Abstract

Diabetic retinopathy (DR) is a condition where the retina is damaged due to fluid leaking from the blood vessels into the retina. In extreme cases, the patient will become blind. Therefore, early detection of diabetic retinopathy is crucial to prevent blindness. In this paper, a system for automatic identification of normal and abnormal retinal images is proposed through automatic detecting of the blood vessels, hard exudates microaneurysms, entropy and homogeneity. The measurements such as exudates area, blood vessels area, micro-aneurysms area, homogeneity and entropy are computed from the processed retinal images. These objective measurements are finally fed to the artificial neural networks (ANNs) classifier for automatic classification. Different approaches for Fundus image restoration are tested and compared. Furthermore, the effect of restoration on the automatic detection process is investigated. The proposed automatic identification system is proved to be reliable under a severe condition of blurred images and can achieve high detection rates with high fidelity features. The system can identify different stages with an average accuracy of more than 93.3 %, a sensitivity of more than 86.6 %, and a specificity of 100 %.

Keywords: Computer-Assisted Diagnostic (CAD), Wavelet Domain Filters, Diabetic retinopathy (DR), Blood Vessels, Exudates, Microaneurysms, Texture Analysis, ANNs.

1. Introduction

Diabetes are the leading cause of new cases of blindness among adults with ages of 20 to 74 and DR is one of the complications caused by diabetes, causes 12,000 to 24,000 new cases of blindness each year (1). People with untreated diabetes are said to be 25 times more at risk of blindness than the general population (1). In Egypt, 7.2% of the population (6,726,000) suffer from diabetes and are at risk of losing their sight due to DR (2). Worldwide, at least 171 million people have diabetes and DR is responsible for 4.8% of the 37 million cases of blindness due to eye diseases (3).

DR leads, eventually, to blindness (4). In its early stages, DR is usually local and it doesn't affect the whole retina, and therefore it causes gradual vision impairments (5), see Figure (1). Consequently, the risk of visual disabilities and blindness due to DR could be greatly minimized by early diagnosis and effective treatments that inhibit the progression of the disease (5). However, patients suffering from DR usually do not
notice any visual imperfections until the disease has affected a large area on the retina. The need for mass-screening of diabetic patients' eyes is clearly a vital concern.

Fundus imaging is a common clinical procedure used to determine if a patient suffers from DR \(^{(4,5)}\). With the new advances in digital modalities for retinal imaging, an ophthalmologist needs to examine a large number of retinal images to diagnose each patient. Although manual diagnosis of this large number of retinal images is possible, the process is prohibitively cumbersome and limits the mass-screening process, i.e. only 40–60% of people with diabetes receive annual examinations by a trained ophthalmologist \(^{(5)}\). Therefore, there is a significant need to develop Computer-Assisted Diagnostic (CAD) tools for automatic retinal image analysis.

Developing CAD systems raised a progressive need of image processing tools that provide fast, reliable, and reproducible analysis of major anatomical structures in retinal Fundus images. Segmentation of these retinal anatomical structures is the first step in any automatic retina analysis system.

In this paper, image deblurring is performed as a pre-processing step prior to the automatic detection process which reducing the effect of blurring and noise on the automatic identification process is presented and discussed. The rest of this paper is organized as follows: Section 2, gives an overview of the retinal image segmentation. Section 3, discusses the implementation issues of the extraction of retinal features algorithms such as blood vessels, exudates and microaneurysms, and texture features. Section 4, illustrates the deblurring methods by Wavelet domain filters. Section 5, discusses the classification of retinal features by Neural Network. Section 6, discusses the result of the automatic detection algorithm with image restoration. Finally, the conclusion of the paper is included in section 7.

![Figure 1: (a) Normal vision (b) A simulation of what someone seen with advanced diabetic retinopathy.](image)

2. Retinal Image Segmentation

Retinal image segmentation includes several steps; contrast enhancement, edge detection, morphological processing, and thresholding. These steps will be explained in the following sub-sections.

2.1 Contrast Enhancement

The retinal images are sometimes poorly contrasted; thus, the retinal structures and exudates are not easily distinguishable from the background. Consequently, a processing of contrast enhancement is vital to improve the contrast of the image. For this reason, a Contrast-Limited Adaptive Histogram Equalization (CLAHE) algorithm is applied.
2.2 Edge Edge Detection

Canny method is used for edge detection. The Canny method performs better than the other edge detection methods, because it uses two thresholds to detect strong and weak edges, and for this reason, canny algorithm is chosen for edge detection in the proposed technique\(^{(7-10)}\).

