An Automated System for Colored Retinal Image Background and Noise Segmentation

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***Abstract*—Retinal images are used for the automated diagnosis of diabetic retinopathy. The retinal image quality must be improved for the detection of features and abnormalities and for this purpose segmentation of retinal images is vital. In this paper, we present a novel automated approach for segmentation of colored retinal images. Our segmentation technique smoothes and strengthens images by separating the background and noisy area from the overall image thus resulting in retinal image enhancement and lower processing time. It contains coarse segmentation and fine segmentation. Standard retinal images databases Diaretdb0 and Diaretdb1 are used to test the validation of our segmentation technique. Experimental results indicate our approach is effective and can get higher segmentation accuracy.**

I. Introduction

Diabetes affects almost every one out of ten persons, and has associated complications such as vision loss, heart failure and stroke. Diabetic eye disease refers to a group of eye problems that people with diabetes may face as a complication of diabetes. Patients with diabetes are more likely to develop eye problems such as cataracts and glaucoma, but the diseaseś affect on the retina is the main threat to vision [1].

Complication of diabetes, causing abnormalities in the retina and in the worst case blindness or severe vision loss, is called Diabetic Retinopathy [1]. There are no such symptoms in the early stages of diabetes but the number and severity mostly increase as the time passes. Most patients develop diabetic changes in the retina after approximately 20 years [2]. The common symptoms of diabetic retinopathy are blurred vision (this is often linked to blood sugar levels), floaters and flashes, and sudden loss of vision [2].

To determine if a person suffers from diabetic retinopathy, retinal image is used. Performing the mass screening of diabetes patients will result in a large number of images, that need to be examined. The cost of manual examination is prohibiting the implementation of screening on a large scale. A possible solution could be the development of an automated screening system for retinal images [1]. Such a system should be able to distinguish between affected retinal images and normal retinal images. This will significantly reduce the workload for the ophthalmologists as they have to examine only those images diagnosed by the system as possibly abnormal [3].

A tool which can be used to assist in the diagnosis of diabetic retinopathy should automatically detect all retinal image features such as optic disk, fovea and blood vessel [5], [6], [7] and all abnormalities in retinal image such as microaneurysms [4], [8], [9], hard exudates and soft exudates [10], [11], hemorrhages, and edema [4].

Retinal images are characterized by 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 . Fig. 1 shows three different quality retinal images taken from standard diabetic retinopathy databases, diaretdb0 and diaretdb1 [12].

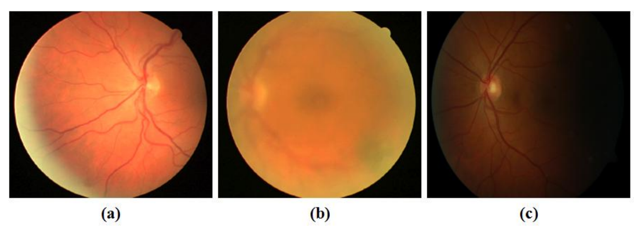

Fig. 1. (a) Uneven illuminated retinal image; (b) Blurred retinal image; (c) Noisy retinal image.

Prior to the detection of retinal image features and abnormalities, segmentation of retinal image must be done for the reliable detection of abnormalities. The purpose of segmentation is to remove the noisy area and unwanted regions from retinal image. It is particularly significant for the reliable extraction of features and abnormalities. Feature extraction and abnormality detection algorithms give poor results in the presence of noisy background area. Fig. 2 shows the input color retinal image and the segmented retinal image.

The aim of segmentation 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 segmentation are filtering and contrast enhancing. Standard contrast stretching techniques have been applied by [4], [13] for segmentation and noise reduction. In [14], [15] and [16] the local contrast enhance-

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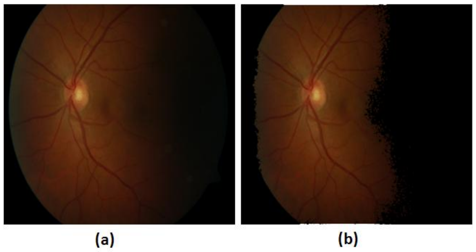

Fig. 2. (a) Original retinal image (b) Segmented retinal image.

