to analyze the severity of the retinal diseases such as central retinal vein occlusion, central retinal artery occlusion, diabetic retinopathy, macular degeneration, retinal detachment and branch retinal vein occlusion. It is obvious that a vast number of algorithms are developed for the precise recognition of retinal blood vessels and optical disc. Central retinal vein occlusion (CRVO) is a circumstance wherein the main vein of the retina is occluded i.e., blood from the retina blocked off either completely or partially. This leads to the blurred vision and other problems related with the eye. The proposed work explained the central retinal vein occlusion recognition and identification and extraction of retinal blood vessels of occluded eye. The proposed method utilized modified fuzzy c-means clustering algorithm for the extraction of the blood vessels. The outcome of the proposed method is compared with existing method to demonstrate its competence.

Keywords: Extraction, Retinal Blood Vessel, Adaptive Histogram Equalization, Modified fuzzy c-means clustering, Green Channel, Classification.

Introduction

Retinal vein occlusions (RVO) are the second worst vision loss threatening vascular disorder. Retinal vein occlusion occurs in middle and old aged people with equal sex distribution. RVO can be classified into two basic types as central retinal vein occlusion (CRVO) and Branch retinal vein occlusion (BRVO). As compared to central retinal vein occlusion, branch retinal vein occlusion is the most widespread among the aged people. The identification of retina blood vessels among the existence of light and gloomy lesions is a tough task.

The impediment of any one of the four retinal veins is the main reason for the Branch Retinal Vein occlusions. Almost a one fourth of the retina is drained by each vein. The impairment of main vein arrangement from the four branches of the retina is the main reason for the central Retinal Vein occlusions. The occlusion of the central retinal vein is the main reason for severe visual loss as compared to branch retinal veins. The possible common threat factors for RVO are:

- High blood pressure i.e. blood pressure is greater than 140/80
- High level of blood cholesterol
- Diabetes, retinal vein occlusion is more regular amid people affected with diabetes.
- Heart disease
- Increased body mass index (obesity)
- Glaucoma
- Smoking, the people who addicted with smoking has a greater risk of vein occlusion
- A number of rare blood disorders usually identified by easy and low cost blood tests.

Central Retinal Vein Occlusion (CRVO) is one of the most common but worst retinal vascular disorder (diseases) that may perhaps weaken human vision acutely if it is not properly identified and treated. CRVO leads to painless vision loss. The automatic identification of CRVO based on the abnormal regions would be beneficial for both patients and physicians to make the procedure very easier. Depends on the severity of vision loss, CRVO can be classified into two subtypes as ischemia and Non ischemic. The Non ischemic CRVO can be development to ischemic within few months. This Non ischemic CRVO is connected with healthier vision and improved projection for natural visual development. The insufficient blood supply to the retina called ischemia which is related with the neovascular glaucoma and visual loss.

The majority of patients with CRVO build up it in one eye. Even though high blood pressure and diabetes are threat features for CRVO, its exact cause is still mysterious. A lot of CRVO patients have a symptom of distorted (blurry) vision owing to inflammation of the macula (center part of the retina). Patients with stern CRVO and other retinal problems such as glaucoma frequently have irritation, redness, pain, and other problems.

Materials And Methods

Figure 1 demonstrates the proposed method for the identification and extraction of the blood vessels from the central retinal vein occluded images. Input is acquired from the DRIVE (Digital Retinal Images for Vessel Extraction) database. http://www.isi.uu.nl/Research/Databases/DRIVE)

