Improved Efficiency of Glaucoma Detection by using Wavelet Filters, Prediction and Segmentation Method

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Abstract—Glaucoma is the second leading cause of peripheral blindness worldwide and it results in the neuro-degeneration of the optic nerve. In this paper, the work is focused on improving the sensitivity of automated classification system for Glaucoma by implementing the two techniques by extracting image features from eye fundus photographs. A data-driven approach is developed which requires no manual supervision. Our goal is to establish a screening system that allows fast, and automated detection of Glaucomatous changes in the eye fundus. Here the work is focused on extracting the energy features extracted from eye fundus images using Discrete Wavelet Transforms and segmentation of optic cup and disc. The wavelet features are obtained from the daubechies (db3), symlets (sym3), and biorthogonal (bio3.3, bio3.5, and bio3.7) wavelet filters. This energy features obtained from the detailed coefficients can be used to distinguish between normal and glaucomatous eye images. Along with this technique Optic cup to disc ratio is also calculated, which improves the accuracy of detecting the Glaucoma. Here optic disc is extracted using disc prediction method and optic cup is segmented using watershed segmentation. System was tested on the samples obtained from K.L.E.Dr.Prabhakar Kore Hospital and Medical Research Center, Belgaum, India and efficiency was found out to be 96%.

Index Terms— Glaucoma, Optic cup, Disc, 2D Wavelet filters of discrete wavelet transform, Pixel based segmentation, Watershed segmentation.

1. INTRODUCTION

Glaucoma is an eye disease caused by elevated Intra-Ocular Pressure (IOP), which is introduced by the aqueous humor secreted in the eye. The aqueous humor provides oxygen and vital nutrients to cornea and lens. It is drained out through the drainage canals of the eye. Glaucoma is developed when the drainage canals become blocked. Due to this, the aqueous humor cannot drain away normally and the pressure inside increases. This elevated pressure destroys the optic nerve. Impact of early stage Glaucoma on vision is as shown in Figure 1.1 and Figure 1.2. Glaucoma causes enlargement of optic cup and loss of vision. Enlargement of optic cup is as shown in Fig.2.1 and Fig. 2.2. If the ratio of Optic cup to disc becomes greater than 0.3 it is detected as Glaucoma. It is important to detect malign changes and abnormal structures of the optic disc as early as possible and
monitor their progress during clinical therapy. As the revitalization of the degenerated optic nerve fibers is not viable medically, Glaucoma often goes undetected in its patients until later stages. Furthermore, in countries, like India, it is estimated that approximately 11.2 million people over the age of 40 suffer from Glaucoma [1]. It is believed that these numbers can be curtailed with effective detection and treatment options.

![Figure 1.1](image1.jpg)  ![Figure 1.2](image2.jpg)

Figure 1.1 Normal vision  Figure 1.2 Vision affected by Glaucoma

Usually Retinal image analysis techniques rely on computational techniques to make qualitative assessments of the eye more reproducible and objective. The goal of using such methods is to reduce the variability that may arise between different clinicians tracking the progression of structural characteristics in the eye. Commonly categorized structural features to detect Glaucoma include disc area, disc diameter, rim area, cup area, cup diameter, cup-to-disc ratio, and topological features extracted from the image. Proper orthogonal decomposition (POD) is an example of a technique that uses structural features to identify glaucomatous progression.

![Fig.2.1](image3.jpg)  ![Fig.2.2](image4.jpg)

Fig.2.1 Fundus image of healthy eye  Fig.2.2 Fundus image of Glaucoma affected eye with showing the Optic Disc and Cup areas enlarged Optic Disc.

2. Objective of the Work

The intent of this work is to improve the accuracy of the Glaucoma detection by calculating the energy features and optic cup to disc ratio (CDR). To this endeavour, two techniques are used to detect the progression of Glaucoma.

- The energy signatures are obtained by using 2-D Discrete Wavelet Transform and the energy obtained from the detailed coefficients can be used to distinguish between normal and glaucomatous eye images. The energy features extracted by using wavelet filters. This data can be used by the physicians and may help in better understanding of Glaucoma.