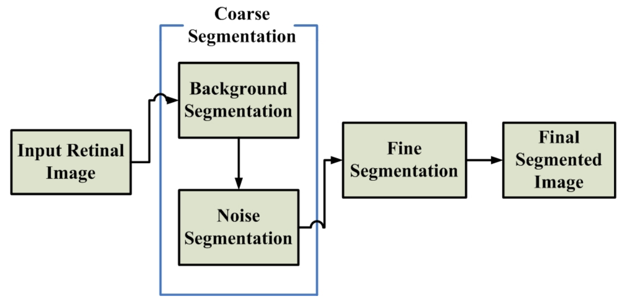

Fig. 3. Flow diagram for retinal image segmentation.

ment 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 background estimation by [11] and [17]. Wang et al. in [18] 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 segmentation technique that detects the dark background using local mean and variance and removes noise using hue and intensity channel values. Our segmentation method consists of two steps. In the first step, it does coarse segmentation that creates binary masks for background segmentation and noise segmentation. 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 II presents the step by step techniques required for color retinal image segmentation. Experimental results are discussed in section III followed by conclusion in section IV.

II. Retinal Image Segmentation

Segmentation is done to extract retinal image from background and to remove 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.

Fig. 3 shows the flow diagram of our segmentation technique.

A. Coarse Segmentation

Coarse segmentation creates background segmentation mask and noise segmentation mask using mean and variance method and HSI (Hue, Saturation, Intensity) color space respectively. The masks created in coarse segmentation have single pixel and edge pixel noise that is why coarse segmentation is followed by fine segmentation to remove these single pixel and edge pixel noise.

1) Background Segmentation Mask: 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 important to distinguish between background and foreground, because feature extraction and abnormality detection algorithms only need to consider the foreground pixels. So it is necessary to remove the foreground from background.

We have used local mean and variance based method for background segmentation. It creates a binary background segmentation mask. Steps for background segmentation are summarized as follows:

- Divide the input retinal image $I(i, j)$ into non-overlapping blocks with size $w \times w$. In our case $w = 8$.
- Compute the local mean value $M(I)$ for each block using equation 1 [19] .

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

- Use the local mean value computed in step 2 to compute the local standard deviation value $std(I)$ from equation 2 [19].

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

- Select a threshold value empirically working on different retinal images. If the $std(I)$ is greater than threshold value, the block is considered as original retinal image area otherwise it belongs to background.

Fig. 4 shows the background segmentation masks for retinal images using our local mean and variance method. These background segmentation masks contain single pixel and edge pixel noise which will be removed in fine segmentation.

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

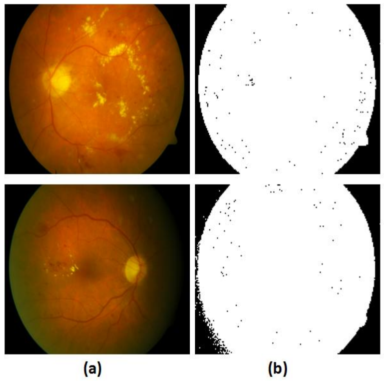

Fig. 4. Column (a): Original color retinal images from database; Column (b): Background segmentation masks.

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 a 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].

Steps for noise segmentation are summarized as follows:

- Divide the input retinal image $I(i,j)$ into non-overlapping blocks with size $w \times w$. In our case $w = 8$.
- Use histogram equalization to enhance the contrast between background and foreground.
- Use a 3x3 median filter to reduce the noise in background of the image .
- Convert the equalized and filtered RGB retinal image into HSI color space using equations 3, 5 and 6.

$$H = \begin{cases} \theta & if B \leq G \\ 360 - \theta & if B > G \end{cases} \tag{3}$$

where

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

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

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

$$I_n = \frac{1}{3}(R+G+B) \tag{6}$$

- Calculate N (noise factor) due to inadequate illumination using equation 7.

$$N(I) = \frac{H}{I_n} \tag{7}$$

- Select a threshold value empirically working on different retinal images. If the $N(I)$ is less than threshold value, the block is considered as normal retinal image area otherwise it belongs to noisy area.