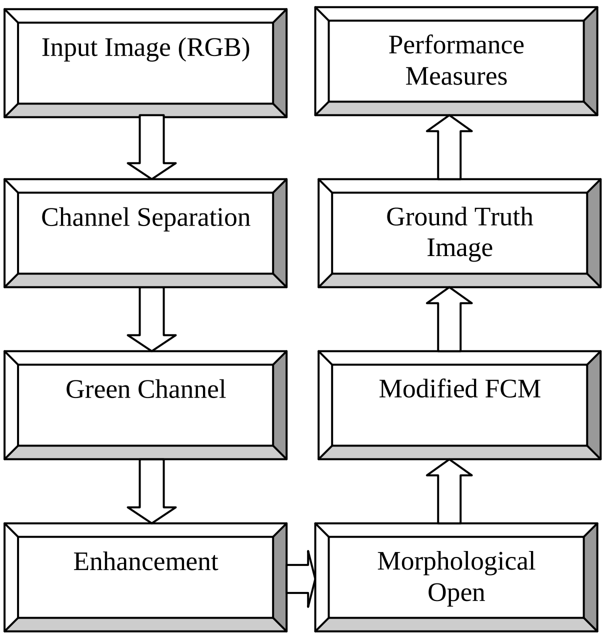


Figure 1: Proposed method for the extraction of blood vessels

For the detection and segmentation of blood vessels of retinal fundus images, freely accessible DRIVE (Digital Retinal Images for Vessel Extraction) database is very useful to facilitate comparative research. Our work employed DRIVE database to assess proposed method. The information integrated in DRIVE database can be employed for research and educational uses at no cost. This database includes the images of more than 400 diabetic patients of various age groups. All the images captured by means of Canon CR5 non-mydriatic CCD camera at the size of 768 by 584 pixels. For the efficient storage all the images were JPEG compressed.

RGB color input image is comprised of three different channels such as red, green and blue. The reason for selecting only green channel of color for binarize the image in image processing applications is simple. Our human eye is more sensitive to green color as compared to others. With natural light source (sunlight), the green channel generally has a large amount of light in it. In digital camera, there are twice as many green pixels as red or blue pixels. In addition, the green channel has not as much of noise than the red or blue channel. This is the reason why green channel of RGB color image is opting for many image processing applications.

The CLAHE (Contrast Limited Adaptive Histogram Equalization) is a procedure to cluster an image into small contextual regions and then apply the adaptive histogram equalization to each and every cluster. The above procedure evenly distributes all the grey levels to exploit hidden treasures (features) of the image more visible. Now the complete spectrum of grey level is used to represent the whole image. While histogram equalization works on the entire image, CLAHE operates on small regions in the image, called tiles. The contrast of every tile is enhanced, so that the histogram of the output region approximately matches a specified histogram. After the process of the histogram equalization, CLAHE combines all adjacent regions (tiles) to remove the unnaturally formed boundaries. The contrast level of the image is limited in order to keep away from the amplification of noise pixels that is incorporated with the image pixels.

Morphological opening operation is applied to the enhanced image.Morphological opening is the composite operation of erosion followed by dilation. For dilation morphological process on binary images, if any of the pixels value is one (1), then the output pixel is marked as one (1). Similarly, for erosion operation if any of the pixels value is zero (0), then the output pixel is marked as zero (0). The result of the opening process leads to (i) even (smooth) the object contour interior (ii) remove the slender portion of the image (iii) the removal of unwanted noise pixels from the image.

The retinal blood vessel segmentation is performed using the modified Fuzzy C-Means Clustering (MFCM), the improved version of the standard fuzzy c-means clustering algorithm. The principal task of the MFCM is to find out the cluster centers and allocate each and every pixel to its adjacent cluster centers. The objective function of the MFCM is represented as

$$J_{Mod} = \sum_{k=1}^{n} \sum_{i=1}^{c} \left(U_{ik}^{m} W_{ji}^{m} \right) \| X_k - V_i \|^2$$

Where (W_{ji}) = weight of the pixels

U_{ik} = membership function

The result of the projected technique is evaluated with the ground truth image to obtain four basic quality measures (true positive, true negative, false positive and false negative). These are the basis for the formation of confusion matrix.

True positive (TP) indicates the exact positive prediction whereas False positive (FP) describes the wrong prediction of positive pixels. Similarly True negative (TN) specifies the precise negative prediction and False negative (FN) denotes erroneous negative prediction. Accuracy, Sensitivity, Specificity and Error rate are the widely used measures obtained from the confusion matrix.

Accuracy is computed as sum of correctly classified pixels divided by the sum of the pixels in the image. The accuracy rated from 0.0 (worst) to 1.0 (best).

Accuracy= (TP+TN)/(TP+TN+FN+FP)

Error rate can be computed as the sum of incorrectly classified pixels divided by the sum of the pixels in the image. The accuracy rated from 0.0 (best) to 1.0 (worst).

Error rate = (FP+FN)/ (TP+TN+FN+FP)

Error rate= 1- Accuracy

Sensitivity, also called true positive rate, is computed as the total number of exactly classified positive predictions divided by the total number of all positives. The value 1.0 is allocated for best sensitivity and 0.0 for worst one.