- The segmentation methods are used to extract the optic cup and optic disc boundaries to calculate the CDR. The pixel based segmentation is used for optic disc extraction and watershed segmentation is used for optic cup extraction.
3. Methodology

3.1 Methodology for glaucoma detection by extracting the energy features using 2d wavelets:

In the proposed method the features are extracted using wavelet filters. Here the input image of a person is captured by fundus camera. Image is decomposed by using wavelet filters. Extracted features are fed to SVM classifier. Depending upon the dataset, The classifier classifies the image as either Glaucoma or Non-Glaucomateous. The proposed method of detecting Glaucoma is as shown in Fig. 3.1 below.

![Block diagram of Classification of Glaucoma and Normal Retinal Images.](image)

3.1.1 Discrete wavelet transform – Based energy features

Most of the signals in practice are time-domain signals in their raw format. That is, whatever that signal is measuring, is a function of time. In other words, when we plot the signal one of the axes is time (independent variable), and the other (dependent variable) is usually the amplitude. When we plot time-domain signals, we obtain a time-amplitude representation of the signal. This representation is not always the best representation of the signal for most signal processing related applications. In many cases, the most distinguished information is hidden in the frequency content of the signal.

The wavelet transform (WT) has gained widespread acceptance in signal processing and image compression. Because of their inherent multi-resolution nature, wavelet-coding schemes are especially suitable for applications where scalability and tolerable degradation are important. Wavelet transform decomposes a signal into a set of basis functions. These basis functions are called wavelets.

In the proposed method three different wavelet filters such as daubechies (db3), symlets (sym3) and biorthogonal (bio3.3, bio3.5, bio3.7) [3] are used on a set of fundus images by employing 2-D DWT. The texture features using wavelet transforms in image processing are often employed to overcome the generalization of features. We calculate the averages of the detailed horizontal and vertical coefficients and wavelet energy signatures obtained by wavelet decomposition. With the help of these filters the obtained wavelet coefficients are then subjected to average and energy calculation resulting in feature extraction. Table 1 shows the obtained features normal range for Glaucoma detection. Based on the average and energy calculations the images are classified either as Normal and Glaucoma.
TABLE I. WAVELET ENERGY FEATURES FOR GLAUCOMA DETECTION

<table>
<thead>
<tr>
<th>Features</th>
<th>Normal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Db3: dh1_Average</td>
<td>0.0010 to 0.0017</td>
</tr>
<tr>
<td>Db3: cv1_Energy</td>
<td>6.9764e-05 to 1.8267e-04</td>
</tr>
<tr>
<td>Sym3: dh1_Average</td>
<td>0.0010 to 0.0017</td>
</tr>
<tr>
<td>Sym3: cv1_Energy</td>
<td>6.9764e-05 to 1.8267e-04</td>
</tr>
<tr>
<td>Rbio3.3: dh1_Average</td>
<td>0.0018 to 0.0036</td>
</tr>
<tr>
<td>Rbio3.3: cv1_Energy</td>
<td>1.7000e-04 to 4.7205e-04</td>
</tr>
<tr>
<td>Rbio3.3: cd1_Energy</td>
<td>5.8229e-05 to 1.5435e-04</td>
</tr>
<tr>
<td>Rbio3.5: dh1_Average</td>
<td>0.0016 to 0.0033</td>
</tr>
<tr>
<td>Rbio3.5: cv1_Energy</td>
<td>1.4163e-04 to 3.9048e-04</td>
</tr>
<tr>
<td>Rbio3.5: cd1_Energy</td>
<td>3.8834e-05 to 9.9975e-05</td>
</tr>
<tr>
<td>Rbio3.7: dh1_Average</td>
<td>0.0014 to 0.0032</td>
</tr>
<tr>
<td>Rbio3.7: cv1_Energy</td>
<td>1.3235e-04 to 3.6286e-04</td>
</tr>
</tbody>
</table>

Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power or a classification algorithm which over fits the training. Feature extraction is a general term which depicts to extract only valuable information from given raw data. The main objective of feature extraction is to represent raw image in its reduced form and also to reduce the original dataset by measuring certain properties to make decision process easier. A feature is nothing but the significant representative of an image which can be used for detection of Glaucoma. The extracted features provide characteristics of input pixel [4]. The spatial features can be extracted by statistical and co-occurrence methods.

