OPTIMIZED AND EFFICIENT DIAGNOSIS OF GLAUCOMA BASED ON WAVELET FEATURE EXTRACTION AND CLASSIFICATION

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Abstract— *Glaucoma is a disease of the retina which is one of the most common causes of permanent blindness worldwide. It damages the optic nerve subsequently causes loss of vision. The methods are expensive and require experienced clinicians to use them. So, there is a need to diagnose glaucoma accurately with low cost. The available scanning methods are Heidelberg Retinal Tomography(HRT), Scanning Laser Polarimetry(SLP) and Optical Coherance Tomography(OCT). The features are considered from the complete fundus or a sub image of the fundus, it is based on feature extraction from the segmented and blood vessel removed optic disc to improve the accuracy of identification. The experimental results indicate that the wavelet features of the segmented optic disc image are clinically more significant in comparison to features of the whole or sub fundus image in the detection of glaucoma from fundus image. Accuracy of glaucoma identification achieved in this work is 94.7% and a comparison with existing methods of glaucoma detection from fundus image indicates that the proposed approach has improved accuracy of classification.*

Keywords— Glaucoma, Segmentation, In-painting, Feature Extraction

1. INTRODUCTION

Glaucoma is a disease of retina in which the optic nerve undergoes a damage caused by the increase in the intraocular pressure (IOP) of the eye. There is a fluid called aqueous humor that flows through the pupil and is absorbed by the blood-stream. In case of glaucoma the flow of this fluid becomes clogged. This results more intraocular pressure in the eye which damages the highly sensitive optic nerve causing vision impairment. It mainly affects the portion inside the optic disk where the size of the optic cup increases resulting in a high cup-to-disk ratio. It causes the successive narrowing of the field of view of affected patients. After diabetic retinopathy, glaucoma is the second highest cause of blindness across the world. Glaucoma is not curable and the loss of vision cannot be regained but with early diagnosis it is possible to prevent further loss of vision by proper medication and surgery.

The glaucoma disease is characterized by change in the structure of nerve fibers and optic disc parameters such as diameter, volume, and area. Structural changes occur due to obstruction to the discharge of aqueous humor, which in turn increases IOP. The fundus images are used for the diagnosis of glaucoma and diabetic retinopathy. Damage to optic nerve fibre is detected using the morphological features such as cup to disc ratio, Automated identification of Glaucoma can be of great help to the Ophthalmologists and the society. Generally, the process of Glaucoma detection involves the extraction of optic disc and cup followed by elicitation of its properties such as cup to disc ratio and ISNT ratio to distinguish normal images from Glaucoma affected.

The term ‘glaucoma’ refers to a large number of optic nerve diseases, which is associated with loss of visual activity and can lead to total, irreversible blindness if left untreated. Glaucomatous optic neuropathy is the second leading cause of blindness worldwide. The optic nerve is a cylindrical structure responsible for carrying the visual information out of the eye towards the brain. Neural fibers, the primary component of the optic nerve, are composed of about 1.2-1.5 million ganglion cell axons.

These axons originating in the ganglion cell layer of the retina, the innermost layer of the eye, form the retinal nerve fiber layer (RNFL). These axons collect the visual information and carry it outside the eye via the optic nerve. The nerve head is the distal portion of the optic nerve. The retinal nerves converge upon the

nerve head from all points of the fundus. The portion of the optic nerve head that is clinically visible by an ophthalmoscope is known as the optic disc. The optic nerve head is slightly vertically oval and it is also the site of entry for the retinal vessels. The shape and size of the optic disc is important in evaluation for glaucoma diagnosis.

2. DATA USED

We have used two databases, private and public, in this study. The proposed method has been applied on both the databases. Brief description about the databases is as follows.

1) Private database: In this database, we have 30 normal and 30 open angle glaucoma images. These images are obtained from Kasturba Medical College, Manipal, India. The image quality and its usability have been certified by the doctors of ophthalmology department. The image is stored in 24-bit JPEG format with resolution of 560×720 pixels. Figs. 1(a) and 1(b) show the sample normal and glaucoma digital fundus images, respectively.

