A METHOD OF SEGMENTATION FOR GLAUCOMA SCREENING USING SUPERPIXEL CLASSIFICATION

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***Abstract* — G**laucoma is a chronic eye disease that leads to vision loss. As it cannot be cured, detecting the disease in time is important. In this thesis, an optic disc and optic cup segmentation is used to identify the glaucoma disease in time. In optic disc and optic cup segmentation, super pixel classification for glaucoma screening is proposed. In optic disc segmentation, histograms and center surround statistics are used to classify each super pixel as disc or non-disc. The segmented optic cup and optic disc is then used to compute the cup to disc ratio for glaucoma screening. From the cup to disc ratio, analysis is performed to identify whether the given image is glaucomatous or not.

A novel approach to automatically extract out true retinal area from a retina image based on image processing and machine learning approaches. To reduce the complexity of image processing tasks and provide a convenient primitive image pattern and grouped pixels into different regions based on the regional size and compactness, called super pixels. The automated extraction of blood vessels in retinal images is an important step in computer aided diagnosis and treatment of glaucoma. Vessel extraction is basically a kind of line detection problem and many methods have been proposed. A class of popular approaches to vessel segmentation is filtering-based methods, which work by maximizing the response to vessel-like structures. Mathematical morphology is another type of approach by applying morphological operators. Trace-based methods map-out the global network of blood vessels after edge detection by tracing out the center lines of vessels. Such methods rely heavily on the result of edge detection.

***Keywords* —** *Retinal image segmentation, Glaucoma, cup disc detection, Cup to disc ratio (CDR)*

I. INTRODUCTION

The automated extraction of blood vessels in retinal images is an important step in computer aided diagnosis and treatment of diabetic retinopathy, hypertension, glaucoma, obesity, arteriosclerosis and retinal artery occlusion, etc. Vessel extraction is basically a kind of line detection problem and many methods have been proposed. A class of popular approaches to vessel segmentation is filtering-based methods, which work by maximizing the response to vessel-like structures. Mathematical morphology is another type of approach by applying morphological operators. Trace-based methods map-out the global network of blood vessels after edge detection by tracing out the center lines of vessels. Such methods rely heavily on the result of edge detection [1]. The main features of a fundus retinal image are defined as the optic disc, fovea and blood vessels. The optic disc is the entrance and exit region of blood vessels to the retina and its localization and segmentation is an important task in an automated retinal image analysis system. Indeed, the fovea corresponds to the region of retina with highest sensitivity [2]. Several methods have been developed vessel segmentation Retinal vascular pattern facilitates the physicians the purposes of diagnosing eye diseases, patient screening, and clinical study [3, 4]. Inspection of blood vessels provides the information regarding pathological changes caused by ocular diseases. Automated segmentation provides consistency and reduces the time required by a physician or a skilled technician manual labeling. A precise and accurate detection of the vascular tree in fundus images can provide several useful features for the diagnosis of various retinal diseases. However, retinal blood vessel segmentation can have a considerable impact on other applications, particularly when used as a reprocessing step for higher-level image analysis [5]. For example, an accurate detection of the blood vessel tree can be used in registering time series fundus images, locating the optic disc or fovea, detecting retinal nerve or in the field of biometric identification.

In this propose a novel and precise method for accurate retinal vessel tree segmentation at a wide range of blood vessel sizes in high-resolution colour fundus images. Our method is based on Interactive evolutionary computation Algorithm (IECA) in combination with minimum error threshold technique and too we use novel vessel segmentation approach to efficiently locate and extract blood vessels in color retinal images. More to the point, this study is concerned with developing fast methods while achieving high accuracy. Supervised methods requiring suitable pre-labeled training datasets and with efficient training time can be easily adjusted to new populations.

