**Automatic Detection of Hard Exudates in Retinal Images Using Haar Wavelet Transform**

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**ABSTRACT**

Diabetic Retinopathy (DR) is a leading cause of vision loss, caused by the abnormalities in the retina due to insufficient insulin in the body. So that Diabetic patients require regular medical checkup for effective timing of sight saving treatment. A completely automated and robust screening system for the detection of Diabetic Retinopathy can effectively reduces the burden of the specialist and saves cost as well as time. Due to noise and other disturbances that occur during image acquisition, DR may lead to false detection and this is overcome by various image processing techniques. This paper presents an automated method for bright lesions i.e. hard exudates in retinal images. The Haar wavelets transform is used in the system for the hard exudates segmentation followed by k nearest neighbor classification method. We have used four databases of fundus images; among them we obtain sensitivity 37.14%, 21.87%, 12.50%, 25.47% for MISP, DB0, DB1 and STARE database respectively. And the specificity is 0% for MISP and 1% for remained databases.

**Keywords:** Retinal images, diabetic retinopathy, hard Exudates, optic disk, DWT wavelet transform.

1. **INTRODUCTION**

This paper represents the introduction and usage of medical imaging, texture analysis, diabetic retinopathy and wavelet transforms. For the implementation of hard exudates detection system, we used four databases named as MISP (Medical Image and Signal Processing Research Center, Iran), DIRETDB0, DIREDB1 and STARE.

1.1. Medical Imaging

In recent years, advances in information technology and telecommunications have acted as catalysts for significant developments in the sector of health care. These technological advances have strong impact in the field of medical imaging, where film radiographic techniques are gradually being replaced by digital imaging techniques, which has provided an impetus to the development of integrated hospital information systems [1]. Furthermore, Medical image processing is an exciting and active field of research, where disciplines such as Engineering, Computer Science, Physics, Biology and Medicine inter-disciplinarily cooperate in order to improve health care. Most frequently, medical images are the basis of diagnostics, treatment planning, and treatment, but also important for medical education, research and epidemiology.

In the recent developments, medical image segmentation has a major trend towards better screening[2] in applications of segmentation [3] like to locate tumors, optic disk and other pathologies, Measure tissue volumes, Computer-guided surgery, Diagnosis Treatment planning Study of anatomical structure [4].

1.2. Texture Analysis

Texture analysis performs an important place in many tasks such as machine vision, scene classification, shape determination and image processing. The major application domains in texture analysis are Texture classification, Texture segmentation, Shape recovery. The problem in texture classification is that textures in real world are often not uniform due to variation in orientation, scale and other visual appearance. A segmentation method ideally locates those sets that correspond to distinct anatomical or pathological regions of interest in the image. Pixel classification is often a desirable objective in medical imaging, particularly when disconnected regions belonging to the same tissue class need to be identified. A typical sequence is as follows:

a. Pre-processing: It may use to normalize image brightness, correct for image non-uniformity, reduce noise, or reduce image artefacts.

b. Segmentation: It decomposes an image into its constituent regions on objects. E.g. Retinal blood vessels, optic nerve head, or pathological lesions.

c. Feature Extraction: It typically computes quantitative information from the segmented objects. The extracted features can be used to classify object according to predetermine criteria such as size, morphology and colour [5], [6].

1.3. Diabetic Retinopathy

In recent years, Diabetic Retinopathy is a leading cause of vision loss in the working class in the world [7], [8]. It is retinopathy (damage to the retina) caused by implications of diabetes, which can eventually lead to blindness because of damage to the blood vessels that nourish the retina [9]. It is considered to be the result of vascular changes in the retinal circulation. These abnormalities in the retina are due to insufficient insulin in the body [10]. It is a progressive...
eye disease that currently affects 250 million of people worldwide [24] in the developed countries [11]. Hence it is significant to monitor the health of the retina for those people who have signs of diabetic retinopathy [12].