2) Public database: It consists of 255 normal and 250 glaucoma images. This database is obtained from Medical

Image Analysis Group (MIAG) and is available online publicly at http://medimrg.webs.ull.es/. The images are stored in 24-bit JPEG file format at various resolutions.

3.PROPOSED METHODOLOG

The image processing phase includes Green channel extraction followed by two segments namely blood vessel segmentation and optic disc segmentation. Blood vessel segmentation involves image compliment, Median filtering, contrast enhancement and Wavelet Transformation through symmlet filters. Optic Disc extraction involves border suppression, optic disc segmentation through K-Means Clustering, Optic Disc Segmentation through Haar Wavelet Transformation, and Optic Disc Segmentation through Histogram analysis, followed by maximum voting to delineate final Optic disc boundary.

4.OPTIC DISC CENTER DETECTION

Optic disc (OD) is the brightest feature of fundus image. The OD is the location where the optic nerve exits, and it is usually a vertically slightly elliptical shaped object. Hence the strategy adopted in this paper is to detect the large bright intensity objects in the fundus image. The manual examination of optic disk (OD) is a standard procedure used for detecting glaucoma. The steps of the proposed method are given in Algorithm 1.

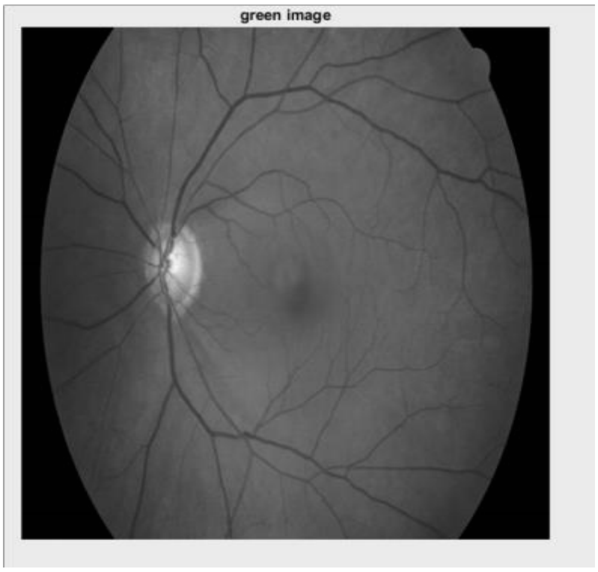
Algorithm1

Step 1: Extraction of Green channel from RGB Fundus image as green channel has maximum information content needed for OD centre detection.

Step 2: A “Kaiser window” of dimensions W × Total no. of columns in the fundus image is created. Where W equals to of 1/10th of the total no. of rows in the fundus image. Fig. 3 shows the Kaiser window.

Step3: This window is passed through all the rows of fundus image and a maximum is selected to get the x-coordinate of center of OD.

Step4: To get the y-coordinate of OD center, a “Hat shaped Kaiser Window” of dimensions W × W as shown in the Fig. 4 is created. This window is passed through all the columns of the obtained row of step 3. The Maxima is selected as y-coordinate of center of OD



5. OPTIC DISK SEGMENTATION

The RGB components of the image, it was found that the optic disc can be easily discriminated from Red channel. In the proposed method, optic disc is segmented from fundus image using a bit plane technique. As OD is clearly discriminated in red channel of fundus image hence it is pro-posed to segment the OD using logical combination of bit planes for three higher most significant bits (MSB’s).

Data base images used has 8 bit representation, hence 6th, 7th and 8th bit planes of red channel of fundus image are considered for optic disc segmentation. The algorithm for segmentation of optic disc from fundus image is explained in Algorithm 2.

