537

# Retinal Image Preprocessing: Background and Noise Segmentation

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## Abstrak

Citra medis merupakan area riset yang sangat populer sekarang ini yang melibatkan diagnosa berbantuan komputer untuk banyak penyakit, dengan menggunakan citra digital sebagai masukan. Citra retina digital digunakan untuk penapisan dan diagnosa penyakit retina mata akibat diabetes. Suatu sistem otomatis untuk diagnosis penyakit retina akibat diabetes seharusnya menonjolkan semua tanda penyakit yang ada dalam citra dan untuk meningkatkan akurasi sistem, kualitas citra retina harus ditingkatkan. Makalah ini mempresentasikan suatu metode peningkatan kualitas citra retina masukan dan metode ini merupakan langkah pemrosesan awal dalam diagnosa otomatis penyakit retina akibat diabetes. Pemrosesan awal terdiri dari estimasi latar belakang dan penghilangan derau dari citra retina dengan mengaplikasikan segmentasi kasar dan halus. Pengujian yang ekstensif dilakukan untuk validasi teknik pemrosesan awal yang diajukan menggunakan basis data citra baku permukaan belakang mata (fundus).

Kata kunci: pemrosesan awal, penyakit retina akibat diabetes, segmentasi latar belakang, segmentasi derau

## Abstract

Medical imaging is very popular research area these days and includes computer aided diagnosis of different diseases by taking digital images as input. Digital retinal images are used for the screening and diagnosis of diabetic retinopathy, an eye disease. An automated system for the diagnosis of diabetic retinopathy should highlight all signs of disease present in the image and in order to improve the accuracy of the system, the retinal image quality must be improved. In this article, we present a method to improve the quality of input retinal image and we consider this method as a preprocessing step in automated diagnosis of diabetic retinopathy. The preprocessing consists of background estimation and noise removal from retinal image by applying coarse and fine segmentation. We perform extensive results to check the validity of proposed preprocessing technique using standard fundus image database.

Keywords: background segmentation, diabetic retinopathy, noise segmentation, preprocessing

## 1. Introduction

One out of ten is affected by diabetes, which result in vision loss, stroke and heart failure. Group of eye problems that people with diabetes may face is known as diabetic eye disease. People affected by diabetic are more facing eye problems like contracts and glaucoma and the main reason for vision loss is the disease affecting on retina[1]. The complications of diabetes affect the vascular structure of human retina and cause the leakage of blood on surface of retina which leads to blindness and it is known as diabetic retinopathy [1]. Diabetic retinopathy is a progressive disease as there are no such signs of disease at its early stages but as the time passes the disease turns into severe [2]. The common symptoms of diabetic retinopathy are blurred vision and even loss of vision if not treated in time [2].

By using retinal image we can check whether a patient suffers from diabetic retinopathy or not. The regular screening of diabetic retinopathy results in a large number of retinal images that need to be examined by the ophthalmologists. Since the cost of manual examination is high so the best solution is an automated screening system for retinal images [1]. This system can be differentiating between normal and abnormal retinal images and will result in reducing the workload for the ophthalmologists. Since the ophthalmologists will examine only the abnormal images which is diagnosed by the system [3].

Healthy retina contains blood vessels, optic disc, macula and fovea as main features. An automated system for screening and diagnosis of diabetic retinopathy should detect all these features automatically [5], [6], [7] and all signs of diabetic retinopathy such as microaneurysms [4], [8], [9], hemorrhages, edema [4], hard exudates and cotton wool spots [10-11]. The accuracy of all these depends on the quality of acquired retinal image as some times it contains uneven illumination, blurry and noisy areas. The center region of a retinal image is usually highly illuminated while the noise increases closer to the edge of the retina [17]. So, Illumination equalization and noise removal are required to enhance the image quality.

In the beginning, before the detection of abnormalities and features in retinal image we must remove the noise and background from retinal image which will increase the quality of the image. This is done in preprocessing step and without this step the automated system will give poor result for feature extraction and abnormality detection.