It is a well-known fact that Fourier Transforms (FT) can be useful for extracting frequency contents of a stationary signal. However, it cannot provide time-evolving effects of frequencies in non-stationary signals. STFT suffers from the limitation that it employs a fixed width of window.
function, chosen a priori, and hence it creates a problem for simultaneous analysis of high frequency and low frequency non-stationary signals.

Hence, wavelet transform arose as an effective tool for those situations where one needs multiresolution analysis, providing short windows at high frequencies and long windows at low frequencies. Here each image is represented as a $p \times q$ gray-scale matrix $I[i,j]$. The resultant 2- DDWT coefficients are the same irrespective of whether the matrix is traversed top-to-bottom or bottom-to-top. Hence, it is sufficient that we consider four decomposition directions corresponding to $0^\circ$ (horizontal, $Dh$), $45^\circ$ (diagonal, $Dd$), $90^\circ$ (vertical, $Dv$), and $135^\circ$ (diagonal, $Dd$) orientations. The decomposition structure for one level is illustrated in Figure 3.4. In this figure, $I$ is the image, $g[n]$ and $h[n]$ are the low-pass and high-pass filters, respectively, and $A$ is the approximation coefficient. Where, $2ds1$ indicates that rows are down sampled by two and columns by one. $1ds2$ indicates that rows are down sampled by one and columns by two. The “$\times$” operator indicates convolution operation. Since the number of elements in these matrices is high, and since we only need a single number as a representative feature, we employed averaging methods to determine such single valued features. These are obtained by the following equations,

$$\text{Average } Dh1 = \frac{1}{p \times q} \sum x = \{p\} \sum y = \{q\}|Dh1(x,y)| \quad (1)$$

$$\text{Average } Dv1 = \frac{1}{p \times q} \sum x = \{p\} \sum y = \{q\}|Dv1(x,y)| \quad (2)$$

$$\text{Energy} = \frac{1}{p^2 \times q^2} \sum x = \{p\} \sum y = \{q\} \ (Dv1(x,y))^2 \quad (3)$$

Energy signatures provide a good indication of the total energy contained at specific spatial frequency levels and orientations [5]. The energy-based approach assumes that different texture patterns have different energy distribution in the space-frequency domain. The energy obtained from the detailed coefficients can be used to distinguish between normal and glaucomatous images with very high accuracy. Hence these energy features are highly discriminatory. This approach is very appealing due to its low computational complexity involving mainly the calculation of first and second order moments of transform coefficients.

![Figure 3.2: Discrete Wavelet Transform decomposition.](image-url)
The energy features are fed into classifier Support Vector Machine (SVM) resulting in high accuracy of classification. The energy features are used to train the Support Vector Machine classifier which classifies each row of the data in the sample using the information from the classifier structure SVMStruct. This classifier is trained using a svmtrain and distinguishes the retinal images into normal or abnormal using the confusion matrix and thereby achieve a high a level of accuracy.

3.2 Methodology for Glaucoma detection using CDR technique:
Glaucoma can also be detected by segmenting the optic cup and optic disc. Here the input image of a person is captured by fundus camera. Then the captured image is subjected to various pre processing steps like gray level transformation and enhancement. The noise in the image is filtered using a mean filter. The optic disc is segmented using disc approximation method based approach. The optic Cup is segmented by using Watershed transformation. Then the area of the optic Disc and Cup are measured to calculate CDR. Depending on the value of CDR the fundus image is classified as Normal or Glaucomatous image. The proposed method of detecting Glaucoma is as shown in Fig. 3.3 below.

![Figure 3.3 Block Diagram of CDR method](image)

3.2.1 Optic Disc Segmentation
To start with the input image is read and converted to gray image (fig 3.4(b)). Filtering of the gray image is done to improve the quality of the image such as the multidimensional filter for optic Disc segmentation. The morphological dilation operation is used to perform the addition of image pixels of highest intensity for making bright accurate circular shape of optic Disc. The following figures show the sequence of the operations performed on an input colour retinal image.

