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Research Article

Retinal Vasculature Segmentation

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Abstract

To identify various retinal pathologies like diabetic retinopathy, hypertension, glaucoma, arteriosclerosis fundus vasculature plays important role. To assist specialists for the determination of diseases it is essential to extract the retinal vasculature. This paper represents a method to segment the retinal vasculature. This paper contains four parts : first part is preprocessing which prepare funds images to extract vessels. Secondly an image enhancement includes bottom-hat transform followed by filtering. In third stage K-means is used to acquire binary segmented image; and lastly wrongly selected and detached group of pixels removed in postprocessing step. Online available databases STARE and DRIVE are used to test the method.

Keywords: *Retinal Vessel, Bottom Hat, K-Mean, Clustering*

Introduction

Now a days examination procedures such as ultrasonography (USG), computer tomography (CT) and retinal funds imaging utilizes automated screening procedures. Extraction of blood vessels from high resolution funds images helps in identification of retinal pathology in automated screening[1]. Retinal images provides numerous attribute such as macula , the optic circle, and retinal vessels. Retinal vasculature have very important role in identification of different retinal illnesses such as diabetic retinopathy, glaucoma, hypertension, and arteriosclerosis. Moreover, funds veins are primary determiners of other significant retinal features like optic disk and macula and they give numerous quantifiable highlights to the identification of retinal diseases. Therefore, blood vessels segmentation is significant for the identification and diagnosis of funds maladies. Funds vein segmentation is a method to get a binary image of vasculature. The goal of this paper is acquire black and white funds image to automat the procedure of identification of funds pathology. Funds vessel extraction has some challenges that is low contrast and uneven illumination in the background region. Many researchers proposed different techniques to handle these challenges. All these strategies are divided into two groups. In first one image is segmented on the basis of specifically design techniques. It incorporates the strategy of 2-D coordinated channel reactions[1,2], vasculature following techniques[3,4] and methodologies based on morphology[5,6]. AI has two types of learning unsupervised and supervised. In supervised learning the input is classified on the basis of some features which is called as planned classifier and incorporate KNN(k-nearest neighbours[7], SVM (support vector machine)[8], Bayesian choice standard[9] and ANN(artificia; neural networks[10] and supervised method comprises fuzzy C-means[11], k-means[12]. Chaudhuri et al. [1] used estimate the value function to design matched filter, on the grounds that modified Gaussian function has similarity with a vasculature. Initially author design the Gaussian part which is rotation variant with twelve pivoted adaptations convolved with green channel of input image and the most extreme incentive as for the point is chosen as greatest channel reaction. At that point, Otsu's algorithm is used for calculation of threshold and get segmented image. Another investigation utilizing a 2D response of matched filter is proposed by Hoover [2]. Later the vessel upgrade methodology, they use a thresholding technique to decide nearby limit and get a twofold segmented image. The strategy was used on physically named vessel pictures from STARE databases [13]. Jiang and Mojon proposed a vessel segmentation technique based on neighborhood thresholding [14]. They partition the gray channel into subchannels. Vessels are acquired by choosing pixels among the greatest and least estimations of each subchannel. At that point, a confirmation method is applied and the checked subchannel is chosen. At long last, the paired vessel image is gained by consolidating these confirmed subchannels before a post-processing stage. They tried their strategy on the STARE information base and gave the outcomes [14]. Soares et al. Proposed Gabor-based vessel extraction technique [9]. In their examination, they utilized a Bayesian classification before that they put out few highlights pull out from multiscale Gabor wavelet transform. Author used STARE [13] and DRIVE [15] databases for testing. A surface based vessel extraction strategy which uses a bank of Gabor energy filters is proposed by Bhuiyan et al. [16]. features from surface properties based Fuzzy C-means clustering strategy is used segment the image. DRIVE database is utilized in this examination [17]. In spite of the fact that there are numerous methodologies for retinal vasculature extraction, there is still space to get further improvement, particularly on images having retinal infection. In this paper, we propose a vasculatur**e** segmentation method formulated on unsupervised K-means clustering techniques preceded by some feature enhancement strategies. This paper is formulated as follows. The image databases are presented in Section 2.1. Section 2.2 gives the preprocessing tasks, and Section 2.3 gives the feature upgradation methods which contain the Bottom hat transformation. Clustering stage is elaborated in Section 2.4. The postprocessing step is given in Section 2.5. Results and conversation is presented in Section 3. Block diagram of proposed method is given in Fig.1.