![Normal Vision and Diabetic Retinopathy](image)

1.3.1. Stages of DR

DR is categorized into four main stages as follows:

1. **Mild non-proliferative Retinopathy (NPDR):** At this earliest stage, micro-aneurisms occur. They are small areas of balloon like swelling in the retina’s tiny blood vessels. It is also called as ‘Background Retinopathy’.

2. **Moderate non-proliferative Retinopathy:** At this stage, disease progresses, and some blood vessels that nourish the retina are blocked.

3. **Severe non-proliferative Retinopathy:** Many more blood vessels are blocked, depriving several areas of the retina with their body supply.

4. **Proliferative Retinopathy:** At this advanced stage, new blood vessels are abnormal and fragile. They grow along the retina and surface of the clear, vitreous gel that fills inside of the eye. By themselves, these blood vessels do not cause symptoms or vision loss. They have thin, fragile walls. If they leak blood, severe vision loss and even blindness can result.

1.3.2. Signs of DR

Early signs are also known as ‘Non-proliferative DR. They are as below:

- **Micro-aneurisms:** Small blow-out swelling of blood vessels.
- **Hemorrhages:** Small bleeds from damaged blood vessels.
- **Cotton wool spots:** Yellow-white spots caused by retinal nerve fibre layer micro-infarcts (cotton wool spots). These arrayed around the optic disc and along the temporal vascular arcades.
- **Exudates:** Small leaks of fluid from damaged blood vessels [geteyesmart.org]

1.4. Fundus Images

Fundus imaging has an important role in diabetic retinopathy detection and monitoring because eye fundus is sensitive to vascular diseases. Therefore, it is considers for non-invasive screening. The success of this type of screening approach depends on accurate fundus image capture and especially on accurate and robust image processing and analysis algorithms for detection of abnormalities [13].

![Normal Retinal Image and Pathological Lesions](image)

Early diagnosis of diabetic retinopathy enables timely treatment and in order to achieve it a major effort will have to be invested into automated screening programs. For automated screening programs to work robustly efficient image processing and analysis algorithms have to be developed. Their digital nature allows automatic analysis to reduce the workloads of the ophthalmologists and the health costs in the screening of the disease [14].

Among lesions caused by DR, exudates are one of the most commonly occurring lesions. They are associated with patches of vascular damage with leakage. The size and distribution of exudates may vary during the progress of the disease. The detection and quantification of exudates will significantly contribute to the mass screening and assessment of NPDR [15], [16]. Global and local thresholding values were used to segment exudate lesions from the red-free images. Before thresholding can be done, the digitized color photographs were preprocessed to eliminate photographic nonuniformities (shade correction), and the contrast of the exudates was then enhanced.
2. RELATED WORK