The aim of preprocessing is to increase the quality of an image by reducing the amount of noise appearing in the image and highlighting features that are used in image segmentation. Two typical techniques used in preprocessing are filtering and contrast enhancing. Standard contrast stretching techniques have been applied by [4], [13] and [23] for segmentation and noise reduction. In [14], [15] and [16] the local contrast enhancement method is used for equalizing uneven illumination in the intensity channel of retinal images. A large mean filter, large median filter and collectively are used for retinal image have used intensity channel values to detect the dark regions from retinal image. Thresholding is also an important and widely used technique in image segmentation [19], because thresholding is effective and simple to implement. In thresholding, pixels within a defined range are selected as belonging to the foreground whereas gray-levels outside the range are rejected to the background [19].

In this paper, we present the retinal image preprocessing technique that detects the background using local mean and variance and removes noise using HSI color space. The proposed preprocessing method consists of two steps i.e. coarse and fine segmentation. In the first step, it does coarse segmentation that creates binary masks for background estimation and noise removal. In the second step, it does fine segmentation that combines background segmented mask and noise segmented mask and applies morphological operations to remove single pixel noise and edge pixels.

This paper is organized in four sections. Section 2 presents the step by step techniques required for color retinal image segmentation. Experimental results are discussed in section 3 followed by conclusion in section 4.

## 2. System Overview

Computer assisted diagnosis for various diseases is very common now a days and medical imaging is playing a vital role in such computer assisted diagnosis. We present an automated preprocessing system to improve the quality of retinal images so that the accuracy of automated screening of diabetic retinopathy can be improved. The proposed preprocessing method is used to improve the quality of image by extracting background and removing the noisy area from the retinal image. In automatic diagnosis of diabetic retinopathy, the processing of the surrounding background and noisy areas in retinal image is not necessary and consumes more processing time in all stages. Cutting or cropping out the region that contains the retinal image feature minimizes the number of operations on the retinal image. Moreover the noisy pixels may cause false features and reduce the accuracy of the automated classification so it is necessary to remove the noisy pixels. Figure 1 shows the flow diagram of our preprocessing technique. It shows the step by step outputs of proposed preprocessing technique.

## 2.1 Coarse Segmentation

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Coarse segmentation creates mask for background and noise estimation using mean and variance method and HSI (Hue, Saturation, Intensity) color model respectively.

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539

(2)



Figure 1. Flow Diagram of Retinal Image Preprocessing

## 2.1.1 Background Estimation

A color retinal image consists of a (semi) circular region of interest on a dark background. This dark background is initially never really black. It is not necessary to apply feature extraction and lesion detection algorithms on this area and it consumes more time so it is important to remove the background from input retinal image.

We present a local mean and variance based method [19] for background estimation. It creates a binary background segmentation mask by applying a threshold on std(I). If the std(I) is greater than threshold value, the block is considered as original retinal image area otherwise it belongs to background.

The algorithm for the background extraction mask is as below:

Step 1: Divide the acquired retinal image into non-overlapping blocks

**Step 2**: Compute the local mean value *M*(*I*) using equation 1

$$M(I) = \frac{1}{w^2} \sum_{i=-w/2}^{w/2} \sum_{j=-w/2}^{w/2} I(i,j)$$
(1)

Step 3: Use local mean value computed in step 2 to compute the local standard deviation value std(I) using equation 2

$$std(I) = \sqrt{\frac{1}{w^2} \sum_{i=-w/2}^{w/2} \sum_{j=-w/2}^{w/2} (I(i,j) - M(I))^2}$$

**Step 4**: Select threshold value empirically

Step 5: for each pixel,

Calculate *std(l)*>Threshold? **if true**, add pixel in original retinal image area pixels

if false, add pixel in background area pixels

## end\_for

## 2.1.2 Noise Segmentation Mask

Noise in color retinal image is normally due to noise pixels and pixels whose color is distorted. Both seem to exist in regions where illumination has been inadequate. Since illumination is usually adequate in the center of the image, poor image quality regions are located near the edge of the retinal image. Regions with poor image quality may cause errors in abnormality detection. That is why they should be detected and removed before detection of abnormalities.