Sensitivity = TP / (TP+FN)

Specificity, also called true negative rate, is computed as the sum of exact negative predictions divided by the sum of negatives. It is also known as true negative rate (TNR). The value 1.0 is allocated for best specificity and 0.0 for worst one.

Specificity = TN / (TN+FP)

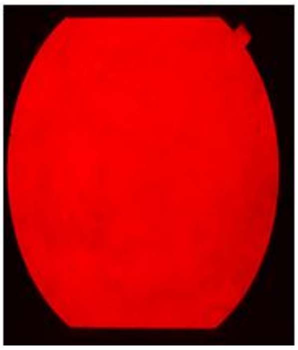
RESULTS AND DISCUSSION

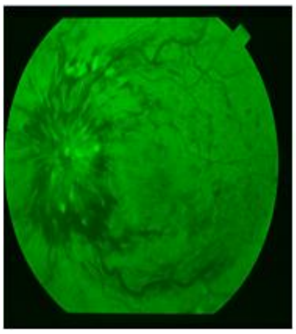
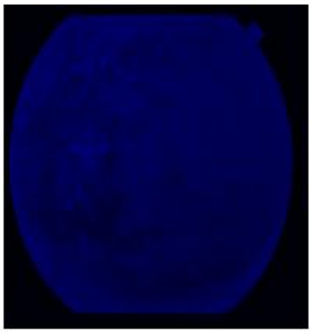
Figure 2 demonstrates the outcome of the proposed method for the extraction of blood vessels of central retinal vein occluded retinal image. The input retinal image which is acquired form DRIVE database is portrayed in fig 2(a). The three channels of RGB color input image is shown in fig 2(b) to 2(d). The corresponding grey scale version is illustrated in fig 2(e) to 2(h). Our human eye is more sensitive to green color as compared to others. With natural light source (sunlight), the green channel generally has a large amount of light in it. In digital camera, there are twice as many green pixels as red or blue pixels. In addition, the green channel has not as much of noise than the red or blue channel. This is the reason why green channel of RGB color image is opting for many image processing applications. The green channel is enhanced using CLAHE algorithm. After the process of the histogram equalization, CLAHE combines all adjacent regions (tiles) to remove the unnaturally formed boundaries. The contrast level of the image is limited in order to keep away from the amplification of noise pixels that is incorporated with the image pixels.

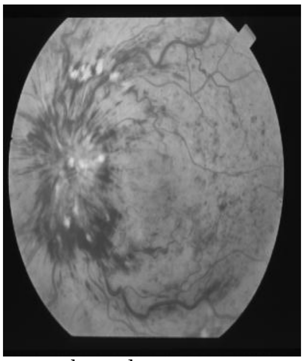
Morphological opening operation is applied to the enhanced image. The result of the opening process leads to (i) even (smooth) the object contour interior (ii) remove the slender portion of the image (iii) the removal of unwanted noise pixels from the image. This outcome of morphological open is illustrated in fig 2(j). The extracted blood vessels of modified fuzzy c-means clustering and segmented image are shown in fig 2(k) and 2(l) respectively.

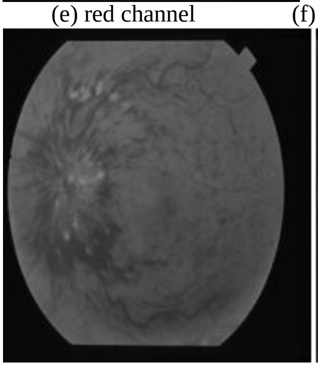
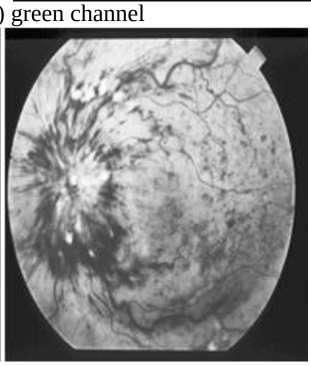
The outcome of the proposed method is compared with the ground truth image to obtain four basic quality measures (true positive, true negative, false positive and false negative). These are the basis for the formation of confusion matrix. The ground truth image also obtained from DRIVE database.