2.3 Morphological Image Processing

Mathematical morphology can be used in the processing of retinal images. The main processes used here are dilation, erosion, opening, and closing. These processes involve a special mechanism of combining two sets of pixels. Usually, one set consists of the image being processed and the other constitutes the structuring element or kernel. Two very important transformations are opening and closing. Intuitively, dilation expands an image object and erosion shrinks it.

Algorithms combining the above processes are used to create mechanisms of edge detection, noise removal and background removal as well as for finding specific shapes in images\(^{(7-10)}\).

2.4 Thresholding

Thresholding is useful to remove unnecessary details from an image to concentrate on essentials\(^{(10)}\). In the case of Fundus images, by removing all gray level information, the blood vessels are reduced to binary pixels. It is necessary to distinguish blood vessels foreground from the background information. Choosing an appropriate threshold value is important, because a low value may decrease the size of some of the objects or reduce the number of these objects and a high value may include extra background information.

3 Extraction of Retinal Features

3.1 Detection of Blood Vessels

The detection of blood vessels is very important in the identification of diabetic retinopathy. The contrast of the Fundus image tends to be bright in the center and diminish at the side, hence preprocessing is essential to minimize this effect and have a more uniform image. The Fundus image is initially resized to a standard size of 576×720. The green channel of the color Fundus image is used for efficient segmentation, since it has the highest contrast between the blood vessels and the retinal background and it shows a good variation between the optic disk and the background. The intensity of the green channel is then inversed before adaptive histogram equalization is applied to improve the contrast and to correct uneven illumination.

Morphological opening is applied to smooth the background and to highlight the blood vessels. Erosion protects the small blood vessels by reducing their sizes, while dilation blows up the larger remaining details, which are intended to be removed.

The optic disc is then removed by subtracting the image after histogram equalization from the image after morphological opening. The binary image, which contains the blood vessels are computed by the image segmentation to adjust the
contrast intensity, and small pixels considered to be noise are removed. Finally blood vessels are obtained as shown in Figure (2).

![Blood Vessel Extraction Diagram](image)

**Figure 2**: Complete flow diagram of blood vessel extraction system.

### 3.2 Detection of Exudates

Exudates appear as bright yellow-white deposits on the retina due to the leakage of blood from abnormal vessels. Their shape and size will vary with the different retinopathy stages. The Fundus image is first preprocessed to standardize its size to 576x720. In order to detect exudates, firstly similar to blood vessels detection, green component of the RGB image is extracted. Two structuring elements (SEs), namely octagon-shaped SEs and disc-shaped SEs, were used. A morphological closing operation was performed using an octagon-shaped SE of size 9. This results in a good contrast image between the exudates and the background. However, the optic disc will also be present together with the exudates, as their gray levels are comparable with those of exudates. Column wise neighborhood operation was performed to remove the unwanted background artifacts, leaving only the exudates and the optical disc.

Exudates have irregular shapes and borders. To solve this problem, thresholding is performed to the image with the threshold value of 0.7. Then morphological closing with a disc-shaped SE of size 10 is used to fill up the holes or gaps of the exudates. The optic disc contains the highest pixel values in the image. Therefore, to remove the optic disc, edge detection using Canny method is used together with a Region of Interest (ROI). First, a radius of 82 is defined as most optic discs are of size 80 x 80 pixels. Next, the optic disc is removed together with the border. Finally, by performing a morphological erosion operation with disk shaped structuring element (SE) of size 3, exudates were extracted as shown in Figure (3).
3.3 Detection of Microaneurysms

Microaneurysms appear as small dark round dots (~15 to 60 microns in diameter) on the Fundus images. They are small bulges developed from the weak blood vessels and are the earliest clinical sign of DR. The Fundus image is first preprocessed to standardize its size to 576×720 and the intensity of the grayscale image is then adjusted.

The image contrast is stretched by applying adaptive histogram equalization before using edge detection (Canny method) to detect the outlines of the image. The boundary is detected by filling up the holes and a disc-shaped structuring element (SE) of radius 6 is created with morphological opening operation (erosion then dilation). The edge detection image is then subtracted from the image with boundaries to obtain an image without boundaries. After that, the holes or gaps are filled, resulting in microaneurysms and other unwanted artifacts.

The blood vessels which are detected using the above mentioned method are subtracted from the image of microaneurysms and artifacts. Now, the resulting image will have only microaneurysms as shown in Figure (4).

Figure 3: Complete flow diagram of exudates extraction system.