![Fig 3.4: (a) Color fundus input image (b) Gray image (c) Filtered image (d) Dilated image.](image)

3.2.1.1 Filtering Process:
Let \( S_{xy} \) represents the set of coordinates in a rectangular sub image window of size \( m \times n \) centered at point \( (x, y) \). The arithmetic mean filtering process computes the average value of the corrupted
image \( g(x, y) \) in the area defined by \( S_{xy} \). The value of the restored image \( f \) at any point \((x, y)\) is simply the arithmetic mean computed using the pixels in the region defined by \( S_{xy} \). In other words,

\[
\hat{f}(x, y) = \frac{1}{mn} \sum_{(s, t) \in S_{xy}} g(s, t)
\]

This operation can be implemented using a convolution mask in which all coefficients have value \( 1/\text{mn} \). A mean filter simply smoothes local variations in an image. Noise is reduced as a result of blurring. The best known order-statistics filter is the \textit{median filter}, which replaces the value of an image pixel by the median of the gray levels in the neighbourhood of that image pixel.

For optic Disc the gray image is filtered by using this multidimensional filter as shown in fig 3.2(c).

Intensity threshold for segmentation
The point based or pixel based segmentation is conceptually the simplest approach used for image segmentation. The pixel values greater than or equal to the threshold value is written as 1’s and determined that the (threshold) gray levels are assumed to belong to that image, and the pixel values below that the threshold values are written as 0’s and are assumed to be outside of that image. Here Fixed thresholding is of the form:

\[
g(x, y) = \begin{cases} 
1 & \text{if } f(x, y) \geq T \\
0 & \text{if } f(x, y) < T 
\end{cases}
\]

That is the pixels equal or above the threshold value are set to 1’s and otherwise set to 0’s.

\subsection*{3.2.1.2 Dilation process}

The dilation of \( f \) by a flat structuring element \( b \) at any location \((x, y)\) is defined as the maximum value of the image in the window outlined by \( b^x \) when the origin of \( b^x \) is at \((x, y)\). Therefore, the dilation at \((x, y)\) of an image \( f \) by a structuring element \( b \) is given by:

\[
[f \bigoplus b](x, y) = \max_{(s, t) \in b} \{f(x - s, y - t)\}
\]

Where we used that \( b^x = b(-x, -y) \), similarly to the correlation, \( x \) and \( y \) are decremented through all values required so that the origin of \( b \) visits every pixel in \( f \). That is, to find the dilation of \( f \) by \( b \), we place the origin of the structuring element at every pixel location in the image. The dilation is the maximum value of \( f \) from all values of \( f \) in the region of \( f \) coincident with \( b \) and that the structuring element is reflected about the origin. The morphological operations are used to simplify image data, preserve essential shape characteristics and eliminate noise. In the proposed method dilation morphological operation is used to perform the addition of image pixels of highest intensity for making bright accurate circular shape of optic Disc. Dilation results, the output of an image are brighter than the input image and expanded an image to the closest picture of neighbourhood pixel values. The area of the circular (or elliptical) optic Disc is calculated by counting the number of intensity of the bright pixels from the morphological gray images as shown in fig 3.2(d).

First step to segment the optic Disc is determination of the center of optic Disc which is the lighter and brightest part in retinal image. The center of the optic Disc is calculated by traversing through left and right of the x-axis and up and down of the y-axis of the binary image of extracted Disc. After determination of the center we have to calculate the radius of optic Disc, this will be done by exploring and counting the intensity of each pixel from the center of optic Disc (in four direction;
two horizontally and the other two vertically) toward the optic Disc edges. Determination of the radiiuses in four directions helps to predict the actual radius. When we determine the center and radius we redraw the optic Disc. Thus the optic Disc is extracted. Area of the optic Disc is calculated by counting the number of pixels within the optic Disc region. This area information of the optic Disc is used to find the optic Cup to optic Disc ratio. Figure 3.4(e) shows the segmented optic Disc area from the input color fundus images which is calculated by above disc prediction method.