Materials and Methods

In this paper, an automated retinal vasculature extraction technique from fundus images is presented. At first various image enhancement techniques are used to upgrade the image. Later on, Bottom-hat transform is used for improvement of clustering method. At last, outlier pixels are eliminated as a post-processing step. vasculature. At this point, binary image is acquired by applying the K-means

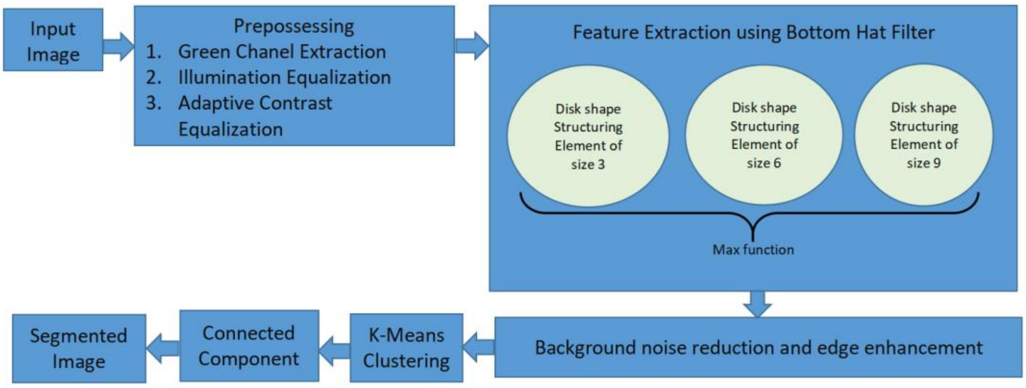


Fig.1. Block diagram of proposed method

Different open access databases are easily accessible online for retinal fundus image investigation that is used by numerous researchers. In this paper, we utilize two normally utilized datasets STARE [13] and funds image for vessel segmentation (DRIVE) [15] to test our strategy. The STARE dataset comprises 20 retinal images (ten of them have different neurotic cases). The pictures have been caught with a TopCon TRV-50 advanced fundus camera at 35° field of view (FOV). The resolution of the pictures are 700 × 605 pixels with 24 bits (8 bits for every color channel). All images from this dataset have respective ground truth image, in which the pixels are marked as vessel or non-vessel by two opthamologist. Furthermore, the DRIVE dataset has 40 pictures (out of which seven is different obsessive type). The pictures has been caught with a Canon CR5 non mydriatic 3CCD computerized retinal fundus camera at 45° field of view (FOV). The components of the pictures are 768 × 584 pixels with 24 bits (8 bits for every each colour channel). All pictures in this dataset additionally have respective ground truth images. The images are divided into two groups training and testing. Testing set is used by this paper for evaluation of result.

2.2. Prepossessing

2.2.1. Calibration of Region of Interest (ROI): The Fundus area is round despite the fact that retinal images are rectangular. Along these lines, retinal area covers must be used so as to choose the region of interest for fundus pictures. Here the DRIVE[15] dataset has a mask whereas STARE[13] doesn't contain any mask to select the fundus area. To adjust to various image areas, we utilize a spatial alignment technique presented in [19]. Pictures are not resized. Or maybe, the width (W) of the ROI. This theory is sensible since the majority of the fundus images are obtained with a field of view (FOV) of 45°. W is utilized to set the kernel sizes of the different filters In the case of eye retinal images obtained with a FOV of 45°.

2.2.2 Illumination Equalization : The illumination of the fundus image is frequently nonuniform, results in local luminosity and contrast variation. Fine vessels are difficult to visualize in these regions of poor contrast and/or low brightness. Subsequently, 1) preprocessing steps are required to address these issues. The illumination equalization method in [18] is used to get rid of the gradual darkening of background.

$$RIe = Ai + RI - RI*Fm1 \quad \ldots\ldots\ldots \qquad (1)$$

A mean filter Fm is used on all i.e. red ,green and blue color channel of the retinal image RI to judge tentative value of its uneven intensities. To improve the variations in shade this output image is subtracted from input image. Lastly to maintain color range average intensity Ai has been added in it.

2) Denoising: to minimize noise without smoothing the area of interest mean filter is convolved on each channel of RIe

Fig.2. a)Original Image b) Preprocessed image

3) Adaptive Contrast Equalization: impulses of contrast is estimated by the standard deviation of neighborhood of each pixel, for every color channel of RInr(Resultant image after noise reduction). Low standard deviation areas represents either minimal difference intensity region or smooth area. To improve these regions, we enhance the retinal image using equation (2) for each color channel independently:

$$RIce = RInr + 1/Nsd\ (IRnr * (1-Fhp)) \ldots\ldots \quad (2)$$

Neighborhood pixel features are added to the resultant image of denoising, weighted by the inverse of the contrast drift. The features are applying a high pass filter (Fhp).