Alireza Osareh, et al., 2001 introduced a method for the detection of exudate regions using Fuzzy C-Means clustering, and classified the regions into exudates and non-exudates patches using a neural network. They achieve 92% sensitivity and 82% specificity. Huiqi Li and Opas Chutatat; 2004 has proposed an algorithm for the automatic and robust extraction features by the combined region growing and edge detection. Principal component analysis (PCA) is employed to locate optic disk and shape detection. They obtain sensitivity and specificity of exudates detection 100% and 71%, correspondingly. Clara I. Sanchez, et al., 2009, proposed an automatic method to detect hard exudates based on mixture models algorithms to dynamically threshold the images in order to separate exudates. The algorithm obtained a sensitivity of 90.2% and a positive predictive value of 96.8% using a lesion-based criterion. Hussain F. Jaafar, et al., 2010, presented hard and soft exudates detection method in retinal images using split-and-merge algorithm based on image features and a statistical hypothesis. Exudates were detected from a database with 89.7% sensitivity, 99.3% specificity and 99.4% accuracy. V. Vijayakumari, N. Suriyanarayanan, 2010, developed frame work for deducing the presence or absence of DR using combination of two images i.e. binary-hypothesis and Minimum Distance Discriminant (MDD) classifier which used for enhancement using RGB values and characterized abnormality by yellowish color and sharp edge which gives better result to achieve good sensitivity. Luca. Giancardo, et al., 2011, introduced methodology for diagnosis of DME based on three feature vectors i.e. Exudate probability map. Color analysis and Wavelet analysis. The algorithm obtained an AUC (Area Under the ROC Curve) between 0.88 and 0.94. Hussain F., et al., 2011, proposed an automated algorithm to detect and grade the severity of hard exudates. The results of hard exudates detection was with sensitivity of 93.2%, PPV (Positive Predictive Value) of 80.7%, specificity of 99.2% and accuracy of 99.4%. Atul Kumar et al., 2012, used SVM (Support Vector Machine) with morphological operation to detect exudates. The sensitivity of method is 97.1% for the classifier and the specificity is of 98.3%. Carla Agurto, et al., 2012, detected pathologies on the macula such as hard exudates micro-anerysms, and hemorrhages with 100% sensitivity in detecting macula with hard exudates and 92% sensitivity in detecting macula with red lesions. R. Radha and Bijee Lakshman; 2013, developed a method to recognizes the retina to be normal or abnormal. They got 98% accuracy in the detection of the exudates in the retina. A. Osareh, et al., 2013, used the Fuzzy C-means clustering algorithm for segmentation and neural network (NN). It demonstrates 93.0% sensitivity and 94.1% specificity in terms of exudates based classification and 95.0% sensitivity and 88.9% specificity. R. F. Mansour, et al., 2013, used Discrete Cosine Transform (DCT) analysis and SVM to perform the classification of retinal exudates. The system achieved a diagnostic accuracy with 97.0% sensitivity and 98.7% specificity. Kullayamma, P. Madhavee Latha, Feb. 2013, classified eye image using Discrete Wavelet Transform (DWT) to obtain texture features and classified based on neural network. It obtained accurate image classification, executes detection and is useful in diabetic diagnosis with better performance compared to other methods. Thomas Walter, et al., 2002, used Histogram Equalization techniques and Fuzzy C-means Clustering algorithm for hard exudates detection. They obtained sensitivity 80% and specificity 99.5%. The morphological transformation approach was used by Harihar Narasimha Iyer, et al., 2007, for preprocessing followed by neural network system technique. They got sensitivity 94.78% and specificity 94.29%. Another approach was used by Luca Giancardoa,b, Fabrice Meriaudeau,a, et al., 2010, as Region Growing for preprocessing, to extract features they used Neural Network System, then for classification Support Vector Machine used. So they obtained accuracy 98.77% for hard exudates. Diego Marin, et al., 2011, used Morphological Reconstruction and Fuzzy C-means Clustering technique for feature extraction. So sensitivity 87.28%, accuracy 99.11, specificity 99.24% was obtained.

3. WAVELET TRANSFORMS

Wavelets have been widely used in signal and image processing for the past 20 years. A milestone paper by Grossmann and Morlet [17] was considered as the beginning point of modern wavelet analysis. The first use of wavelets was by Alfred Haar in 1909 and first introduced to medical imaging research in 1991 for noise reduction in MRI images [18].

In our approach, we have used Haar family orthogonal wavelet. It can keep track of time and frequency information. There are two main types of wavelet transform continuous and discrete. Because of computers discrete nature, computer programs use the discrete wavelet transform. It is an important tool for image denoising due to its energy compaction property [18]. Wavelet transform computes the approximation coefficients matrix and details coefficients matrices i.e. horizontal, vertical, and diagonal, respectively. Here, inverse wavelet i.e. reconstructed image gives good result. Therefore, exudate parameters viz. area and number of exudates are computed.