![Segmented Optic Disc](image)

**Fig 3.4(e): Segmented Optic Disc**

### 3.2.2. Optic Cup segmentation

To start with the image is filtered and watershed transformation is applied to locate the optic Cup boundaries. Since the optic Cup represents a bright area, and as blood vessels emerge dark in gray level retinal images, the gray level variation within the optic Cup region is very high. This variation is first removed using a closing morphological operation to facilitate later watershed operation. Particularly, we show how the watershed transformation contributes to improve the numerical results for optic Cup segmentation problems. Let \( f(x, y) \) with \( (x, y) \in \mathbb{R}^2 \), be a scalar function describing an image \( I \). The morphological gradient of \( I \) is defined by

\[
g = (f \oplus b) - (f \ominus b)
\]

where \( (f \oplus b) \) and \( (f \ominus b) \) are respectively the elementary dilation and erosion of \( f \) by the structuring element \( b \). The morphological Laplacian is given by

\[
G_L = (f \oplus b) - 2f + (f \ominus b)
\]

We note here that this morphological Laplacian allows us to distinguish influence zones of minima and suprema: regions with \( G_L < 0 \) are considered as influence zones of suprema, while regions with \( G_L > 0 \) are influence zones of minima. Then \( G_L = 0 \) allows us to interpret edge locations, and will represent an essential property for the construction of morphological filters. The basic idea is to apply either dilation or erosion to the image \( I \), depending on whether the pixel is located within the influence zone of a minimum or a maximum.

If we view an image as a surface, with mountains (high intensity) and valleys (low intensity), the watershed transform finds intensity valleys in an image. Fig. 3.5 illustrates this approach. We have considered the same original image as previously. Fig. 3.5.(a) shows the watershed of the image and Fig. 3.5.(b) shows the watershed of its gradient and Fig 3.5.(c) shows the segmentation results of the filtered image and finally Fig 3.5(d) shows the optic Cup segmented image.
As a first step, we eliminate large gray level variations within the papillary region by filtering the image using morphological closing operator. The removal of large peaks involves opening operator with large structuring element which alters the shape of the papillary region. So calculate the morphological reconstruction by dilation. Before we apply the watershed transformation to the morphological gradient, we impose internal and external markers. We use the locus of optic Cup, \( f(x, y) \) as an internal marker that has been calculated and a square containing the optic Cup with center at \( (x, y) \) as an external marker.

The Catchment basin \( C(M) \) associated to a minimum \( M \) is the set of pixels of \( p \) such that a water drop falling at \( p \) flows down along the relief, following a certain descending path, and eventually reaches \( M \). The catchment basins of an image \( I \) correspond then to the influence zones of its minima, and the watershed will be defined by the lines that separate adjacent catchment basins.

We consider \( k_{\text{min}} \) and \( k_{\text{max}} \) the smallest and the largest values taken by \( f \). Let \( T_k = \{ p \in \Omega, f(p) \leq k \} \) be the threshold set of \( f \) at level \( k \). We define a recursion with the gray level \( k \) increasing from \( k_{\text{min}} \) to \( k_{\text{max}} \), in which the basins associated with the minimum of \( f \) are successively expanded. We consider \( X_k \) the union of the set of basins computed at level \( k \). A connected component of the threshold set \( T_{k+1} \) at level \( k+1 \) can be either a new minimum, or an extension of a basin in \( X_k \).

Finally, by denoting by \( m_k \) the union of all regional minima at level \( k \), we obtain the following recursion which defines the watershed by immersion.

\[
X_{k_{\text{min}}} = T_{k_{\text{min}}},
\forall k \in [k_{\text{min}}, k_{\text{max}} - 1], X_{k+1} = \text{min}_{k+1} \cup IZ_{T_{k+1}}(X_k)' \tag{9}
\]

With \( IZ_{T_{k+1}} = \bigcup_{i=1}^{k} iZ T_{k+1}(X_k) \) \( \tag{10} \)

Where \( k \) is the number of minima of \( I \) and \( iZ T_{k+1}(X_k) \) is defined by

\[
iZ T_{k+1}(X_k) = \{ z \in \Omega, \forall n \neq i, d_{\Omega}(z, Y_i) \leq d_{\Omega}(z, Y_n) \} \tag{11}
\]

The set of the catchment basins of a gray level image \( I \) is equal to the set \( X_{k_{\text{max}}} \). At the end of this process, the watershed of the image \( I \) is the complement of \( X_{k_{\text{max}}} \) in \( \Omega \).