Figure 4: Complete flow diagram of microaneurysms extraction system.
3.4 Texture Analysis:

Texture analysis is the description of regions of an image by their variations in the pixel intensities or gray level. Structural computation is the arrangement of texture elements, while spectral computation is the analysis based on frequency domain. Statistical analysis is based on the intensity relationship of the pixels in statistical features like co-occurrence matrix. Co-occurrence matrix captures the spatial distribution of gray levels and obtains features such as entropy, contrast, homogeneity and correlation. Two texture properties of the image are being measured. Entropy is measured after applying histogram equalization to the green component of the image, while homogeneity is measured by using Gray-Level Co-occurrence Matrix (GLCM) on the grayscale image.

3.4.1 Homogeneity

Homogeneity measures how close the distribution of elements in the GLCM is to the diagonal of GLCM. Homogeneity weights values by the inverse of the contrast weight, with weights decreasing exponentially away from the diagonal as shown in Equation (1). The addition of value ‘1’ in the denominator is to prevent the value ‘0’ during division. As homogeneity increases, the contrast typically decreases.

\[ H = \sum_i \sum_j \frac{1}{1 + (i - j)^2} p_d(i, j) \]  

Where \( p_d \) is the probability of having a pair of pixel values \((i, j)\) occurring in each image and \((i, j)\) denotes a possible pair of the horizontally adjacent pixels i and j.

3.4.2 Entropy:

\[ E = -\sum_i \sum_j p_d(i, j) \ln p_d(i, j) \]

Entropy is understood from the concept of thermodynamics. It is the randomness or the degree of disorder present in the image. The value of entropy is the largest when all elements of the co-occurrence matrix are the same and small when elements are unequal.

4 Wavelet Domain Deblurring Algorithms

Image restoration recovers the original image from a degraded image, which can be approximately described by this equation:

\[ G(u, v) = H(u, v) F(u, v) + N(u, v) \]  

Where \( G(u,v) \) is the blurred image, \( H(u,v) \) is Point Spread Function (PSF), \( F(u,v) \) is the original true image and \( N(u,v) \) is additive noise, introduced during image acquisition, which corrupts the image.

The following are the wavelet restoration steps:

First, the image is decomposed using wavelet packets into various sub-bands. Then, Restoration algorithm is applied to the detail components of these sub bands to remove the unwanted coefficients as a final step, the inverse discrete wavelet transform is applied to reconstructed image.
**4.1 Wiener Filter Deblurring Method**

Wiener filtering is performed on wavelet coefficients. The Wiener filter isolates lines in a noisy image in frequency domain by finding an optimal tradeoff between inverse filtering and noise smoothing. It removes the additive noise and inverts the blurring simultaneously so as to emphasize any lines which are hidden in the image (25).

\[
\hat{F}(u, v) = \Psi(u, v)G(u, v) = \frac{G(u, v)H^*(u, v)}{|H(u, v)|^2 + P_n(u, v) / P_f(u, v)}
\]

Where \( H(u, v) \) is the blur frequency response, \( P_n(u, v) \) and \( P_f(u, v) \) are the power spectra of the original image and the noise respectively.

**4.2 Log Gabor Filter**

Images are better coded by filters that have Gaussian transfer functions when viewed on the logarithmic frequency scale. Gabor functions have Gaussian transfer functions when viewed on the linear frequency scale. On the linear frequency scale the Log-Gabor function has a transfer function of the form (23-25):

\[
G(\omega) = e^{-\log(\omega/\omega_0)^2 / 2 \log(k/\omega_0)^2}
\]

Where \( \omega_0 \) is the filter centre frequency.

**4.3 VisuShrink**

It uses a threshold value \( T \) that is proportional to the standard deviation of the noise. It follows the hard thresholding rule. It is also referred to as universal threshold and is defined as:

\[
T = \sigma \sqrt{2 \log n}
\]

\( \sigma \) is the noise variance and \( n \) represents the signal size or number of samples. An estimate of the noise level \( \sigma \) was defined based on the median absolute deviation given by:

\[
\hat{\sigma} = \frac{\text{median}(\{|g_{j-1,k}| : k = 0, 1, \ldots, j-1\})}{0.6745}
\]

Where \( g_{j-1,k} \) is refers to the detail coefficients in the wavelet transform.