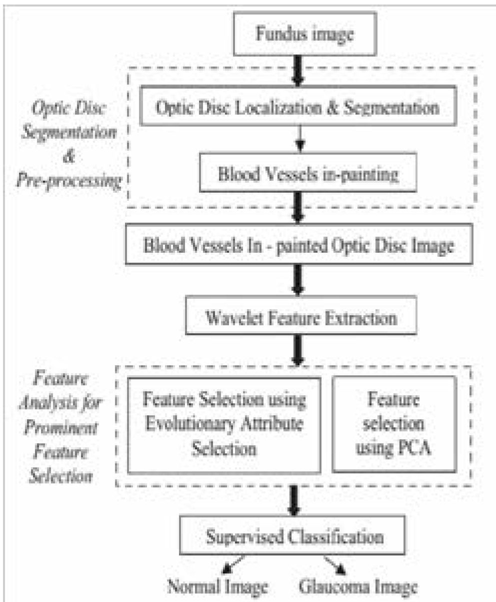


Fig: Block diagram of proposed method

Algorithm 2

Step1: I is the red channel of RGB fundus image and (Xo , Yo) is the centre of optic disc.

Step2:Extraction of Circular sub image Isusing centre(Xo,Yo)and radius Ro. where r and c are no. of rows and no. of columns in fundus image respectively. This sub-image will cover the whole OD and this calculation also provides some additional margin area.

Step3: Segment the common area of 7th and 8th bit planes of Is I1 = I7 + I8
Where I7 and I8 are 7th and 8th bit planes of Circular sub image Is respectively and "+" denotes logical "AND" operation.
Step4: it is found that if OD is segmented accurately using strategic logical combinations of 7th and 8th bit plane then bright pixels near to OD area will be very less, otherwise there will be considerably more number of bright pixels that will appear near to segmented OD. This seems to be a good choice and is used to consider this as

a check point to know whether OD is accurately segmented using these bit planes of the image.

Step5: If OD is segmented accurately using 7th and 8th bit plane and passes the check point in step 4 then final segmentedOD(Iod)
Else
go to Step 6.

Step 6: Segment common area of 6th bit plane and I1 I2 = I6 + I1
Where I6is is 6th bit plane of Circular sub image Is and "+" denotes logical AND" operation.

Step 7: Iod = I2

Step 8: Removal noisy pixels from Iod
To remove noisy pixels from final segmented OD, theobjects are labeled and objects are selected which has largestarea and roundness. Object having largest area and roundnessis considered as the optic disc.

6.BLOOD VESSEL IN-PAINTING

The blood vessels act as noisy pixels which covers the OD and it has to be removed for improved accuracy of OD detection. Removal of blood vessels in this paper is done using an algorithm based on the fact that pixel intensity is a function of the distance from the center of optic disc. The gray level pixel values decrease as the distance from the optic disc center increases outwards. It follows that all the pixels that are at equal distance from the OD center have similar intensity values and any deviation from this pattern may indicate the presence of a blood vessel. This logic seems to be a good choice to remove blood vessel pixels from the optic disc image with-out tampering the OD pixels. The algorithm for blood vessel in-painting is explained stepwise in Algorithm 3.

Algorithm 3
Step 1: I is optic disc image and (Xo , Yo) is centre of OD.

Step 2: Let P = {P1 , P2 , . . ., Pq , ..., Pk−1 , Pk } is a set of pixels that are on equal distance R from the optic disc centre.

Step 3: Calculate
T = min(P) +{max(P) − min(P)}2(2)

Step 4: if Pq< T then Pq is assumed to be a blood vessel pixel.

Step 5: To remove the blood vessel pixel Pq, the pixel value Pq is replaced by the median of these k pixels of P.
Pq(new)= median(P1, P2, . . ., Pk)

7.WAVELET FEATURE EXTRACTION

Blood vessel in-painted optic disc image is transformed in wavelet domain for feature extraction. Discrete wavelet transform (DWT) is a multi-scale analysis method, in which analysis can be performed on various scales and levels. Each level of the transformation provides an analysis of the source image at a different resolution, resulting in its independent approximation and detailed coefficients.
The wavelet transform captures both the spatial and frequency information of an image. In the wavelet transform, the image is represented in terms of the frequency of content of local regions over a range of scales. This representation provides a good framework for the analysis of image features, which are size independent and can often be characterized by their frequency domain properties.

Algorithm 4 is the stepwise procedure for wavelet feature extraction from the segmented vessel in-painted optic disc image.

Algorithm 4
Step 1: Read the segmented and blood vessels-removed optic disc image as the input image I.