4) Colour Calibration: Color standardization is important so as to acquire resultant image with a normalized shading range. We perform histogram stretching and clipping in the range of mean and standard deviation of the ROI. The subsequent preprocessed picture is shown in Fig.2.

2.3. Feature Extraction

2.3.1. morphological operators :Morphology depends on set hypothesis, thus sets are the principal objects. In image processing sets are the group of pixels. A detailed mathematical foundation is described by Serra (1988)[19]. That of erosion, dilation, opening and closing are the most basic morphological process. Suppose A is a set(image) and S is a structuring component . here S is 2D matrix S(i,j) then the erosion operation results in set of all pixels of A for which S is contained within A. It is known as $A \ominus S$ and can be written as

$$A \ominus - S = \{(i, j) : S(i,j) \subset A\}$$

Dilation process is exactly opposite of erosion process. It is defined just like an erosion but with its set's complement. If Ac denotes the A complement, the dilation of the set A by the S set, denoted $A \oplus S$, is defined by $A \oplus S = (Ac\text{-}S)\ c$.

Opening is a process of dilation followed by erosion and Closing is a process of erosion followed by dilation. They are complementary in that it is similar to adding one to A to add the other to A complement.

$$A \circ B = (A \ominus S) \oplus S \ldots\ldots \quad (3)$$

$$A \cdot B = (A \oplus S) \ominus S \ldots\ldots \quad (4)$$

Morphological operations transform the image. To pull out small components and details form images top-hat and black-hat transforms are used in morphology and image processing.

*2.3.2. Selecting a Structuring Element :*In this section, we are interested in set of black pixels as black pixels represents the vessels features. Set of black pixel is consider as a object (A) and performing different set operations on it like union and intersection, let S be the simple set of 2x2 then S can be translated into positions such that S $\subset$ A, where $\subset$ denotes 'is a subset of'. so this is essential to analyze the shape features from an input image. Here S is the structuring element[20]. Choosing a Structuring element in the correct form and size plays an important role in morphological operations to obtain the specified outcome. The features are highlighted in the resulting image according to the shape and size of the structuring element. Generally speaking, the form and size of a Structuring element is chosen randomly, but for different diagnoses in medical imaging the Structuring element should be selected in the right shape and size. In the proposed method we choose the disk-shaped structuring element, Since the disk-shaped Structuring element is independent of rotation shifts as it is identical in all direction. Size of structuring element is dependant on the features which is to be extracted and it will change accordingly here the retinal vessels are varying in size it is thick at optic disc and become thinner as it goes away from OD (36 micron to 180 micron)[21]. so the brute force method is used to choose the disk radius depending on the size of vessels to be extracted from the funds image.

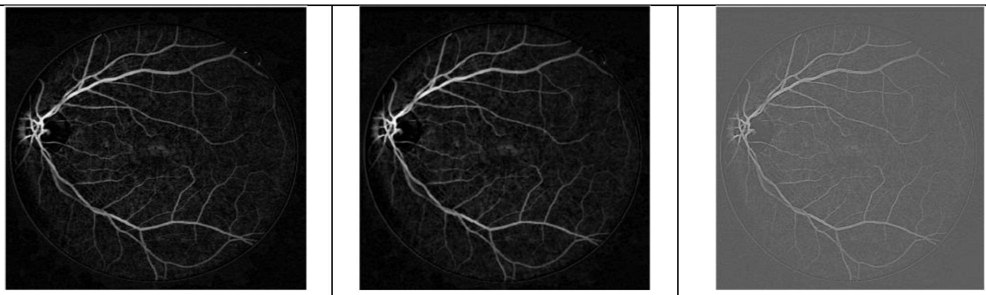
2.3.3 Bottom- Hat Filter : Morphological operations transform the image. To pull out small components and details form images top-hat and black-hat transforms are used in morphology and image processing. various image processing tasks, such as background equalization, feature extraction, image enhancement are performed by using these two operations. The white top-hat transform is defined as the difference between the input image and its opening by some structuring element;

Top-Hat(A)=Ath=A-(A∘S).......... (5)

The black top-hat transform is defined dually as the difference between the closing and the input image.