3.1. Dual–tree Complex Wavelet Transform

The Dual-Tree Complex Wavelet Transform (DT-CWT) has been developed to incorporate the good properties of the Fourier transform in the wavelet transform. As the name implies, two wavelet trees of real filters are used to generate the real and imaginary parts of the wavelet coefficients separately with the following properties:

1. Shift Invariance

DT-DWT has approximate shift-invariance, or improved time-shift sensitivity in comparison with standard DWT. The reconstructed details at various levels and approximation at the last level have almost uniform shifts for the time-shifted unit step functions.
2. Good Selectivity and Directionality
DT-DWT gives better directional selectivity in 2-D with Gabour like filters (also true for higher dimensionality m-D). DT-DWT has 12 directional wavelets (6 for each of real and imaginary trees) oriented at angles of in 2-D. The improved directionality with more orientations suggests the advantage of DT-DWT in a wide range of directional image processing applications, e.g. texture analysis.

3. Phase Information
Local phase extraction is possible through analytic interpretation of two parallel trees of DT-DWT. The phase of any given subband at a given level can be computed with its corresponding real and imaginary coefficients.

4. Perfect Reconstruction (PR)
The DT-DWT structure follows PR conditions; hence, the original signal can be reconstructed from the transform domain complex wavelet coefficients.

5. Limited Redundancy
Though DT-DWT structure is expensive than standard DWT, it is significantly less expensive than WP, or non-decimated DWT (SWT) for the same advantage of reduced shift-sensitivity. Moreover, DT-DWT has other advantages such as improved directionality and phase information to compensate for its limited redundancy over standard DWT [18], [20].

4. METHODOLOGY
In our approach, we have used some morphological operations for geometrical transformations, color normalization, and contrast enhancement in preprocessing. So that we can get the exudates probability map. Then the haar wavelet transform is applied for the image decomposition and reconstruction. Hence, exudates are bright and clear in reconstruction. Then KNN (k Nearest Neighbor) is used to correctly classify how many images have been correctly classified into exudates and non-exudates.

Fig.3. Process flow of hard exudates detection using (a) probability map and (b) sobel edge operator

4.1. Preprocessing
Here, we have used the green channel of the image, because green channel shows high intensity as compared to red and blue [21]. We resize the image to a height of 720 pixels maintaining the original height/width ratio. The mathematical formula for finding green channel is as below:

\[ g = \frac{G}{R + G + B} \]  

Here, \( g \rightarrow \) green channel  
\( R, G, B \rightarrow \) Red, Green, Blue respectively.

Fig.4. (a) Original Retinal Image  (b) Green channel Image
4.2. Colour normalization
Color normalization is necessary due to the significant intra-image and inter-image variability in the colour of the retina in different patients. Mathematical expression for histogram equalization technique of the standard image is given below. Let \( Ps(s) \) and \( Pd(s) \) represent the standard image and desired image probability density functions, respectively.

\[
u = T(s) = \int_0^s p_s(x)dx \tag{2} \]

The non-flat structuring element is used to remove optic disk [22] from an image. For background estimation, the contrast limited adaptive histogram equalized image is subtracted from structuring element.

![Fig.5. (a) Color Normalization          (b) Removing Optic Disk](image)

4.3. Contrast Enhancement
This technique is used to makes an object distinguishable from other objects and the background. Therefore, to enhance the contrast of reference image Contrast-Limited Adaptive Histogram Equalization (CLAHE) algorithm is used, which transforms the values. So resulted image would have uniform background and high contrast. After applying CLAHE, the reference image is converted into binary image or threshold for clear exudation.

![Fig.6. CLAHE and Threshold Image](image)

4.4. Haar Wavelet Transform
The Haar transform \( H^N(f) \) of an \( N \)-input function \( X^N(f) \) is the \( 2^N \) element vector

\[
H^N(f) = H^N X^N(f) \tag{3}
\]

The Haar transform cross multiplies a function with Haar matrix that contains Haar functions with different width at different location.

The Haar transform is performed in levels. At each level, the Haar transform decomposes a discrete signal into two components with half of its length: an approximation (or trend) and a detail (or fluctuation) component. The first level of approximation \( a^1 = (a_1, a_2, \cdots , a_{N/2}) \) is defined as

\[
a_m = \frac{x_{2m-1}+x_{2m}}{\sqrt{2}} \tag{4}
\]

\( Form = 1,2,3,\cdots,N/2 \) where \( x \) is the input signal. The multiplication of \( \sqrt{2} \) ensures that the Haar transform preserves the energy of the signal. The values of \( a^1 \) represents the average of successive pairs of \( x \) value.