**4.4 Sure Shrink**

A threshold chooser based on Stein’s Unbiased Risk Estimator (SURE) was proposed by Donoho and Johnstone and is called as Sure Shrink. It is a combination of the universal threshold and the SURE threshold (26,27). This method specifies a threshold value \( t_j \) for each resolution level in the wavelet transform which is referred to as level dependent threshold. The goal of Sure Shrink is to minimize the mean squared error (28), defined as:

\[
MSE = \frac{1}{n^2} \sum_{x,y=1}^{n} (z(x, y) - s(x, y))^2
\]

Where \( z(x, y) \) is the estimate of the signal, \( s(x, y) \) is the original signal without noise and \( n \) is the size of the signal. SureShrink suppresses noise by threshold the empiricalwavelet coefficients. The Sure Shrink threshold \( t^* \) is defined as:
\[ T^* = \min\left( t, \sigma \sqrt{2 \log n} \right) \]  

Where denotes the value that minimizes Stein’s Unbiased Risk Estimator. \( \sigma \) is the noise variance computed from Equation (7), and \( n \) is the size of the image.

5. Classification

The ANN used for this approach is the feed-forward network and it uses supervised learning to train the neural network. Supervised learning is a technique in which the network is trained by providing it with input and matching it with a desired output (11-13). The input layer is made up of nodes to accept the 5 data values which represent the metrics defined above, while the subsequent layers process the values using an activation function. There are 10 neurons for each “hidden layer” and the trained network would output binary numbers, which represent the two different cases of normal stage and abnormal stage.

6. Experimental Results

6.1 Performance Evaluation of the DR Identification System

Typically, performance of the DR identification systems is usually evaluated with Sensitivity and Specificity. Sensitivity measures the proportion of actual positives which are correctly identified as such (e.g. the percentage of sick people who are identified as having the condition). Specificity measures the proportion of negatives, which are correctly identified (e.g. the percentage of healthy people who are identified as not having the condition). A theoretical optimal prediction can achieve 100% sensitivity (i.e. predict all people from the sick group as sick) and 100% specificity (i.e. not predict anyone from the healthy group as sick) (14). In this approach, the system was designed to screen people for different stages of DR as shown in Figure (5). Each person taking the test either has or does not have the disease. The test outcome can be positive (predicting that the person has the disease) or negative (predicting that the person does not have the disease). The table shown below shows the accuracy of the classifier with image restoration. Sensitivity refers to the probability of a positive test among the subjects with the condition, while specificity refers to the probability of a negative test among the subjects without the condition. The sensitivity of the test indicates the probability that it would indicate a TP result when used on an infected subject. The specificity of the test can be determined by the formula.

\[ Sensitivity \ y(SE) = \frac{TP}{TP + FN} \times 100 \]  

(10)

The specificity of a test is the probability that a test will produce a TN result when used on a non-infected population. The specificity of a test can be determined by calculating:

\[ Specificity \ y(SP\%) = \frac{TN}{TN + FP} \times 100 \]  

(11)

The Accuracy of the test indicates the closeness of the test results to the true value and repeatability of the test. The accuracy of the test can be determined by the formula:

\[ Accuracy \ ( AC\%) = \frac{TP + TN}{TP + FN + TN + FP} \times 100 \]  

(12)
6.2 Results

Computer simulations were carried out using MATLAB (R2010a). The quality of the reconstructed image is specified in terms of the Peak Signal-to-Noise Ratio (PSNR)\(^{30}\).

\[
PSNR = 10 \log_{10} \frac{255^2}{MSE}
\]  

Experimental results are conducted on 30 images of Fundus images which contain 15 images of healthy patients, 15 images of patients with diabetic retinopathy\(^{29}\).

Gaussian noise was added to the images with different variances (0.01, 0.05 and 0.1) PSNR output values and CPU time for the Fundus image are shown in Table (1). Table (2), Table (3) and Table (4), show the numerical results of applying the previous mentioned filtering methods to Fundus images.

Table 1: PSNR output values of the Fundus images with gaussian noise variance of (0.01: 0.1) at blur length=10.

<table>
<thead>
<tr>
<th>Filters</th>
<th>Blur length=10</th>
<th>Noise variance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Noise variance</td>
<td></td>
</tr>
<tr>
<td>Visushrink</td>
<td>27.874</td>
<td>22.558</td>
</tr>
<tr>
<td>Sureshrink</td>
<td>25.345</td>
<td>20.434</td>
</tr>
<tr>
<td>Wiener</td>
<td>24.762</td>
<td>19.200</td>
</tr>
</tbody>
</table>

Table 2: PSNR output values of the Fundus images with gaussian noise variance of (0.01: 0.1) at blur length=15.