Watershed segmentation of the imposed minima image is accomplished with the watershed function. The watershed function returns a label matrix containing nonnegative numbers that corresponds to watershed regions. Pixels that do not fall into any watershed region are given a pixel value of 0. This technique modifies a gray-scale image so that regional minima occur only in marked locations. Other pixel values are pushed up as necessary to remove all other regional minima. Thus
the optic Cup is segmented by mathematical morphology and watershed transform. The extracted optic Cup by watershed transformation method is as shown in fig 3.5(e).

![Fig 3.5(e): Segmentation result of optic Cup.](image)

3.2.3 Calculation of CDR

The area of optic cup and optic disc is calculated by counting the number of pixels present in the optic disc and optic cup respectively. Then the ratio of optic cup to optic disc is calculated. If the optic cup to optic disc ratio exceeds 0.3 then the image is classified as Glaucoma or else it is classified as Normal.

4. Experimental Results

The following section provides a detailed description of the results obtained from feature selection and classification.

4.1. Results of wavelet based energy features

Figure 4.1 shows the resulting retinal image obtained after converting an color input retinal image to gray image. Figure 4.1 (a) shows the input image and (b) shows the gray scale image.

![Figure 4.1 (a) Retinal input image (b) Gray scale image](image)

The energy-based approach assumes that different texture patterns have different energy distribution in the space-frequency domain. This approach is very appealing due to its low computational complexity involving mainly the calculation of first and second order moments of transform coefficients. Figure 4.2 provides a snapshot of the results obtained from Feature extraction described in the methodology section.

![Figure 4.2: Output of daubechies (db3), the symlets (sym3), and the biorthogonal (bio3.3, bio3.5, and bio3.7) wavelet filters](image)
Figure above shows the results obtained from daubechies (db3), the symlets (sym3), and the biorthogonal (bio3.3, bio3.5, and bio3.7) wavelet filters. The horizontal and vertical coefficients of wavelet filters are used to extract energy features. The different texture patterns have different energy distribution in the space-frequency domain.

The energy features are extracted for all sample input retinal images. Thus for normal images the range is being calculated by using the equations 1, 2, 3. We calculate the averages of the detailed horizontal and vertical coefficients and wavelet energy signature from the detailed vertical coefficients for daubechies (db3), the symlets (sym3), and the biorthogonal (bio3.3, bio3.5, and bio3.7) wavelet filters. If the input retinal image energy features are within the range of threshold value then the image is classified as normal otherwise it is glaucomatous eye.

**Figure 4.3: Result of wavelet transform energy features method.**

The extracted features were used for Classification [3]. The accuracy of the system is calculated.

**Figure 4.4: SVM Classifier output**

### 4.2. Results of CDR method

The following section provides a detailed description of the results obtained from the optic Disc extraction and Cup extraction from colored Glaucomatous retinal fundus images. The pixel based threshold approach is used for optic Disc and optic Cup from watershed transform method. If CDR is greater than 0.3 then the image is classified as Glaucoma or it is classified as normal as shown in figure 4.5.

**Figure 4.5: GUI screen after classification as abnormal**
The efficiency of the classifier designed was found to be 96% when tested on the samples obtained from K.L.E Dr. Prabhakar Kore Hospital and Medical Research Center, Belgaum, India. This is inclusive of the Methodology for Glaucoma detection by extracting the energy features using 2D wavelets and CDR technique.

Conclusion

In the proposed method, the Glaucoma is detected by finding the energy features from discrete wavelet transform and through the measurement of CDR. These two methods together make the system more reliable in detecting the Glaucoma. The efficiency of the classifier designed was found to be 96%.

Here a wavelet-based texture feature set has been used to detect the Glaucoma. The texture feature set can be enhanced in accuracy by making use of more number of test images. The optic disc has been segmented based on the principle of disc prediction method. The optic cup has been segmented based on the watershed transformation. Then the cup-disc ratio is calculated to find the progression of Glaucoma. Further for both the methodologies test images can be used to decide the threshold value and improve the accuracy of the system.

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References