Fig. 5 shows the noise segmentation masks for retinal images using HSI color space. These noise segmentation masks contain single pixel and edge pixel noise which will be removed in fine segmentation.

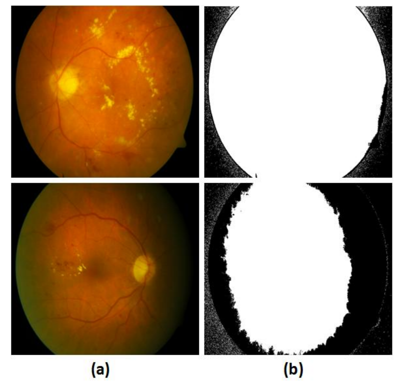

Fig. 5. Column (a): Original color retinal images from database; Column (b): Noise segmentation masks.

B. 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 5×5 square structuring element for morphological operations [19].

Background segmentation mask contains black single pixel noise (fig. 4). 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. Fig. 6 shows the results of coarse background segmentation and fine background segmentation.

Noise segmentation mask contains white single pixel noise and edge pixels (fig. 5). 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. Fig. 7 shows coarse noise segmentation masks and fine noise segmentation masks.

C. 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. Fig. 8 shows the final segmentation masks for retinal image segmentation.

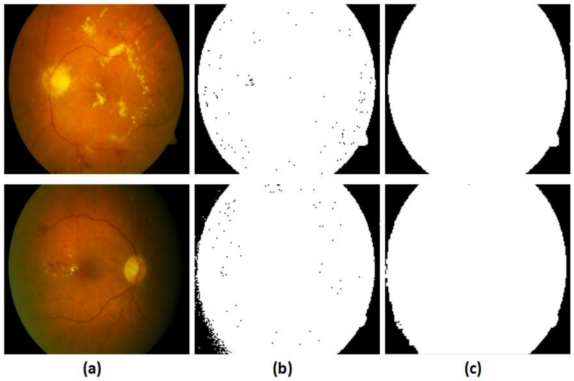

Fig. 6. Column (a): Original color retinal images from database; Column (b): Coarse background segmentation masks; Column (b): Fine background segmentation masks.

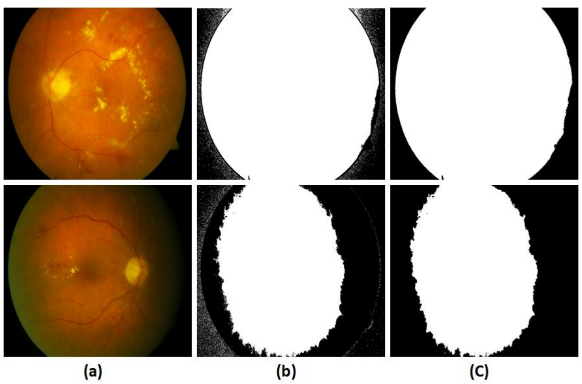

Fig. 7. Column (a): Original color retinal images from database; Column (b): Coarse noise segmentation masks; Column (c): Fine noise segmentation masks.

III. Experimental Results

We have extensively tested our algorithms on standard diabetic retinopathy retinal image databases: diaretdb0 and diaretdb1 [12]. Diaretdb0 database contains 130 retinal images while diaretdb1 database contains 89 retinal images. These databases contain overall 219 retinal images with a resolution of 1500 X 1152 pixels and of different qualities in terms of noise and illumination. The decision for accurate segmentation and poor segmentation is based on human eye observation. Fig. 9 shows final segmented retinal images.

Statistical results of our segmentation technique are summarized in table I and table II. Table I separately shows the accuracy of background segmentation mask, noise segmentation mask and final segmentation mask. Table II shows the results of coarse segmentation, fine segmentation after applying morphological operations and final segmentation after applying median filter. These tables show the number and percentage of accurate segmented retinal images and poorly segmented retinal images.

Retinal images of different illumination and noise values are shown in fig. 10. Fig. 10 shows the background segmentation masks, noise segmentation masks, final segmentation masks and final segmented retinal image for each color retinal image.