<table>
<thead>
<tr>
<th>Filters</th>
<th>Blur length=15</th>
<th>Noise variance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Noise variance</td>
<td></td>
</tr>
<tr>
<td>Visushrink</td>
<td>27.309</td>
<td>22.335</td>
</tr>
<tr>
<td>Sureshrink</td>
<td>25.194</td>
<td>20.307</td>
</tr>
<tr>
<td>Wiener</td>
<td>24.578</td>
<td>19.151</td>
</tr>
<tr>
<td>Log Gabor</td>
<td>23.962</td>
<td>18.739</td>
</tr>
</tbody>
</table>
Table 3: CPU time output values of the Fundus image with gaussian noise variance of (0.01: 0.1) at blur length=10.

<table>
<thead>
<tr>
<th>Filters</th>
<th>Blur length=10 Noise variance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.01</td>
</tr>
<tr>
<td>Visushrink</td>
<td>3.46</td>
</tr>
<tr>
<td>Sureshrink</td>
<td>12.137</td>
</tr>
<tr>
<td>Wiener</td>
<td>12.461</td>
</tr>
<tr>
<td>Log Gabor</td>
<td>13.205</td>
</tr>
</tbody>
</table>

Table 4: CPU time output values of the Fundus image with gaussian noise variance of (0.01: 0.1) at blur length=15.

<table>
<thead>
<tr>
<th>Filters</th>
<th>Blur length=15 Noise variance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.01</td>
</tr>
<tr>
<td>Visushrink</td>
<td>3.4396</td>
</tr>
<tr>
<td>Sureshrink</td>
<td>12.618</td>
</tr>
<tr>
<td>Wiener</td>
<td>15.852</td>
</tr>
<tr>
<td>Log Gabor</td>
<td>16.395</td>
</tr>
</tbody>
</table>

Results show that the Visushrink gives the best PSNR value and the best CPU time.

Table 5: Sensitivity, Specificity, Positive predictive accuracy, Accuracy with different deblurring methods.

<table>
<thead>
<tr>
<th>The Method</th>
<th>Visushrink</th>
<th>Sureshrink</th>
<th>Wiener</th>
<th>Log Gabor</th>
</tr>
</thead>
<tbody>
<tr>
<td>TN</td>
<td>15</td>
<td>15</td>
<td>14</td>
<td>14</td>
</tr>
<tr>
<td>TP</td>
<td>13</td>
<td>12</td>
<td>13</td>
<td>12</td>
</tr>
<tr>
<td>FP</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>FN</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Se%</td>
<td>86.60%</td>
<td>80%</td>
<td>86.60%</td>
<td>80%</td>
</tr>
<tr>
<td>Sp%</td>
<td>100%</td>
<td>100%</td>
<td>93.30%</td>
<td>93.3%</td>
</tr>
<tr>
<td>Ac%</td>
<td>93.30%</td>
<td>90%</td>
<td>90%</td>
<td>86.6%</td>
</tr>
</tbody>
</table>

Table (5) gives the evaluation parameters of wavelet domain deblurring methods. From Table (6), it can be noted that Visushrink has the best performance amongst the other methods.

Table 6: The Result of Proposed and Literature Reviewed Methods.

<table>
<thead>
<tr>
<th>Author</th>
<th>Sensitivity</th>
<th>Specificity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apichat Suansilpong.</td>
<td>65.6%</td>
<td>84.9%</td>
</tr>
<tr>
<td>Iqbal, M.I et al..</td>
<td>98%</td>
<td>61%</td>
</tr>
<tr>
<td>Lin et al.</td>
<td>78%</td>
<td>86%</td>
</tr>
<tr>
<td>Maberley et al.</td>
<td>84.4%</td>
<td>79.2%</td>
</tr>
<tr>
<td>Herbert et al</td>
<td>38.2%</td>
<td>95.5%</td>
</tr>
<tr>
<td>Proposed Method</td>
<td>86.6%</td>
<td>100%</td>
</tr>
</tbody>
</table>
7. Conclusions

In this paper, we have investigated an automatic detection system for Fundus images under a severe condition of blurred images. The paper suggested the application of the Visushrink deblurring algorithm prior to the automatic detection step to enhance the performance of the automatic detection system. Simulation results have shown that Visushrink plays a vital role in enhancing the Fundus images and achieves high detection rates with high fidelity features. The system can identify different stages with an average accuracy of more than 93.3 %, a sensitivity of more than 86.6 %, and a specificity of 100 %.

References

[10] A. McAndrew, "Introduction to Digital Image Processing With Matlab", Published April 7th 2004 by Course Technology.