In our technique, we create binary noise segmentation mask which includes the noisy area and it is applied on retinal image to ensure not to process the noisy area in upcoming steps i.e. feature extraction and abnormality detection. In this segmentation technique, we convert RGB (Red, Green, Blue) retinal image into HSI color space because firstly it is closer to the way a human experiences colors and secondly noise can be easily removed in HSI color space [19]. The RGB retinal image is converted into HSI color space using equations 3, 5 and 6

$$H = \begin{cases} \theta & ifB \le G\\ 360 - \theta & ifB > G \end{cases}$$
(3)

where

$$\theta = \cos^{-1} \left\{ \frac{\frac{1}{2} [(R-G) + (R-B)]}{[(R-G)^2 + (R-B)(G-B)]^{\frac{1}{2}}} \right\}$$
(4)

here R, G and B represent RED, GREEN and BLUE components of RGB retinal image.

$$S = 1 - \frac{3}{(R+G+B)} [min(R,G,B)]$$
(5)  
$$I_n = \frac{1}{3} (R+G+B)$$
(6)

The algorithm for noise removal mask is as below:

Step 1: Divide the input retinal image *I*(*i*,*j*) into non-overlapping blocks with size *w x w*.

Step 2: Use histogram equalization to enhance the contrast

Step 3: Use a 3x3 median filter to reduce the noise in background of image.

Step 4: Convert the equalized and filtered RGB retinal image into HSI color space.

**Step 5**: Calculate *N* (noise factor) which is a ratio of Hue and Intensity

**Step 6**: Select a threshold value empirically.

Step 7: for each pixel,

Calculate N(I)<Threshold?

if true, add pixel in normal retinal image area pixels

if false, add pixel in noisy area pixels

end\_for

Figure 2 shows the coarse background and noise segmentation masks for retinal images. These segmentation masks contain single pixel and edge pixel noise which will be removed in fine segmentation.





# 2.2 Fine Segmentation

Background and noise segmentation masks that are formed by coarse segmentation contain single pixel noise and edge pixels. Fine segmentation is done to remove these noises from segmentation masks. In fine segmentation, morphological operations i.e. morphological dilation, morphological erosion and morphological opening are applied to remove single pixel noise from binary masks [19]. We have used 5 x 5 square structuring element for morphological operations [19]. Background segmentation mask contains black single pixel noise (Figure 2). In order to remove the black pixel noise, square structuring element is used for dilation. Dilation removes all black single pixel noise and edge pixels and it gives a fine background segmentation mask contains white single pixel noise and edge pixels (Figure 2). In order to remove the white pixel noise, square structuring element is used for opening followed by erosion. Opening removes all edge pixels and erosion removes all white single pixel noise and it gives a fine noise segmentation mask. Figure 3 shows coarse segmentation masks and fine segmentation masks.



Figure 3. Fine segmentation. a) Original Color Retinal Images from database; b) Coarse Segmentation Masks; c) Fine Segmentation Mask.

### 2.3 Final Segmentation Mask

Final segmentation mask is prepaid by combining fine background segmentation mask and fine noise segmentation mask. For more fine segmentation mask, small regions are removed by filtering the combined mask by a medium size median filter [19]. Final noise free segmentation mask is then applied on retinal image for its segmentation. Figure 4 shows the final segmentation masks for retinal image segmentation.





Figure 4. (a): Original Color Retinal Image from database; (b): Fine Background Segmentation Mask; (c): Fine Noise Segmentation Mask; (d): Final Segmentation Mask Figure 5 Subjective Validity: (a): Original Color Retinal Images from database; (b): Final Segmentation Masks; (c): Final Segmented Mask.