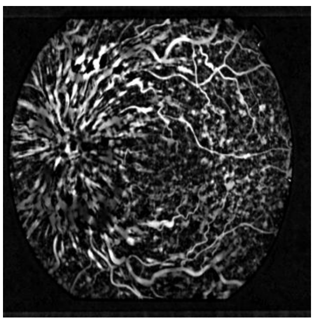
The pixel to pixel comparison is performed to obtain the image quality measures as mean square error (MSE), peak signal to noise ratio (PSNR), Sensitivity, specificity, accuracy and error rate. The result of the proposed method is compared with the k-means clustering and fuzzy c-means clustering. The comparison is tabulated and shown in table 1.

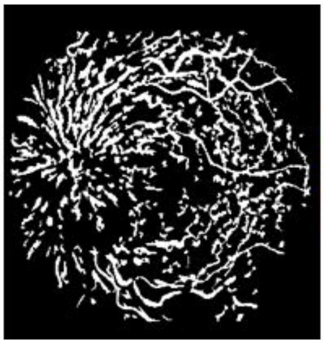
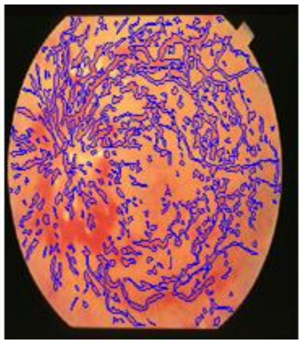

(a) input image

(b) red channel


(c) green channel

(d) blue channel


(e) red channel

(f) green channel


(h) blue channel

(i) enhanced image of (f)


(j) morphological open


(k) vessel segmentation

(l) proposed method

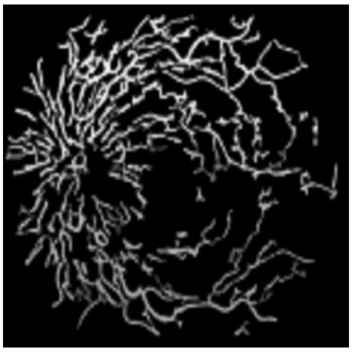

(m) Ground truth image

Figure 2: Result of the proposed approach

Table 1: Comparison of proposed method with K-means and FCM

Sl. No	Parameter	K-Means	FCM	Proposed Method
1	MSE	28.9949	22.9846	12.4563
2	PSNR	21.0845	24.6158	33.4242
3	Sensitivity (%)	71.8675	70.6244	72.4722
4	Specificity (%)	82.6091	81.5653	97.8047
5	Accuracy (%)	78.4003	78.3823	96.9625
6	Error Rate (%)	21.5997	21.6177	3.0375

The graphical representation of comparative study of performance of proposed method with k-means and fuzzy c-means clustering for the extraction of blood vessels of central retinal vein occluded image is shown in fig 3.

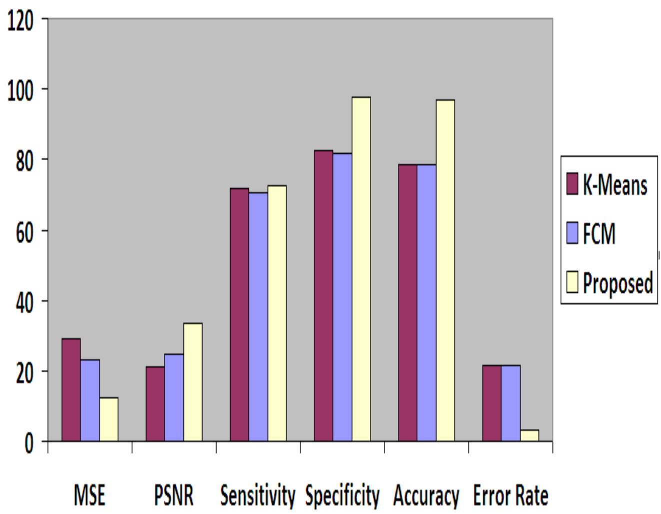


Figure 3: Comparison of proposed method with K-means and FCM

CONCLUSION

The proposed approach explained the central retinal vein occlusion recognition and identification and extraction of retinal blood vessels of occluded eye. The proposed method utilized modified fuzzy c-means clustering algorithm for the extraction of the blood vessels. The outcome of the proposed method is compared with existing methods to demonstrate its competence. The result displayed on table 1 clearly indicates that proposed method outperform other methods. The accuracy of the proposed approach is 96.96% for the applied input image and error rate is only 3.03%

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