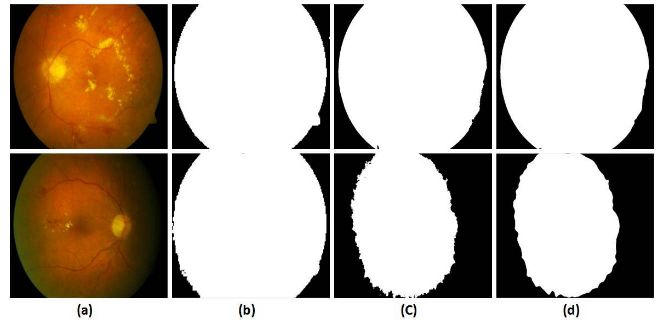

Fig. 8. Column (a): Original color retinal images from database; Column (b): Fine background segmentation masks; Column (c): Fine noise segmentation masks; Column (d): Final segmentation masks

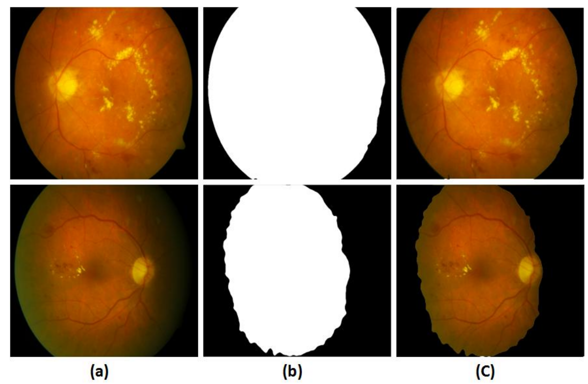

Fig. 9. Column (a): Original color retinal images from database; Column (b): Final segmentation masks; Column (c): Final segmented image.

These results support the validity of our technique and show that our technique gives good results for both low and high noisy areas.

IV. 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, retinal image segmentation is done on the colored retinal images by extracting background and noise effect from the image. Background and noise segmentation masks are created in coarse segmentation

TABLE I
Segmentation Results I

Type of Segmentation Mask	Accurately Processed (Numbers)	Accurately Processed (%)	Poorly Processed (Numbers)	Poorly Processed (%)
Background Segmentation	217	99.08	2	0.92
Noise Segmentation	211	96.34	8	3.66
Final Segmentation	209	95.43	10	4.57

TABLE II
SEGMENTATION RESULTS II

Type of Segmentation Mask	Accurately Processed (Numbers)	Accurately Processed (%)	Poorly Processed (Numbers)	Poorly Processed (%)
Coarse Segmentation	201	91.78	18	8.22
Fine Segmentation	207	94.52	12	5.48
Final Segmentation	209	95.43	10	4.57

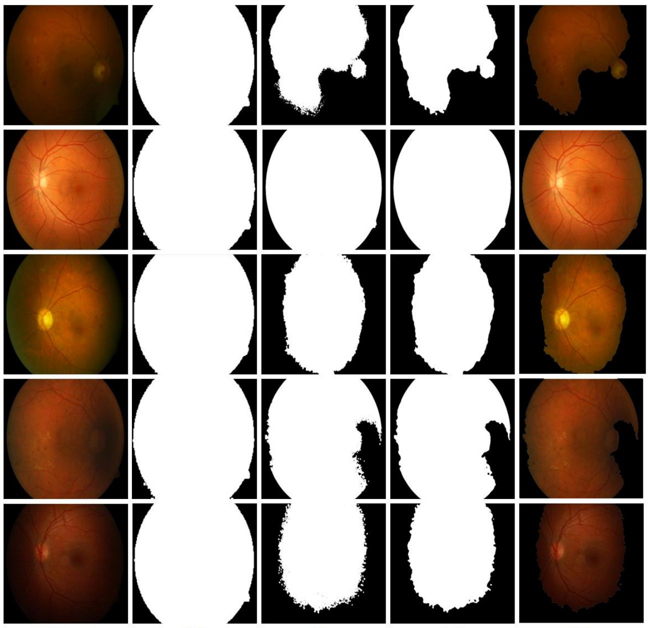

Fig. 10. Column (a): Original color retinal images from database; Column (b): Fine background segmentation masks; Column (c): Fine noise segmentation masks; Column (d): Final segmentation masks; Column (e): Final segmented images

and their quality is improved using morphological operations in 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.

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