## 3. Experimental Results

In medical image processing, the validity and evaluation of automated diagnostic systems are very important so we have used four standard retinal image databases i.e. diaretdb0 [12], diaretdb1 [20], DRIVE [21] and STARE [22] to extensively check the proposed method. Diaretdb0 and DiaretDB1 databases contain 130 and 89 retinal images with a resolution of 1500 X 1152 pixels and of different qualities in terms of noise and illumination. DRIVE and STARE databases consist of 40 and 20 images respectively. We have used both objective and subjective criteria for evaluation of proposed method. Figure 5 shows final segmented retinal images and it depicts the subjective validity of proposed method.

Statistical results of our segmentation technique for all 279 images are summarized in table 1 and table 2. Table 1 separately shows the accuracy of background segmentation mask, noise segmentation mask and final segmentation mask. Table 2 shows the results of coarse segmentation, fine segmentation after applying morphological operations and final segmentation after applying morphological operations and final segmentation after applying morphological operations. In order to further evaluate the proposed system, manually labeled preprocessing masks are created by the two experts and these manually labeled masks act as ground truth for accuracy calculations. Table 3 shows the accuracy results of proposed system with respect to manually labeled segmentation masks.

Table 1. Background and Noise segmentation results					
Type of Segmentation Mask	Accurately Processed (Numbers)	Accurately Processed (%)	Poorly Processed (Numbers)	Poorly Processed (%)	
Background Segmentation	275	98.56	4	1.43	
Noise Segmentation	267	95.69	12	4.31	
Final Segmentation	264	94.65	15	5.37	

Table 2. Coarse and fine segmentation results

Type of Segmentation Mask	Accurately Processed (Numbers)	Accurately Processed (%)	Poorly Processed (Numbers)	Poorly Processed (%)
Coarse Segmentation	257	92.11	22	7.89
Fine Segmentation	265	94.98	14	5.02
Final Segmentation	269	96.41	10	3.59

Table 3. Accuracy results for proposed preprocessing method

Database	Accuracy		
DRIVE	0.9982		
STARE	0.9861		
Diaretdb	0.9569		
Average	0.9804		

Retinal images of different illumination and noise values are shown in Figure 6. Figure 6 shows the background segmentation masks, noise segmentation masks, final segmentation masks and final segmented retinal image for each color retinal image. These results support the validity of our technique and show that our technique gives good results for both low and high noisy areas. Figure 7 shows the manually created preprocessing masks and the masks created by proposed algorithm. In order to find out the accuracy, pixel by pixel comparison is done. In order to check the validity of proposed system, we further calculate the receiver operating characteristics curves using manually labeled data as ground truth and comparing the segmented masks with it. Figure 8 shows the ROC curves for DiaretDB0 and DiaretDB1 databases.



Figure 6. Preprocessing results: (a): Original Color Retinal Images from database; (b): Fine Background Segmentation Masks; (c): Fine Noise Segmentation Masks; (d): Final Segmentation Masks; (e): Final Segmented Images.



Figure 7: Accuracy results; row 1: Original retinal images taken from diaretdb database; row 2: Manually created masks by ophthalmologists used as ground truth; row 3: Preprocessing masks created by proposed algorithm





## 4. Conclusion

The problem with retinal images is that the quality of acquired images is usually not good. They contained uneven illuminated, blurred and noisy regions. It is very vital to enhance the quality of colored retinal images for reliable detection of abnormalities. In this paper, we presented a method for the preprocessing of retinal image prior to screening and diagnosis of diabetic retinopathy. The proposed method consisted of background estimation using mean and variance based method and noise modeling and removal using HSI color model. We further divided our algorithm into two phases i.e. coarse and fine segmentation. Final segmented mask is prepaid by combining the background mask and noise segmentation mask. For further improving the quality of segmentation mask, median filter are applied on final segmentation mask to remove small regions. Final segmented masks are then applied on poor quality retinal images for their segmentation. The results are confirmed by visual inspection of segmented images taken from the standard diabetic retinopathy databases. We further used accuracy and ROC curves to validate the proposed method.

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