Bottom-Hat=Abt=(A·S)-S……… (6)

In this paper the dark, small and narrow features has been extracted from image by using bottom hat transform. Three different sized disk structural kernels (i.e. 3, 7 and 9) of bottom hat transform has been used to change the thickness to approximate the vessel diameter distribution. The closing operation eliminates narrow dark vasculature from the retinal image and it reappears in the difference of he closing and original image. Bottom up transform is not sufficient to handle the variations in the background intensities. To overcome the background intensity variation problem median filter has been used as it is less sensitive to high values and able to reduce noise in smooth patches of regions without much affecting the edges. At the same time as reducing the background sensitivity in an image, it is important to preserve the sharpness of the edges. Laplacian filter applied to enhance the edges. Fig.3. shows the subsequent results.



a) b) c)

Fig.3. a) Max of structural kernels of size 3, 7, 9; b)Median filter; c)Laplacian filter

2.3.5. Clustering : The retinal structure of each and every image is varying in nature that means there is no standard shape or corresponding target values to define or identify it, so we need a clustering algorithm which discovers and determines how the data is distributed in the space. There are numbers of methods to image segmentation, however the primary concern is to estimate the structure of vasculature in retinal images which will bring out better results in quicker and less computational complexity for this reason k means clustering algorithm has been chosen. Next thing we need to do is define the number of clusters we want to find. Here the target is to separate the vessels from the background so select 2 clusters for this one. Result of k means cluster is depicted in Fig.4.

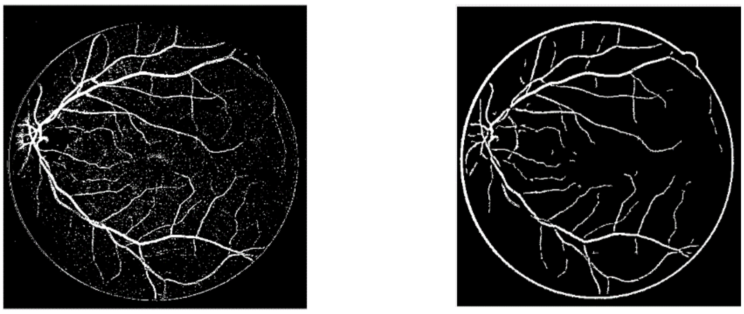


Fig. 4. a) Result of k-means b) after post processing

2.3.5. Post processing

It is observed from the result of k-means clustering algorithm (Fig.4.a.) that it is essential to think on the connectivity of the objects, which was not taken into consideration while performing the operations discussed in the preceding part. In which the process worked on locally or on neighbourhood, but the complete vessel tree is not consider as a single object, which is a one of the characteristic form of the vessel tree. Connected components used to identify a vessel tree as a whole object in an image. It simply lebal and counts the components from an image and eliminates the unwanted objects, the final resultant image is shown in the fig. 4.b.

Results and Conclusion

The proposed segmentation method was validated on publicly accessible dataset DRIVE using BF Score presented in[21] which is defined as contour matching score between the predicted segmentation in prediction and the true segmentation in ground Truth are shown in Fig.5. In medical image analysis, mostly the infected areas or areas of interest are segmented from background. We used retinal vasculature for the analysis. Retinal vessels have irregular intensity, line shape structure and the different noise intensities in different parts of the fundus image. This paper presents a strategy that utilizes feature(vasculature) enhancement techniques followed by unsupervised classification (clustering) methods.

One of the main features of the developed method is different sized structuring elements which handles the uneven width of vessels (region of interest) instead of a single one. The second important characteristic of this method is taking cluster size as two or binary classification, that reveals better performance in any case. This facilitates us to bring forth an an algorithm which helps in automation the procedure. The next important characteristic of the proposed system that it is not required any kind of training as unsupervised k-means algorithms is used, that can be helpful when the manual segmentation of the images is not available. Additionally, bottom up transform followed by k-means clustering is a new combination of methods that can recognize retinal blood vessels with efficient time and simplicity of implementation. In the future work, we aim to apply enhanced post-processing techniques to achieve the better results for the vessels segmentation

Image No.	BF Score	Image No.	BF Score
21	0.81613	31	0.76851
22	0.75046	32	0.75838
23	0.69565	33	0.79643
24	0.79923	34	0.77023
25	0.68615	35	0.78937
26	0.75074	36	0.81234
27	0.80724	37	0.78043
28	0.7965	38	0.82817
29	0.78856	39	0.84167
30	0.70884	40	0.82239

Fig.5.BF score of images

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