The first level detail
\( d^1 = (d_1, d_2, \cdots, d_N) \) \hspace{1cm} (5)

Is defined as

\[ d_m = \frac{x_{2m-1} - x_{2m}}{\sqrt{2}} \] \hspace{1cm} (6)

For \( m = 1, 2, 3, \cdots, N/2 \) the values of \( d^1 \) represents the difference of successive pairs of \( X \) value. The first level Haar transform is denoted as \( H_1 \). The inverse of this transformation can be achieved by

\[ X = \frac{x_1 + d_1}{\sqrt{2}}, \frac{x_2 - d_1}{\sqrt{2}}, \ldots, \frac{x_{N/2} + d_{N/2}}{\sqrt{2}}, \frac{x_{N/2} - d_{N/2}}{\sqrt{2}} \] \hspace{1cm} (7)

The successive level of Haar transform, the approximation and detail component are calculated in the same way, except that these two components are calculated from the previous approximation component only.

**Fig. 7.** Approximation decomposition in Horizontal, Vertical and Diagonal

**Fig. 8.** Reconstruction using Haar Transform
5. Performance Analysis

Quantitative evaluation of the segmentation algorithm is done by calculating the positive and negative values using the following formulae.

\[
\text{Table 3.1: Performance Analysis}
\]

<table>
<thead>
<tr>
<th>Method Result</th>
<th>Ground Truth</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Positive</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Positive</td>
<td>True Positive (TP)</td>
<td></td>
<td>False Positive (FP)</td>
</tr>
<tr>
<td>Negative</td>
<td>True Negative (TN)</td>
<td></td>
<td>False Negative (FN)</td>
</tr>
</tbody>
</table>

Using this table, sensitivity and specificity are evaluated (see following eq.) Sensitivity is the percentage of abnormal fundus images classified as abnormal, and specificity is the percentage of normal fundus images classified as normal by the screening. The higher the sensitivity and specificity values, the better the diagnosis.

\[
\text{Sensitivity} = \frac{TP}{TP + FN} \quad (8)
\]

\[
\text{Specificity} = \frac{TN}{TN + FP} \quad (9)
\]

Where,
- TP/TPR \(\rightarrow\) number of true positive instances
- FP \(\rightarrow\) number of false positive instances
- TN/TNR \(\rightarrow\) number of true negative instances
- FN \(\rightarrow\) number of false negative instances

(Positive Predictive Value) \(PPV = \frac{TP}{TP + FP}\) \quad (10)

(Negative Predictive Value) \(NPV = \frac{TN}{TN + FN}\) \quad (11)
Following graph (1) shows the sensitivity, specificity, Positive Predictive Value, Negative Predictive Value and Accuracy for exudates detection.

\[
\text{(Accuracy)} = \frac{TP + TN}{TP + FN + TN + FP}
\] (12)

**Graph1:** Performance Analysis Graph

### 6. Conclusion and Future Scope

In this work we tried to develop the system for hard exudates detection from retinal images using haar wavelet transforms. DTCWT will be very much useful to detect Architectural Distortion and Micro-Aneurisms, which are the principal sign of early detection of diabetic retinopathy. As wavelets are specially designed for multi-resolution analysis, the exudates are not detected in multi-resolution images. So, the pre-processing steps have applied for the exudates probability map. Then using haar wavelet reconstruction, diabetic retinopathy lesion viz. hard exudates get bright and clearly detected. We obtain 37.14% sensitivity and 0% specificity for MISP database. Also sensitivity 21.87%, 12.5%, 25.47%, accuracy is 22.48%, 13.48%,31.48% for DB0, DB1 and STARE database respectively and 1% specificity for each. It will be useful to ophthalmologists in early detection of non-proliferative diabetic retinopathy. In future, we will try to improve the system to get good of hard exudates detection.

### REFERENCES