Step 2: Input image I is transformed into wavelet domain using two-dimensional discrete wavelet transform and first level approximation and detailed wavelet coefficients are obtained as explained in equation
[A Ch Cv Cd]= dwt(I)
Where "dwt" represents two-dimensional discrete wavelet transform, A is first level approximation coefficient and Ch, Cv and Cd represents detailed horizontal, vertical and diagonal coefficients respectively.

Step 3: Single-valued features mean and energy are calculated for first level horizontal, vertical and diagonal wavelet coefficients. The definition of mean and energy features for horizontal detailed coefficient Ch is explained in Eqs respectively where p and q represents number of pixels in the rows and columns of horizontal wavelet coefficient ch respectively.

Step 4: These features are calculated for wavelet coefficients obtained using db3, Symlet3, Haar and Biorthogonal filters. A feature vector containing 18 features is obtained to represent optic disc image in wavelet feature space. To improve the accuracy of glaucoma image classification only prominent features from the 18 features extracted are selected for further processing and used in the classification.

8. GLAUCOMA CLASSIFICATION

The performance of glaucoma image classification may be increased if only the prominent features are considered for classification and redundant features are ignored. The complexity of classifier will reduce if less number of features is used for classification. Keeping in mind the issue of higher accuracy and less complexity, only prominent features are used for further glaucoma image classification. The performance of most popular classification algorithms Decision Tree, k-NN, Random Forest, Kstar, support vector machine (SVM), artificial neural network (ANN) with various parameter configuration. Prominent features are selected for the classification process, performance of classification algorithm is measured for different possible parameters and the best possible set-ting parameters which have the best performance are finally selected. The best parameters setting for the classification algorithms for the features selected using evolutionary attribute selection method and feature set compressed using PCA.The first method prominent features are selected using evolutionary attribute selection method and then only selected prominent features are considered for further classification. Another technique tried was based on the feature reduction using principal component analysis (PCA)

A. Random Forest Classifier

In random forest classification algorithm number of trees is the main control parameter which specifies the number of random trees to generate. Accuracy of this classification algorithm is measured for different values of tree and tree value which provides the best accuracy is selected for classification.

B. Naïve Byes Classifier

In the Naïve Byes classifier Laplace Correction is an expert parameters used to avoid the case of zero probabilities. The value of Laplace correction can be selected as True/False pending on the performance of classification.

C. k-NN Classifier

The value of no. of nearest neighbors, weighted vote and distance measure metrics are the main control parameters for kNN classification algorithm. Accuracy of this classification algorithm highly depends upon the no. of nearest neighbors used. Artificial Neural Network (ann)
The control parameters for ANN classifiers are number of hidden layers, number of neurons in the hidden layers, training cycles, learning rate, momentum, decay and shuffle. Performance of ANN classification algorithm highly depends on some main control parameters number of neurons in the hidden layers and training cycles used to train the ANN classifier.

D.Support Vector Machine (svm)
The complexity parameter and accuracy of SVM classifier depends on the kernel function used to distribute the data into different classes. Performance of SVM classifier is measure for different kernel functions and the best kernel function which has the best accuracy is finally selected for classification.

9.CONCLUSION

In this work, an automatic image analysis based system is proposed for diagnosis of glaucoma from the digital fundus image using wavelet features from the segmented optic disc. The noisy blood vessels were removed from the segmented optic disc and the features were extracted from this denoised image. Experimental results indicate those glaucoma images were classified with 94.7% accuracy using first level wavelet features from segmented and blood vessels in-painted optic disc image which outperforms the related works. Performance of glaucoma image classification were measured for five supervised classifiers using prominent feature selected using evolutionary attribute selection and principal component analysis. It is observed that all the five classifiers present accuracy more that 85%. Random forest and artificial neural network classifiers can identify the presence of glaucoma with 94.7% accuracy for feature set selected using evolutionary attribute selection whereas SVM and k-NN presents 94.7% accuracy for feature selected using principal component analysis. This proposed study is clinically significant, as the accuracy obtained is comparable to the accuracy achieved by existing methods. Some future work in this direction may be use of other feature selection methods and different classification approaches to improve accuracy and efficiency.

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