The automated extraction of blood vessels in retinal images is an important step in computer aided diagnosis and treatment of diabetic retinopathy, hypertension, glaucoma, obesity, arteriosclerosis and retinal artery occlusion, etc. Vessel extraction is basically a kind of line detection problem and many methods have been proposed. A class of popular approaches to segmentation is filtering-based methods, which work by maximizing the response to vessel-like structures. Mathematical morphology is another type of approach by applying morphological operators. Trace-based methods map-out the global network of blood vessels after edge detection by tracing out the center lines of vessels. Such methods rely heavily on the result of edge detection. Glaucoma is an irreversible chronic eye disease that leads to vision loss. As it can be slowed down through treatment, detecting the disease in time is important. However, many patients are unaware of the disease because it progresses slowly without easily noticeable symptoms. Currently, there is no effective method for low-cost population-based glaucoma detection or screening.

Early detection and treatment of retinal eye diseases is critical to avoid preventable vision loss. Conventionally, retinal disease identification techniques are based on manual observations. Optometrists and ophthalmologists often rely on image operations such as change of contrast and zooming to interpret these images and diagnose results based on their own experience and domain knowledge. These diagnostic techniques are time consuming. Automated analysis of retinal images has the potential to reduce the time, which clinicians need to look at the images, which can expect more patients to be screened and more consistent diagnoses can be given in a time efficient manner. The 2-D retinal scans obtained from imaging instruments [e.g., fundus camera, scanning laser ophthalmoscope (SLO)] may contain structures other than the retinal area. In a retinal scan, extraneous objects such as the eyelashes, eyelids, and dust on optical surfaces may appear bright and in focus.

The main features of a fundus retinal image are defined as the optic disc, fovea and blood vessels. The optic disc is the entrance and exit region of blood vessels to the retina and its localization and segmentation is an important task in an automated retinal image analysis system. Indeed, the fovea corresponds to the region of retina with highest sensitivity. Several methods have been developed segmentation retinal vascular pattern facilitates the physicians the purposes of diagnosing eye diseases, patient screening, and clinical study. Inspection of blood vessels provides the information regarding pathological changes caused by ocular diseases. Automated segmentation provides consistency and reduces the time required by a physician or a skilled technician manual labeling. A precise and accurate detection of the vascular tree in fundus images can provide several useful features for the diagnosis of various retinal diseases. However, retinal image segmentation can have a considerable impact on other applications, particularly when used as a reprocessing step for higher level image analysis. For example, an accurate detection of the retinal can be used in registering time series fundus images, locating the optic disc or fovea, detecting retinal nerve or in the field of biometric identification.

The glaucoma is classified by the appearance of the iridocorneal angle. There are open-angle, closed-angle, and developmental categories, which are further divided into primary and secondary types. Primary open angle glaucoma can occur with or while not elevated intraocular pressure; the latter is typically known as normal- tension glaucoma. Primary open-angle glaucoma includes each adult onset disease (occurring after 40 years of age) and juvenile-onset disease (occurring between the ages of 3 and 40 years of age). Samples of secondary open-angle glaucoma embody those associated with exfoliation or pigment dispersion syndrome. Closed-angle glaucoma are often primary (e.g., papillary block) or secondary (e.g., inflammatory or neo vascular causes). Developmental forms of glaucoma include primary congenital glaucoma and glaucoma associated with syndromes. Primary open-angle glaucoma, the predominant form of glaucoma in Western countries, most likely comprises several clinically indistinguishable diseases. This thesis focuses on automatic glaucoma screening from 2-D fundus images. It includes a super pixel classification based disc and cup segmentations for glaucoma screening and also introduce super pixel classification based segmentation including the generation of super pixels, the extraction of features from super pixels for the classification and the computation of the self-assessment reliability score and also super pixel classification based cup segmentation, where the procedure is similar to that in disc segmentation.

In this proposed method for accurate retinal segmentation at a wide range of glaucoma in high-resolution color fundus images. In this method is based on Interactive evolutionary computation Algorithm in combination with minimum error threshold technique and too use novel segmentation approach to efficiently locate and extract blood vessels in color retinal images. More to the point, this study is concerned with developing fast methods while achieving high accuracy. Supervised methods requiring suitable pre-labeled training datasets and with efficient training time can be easily adjusted to new populations. The proposed method achieves good accuracy for glaucoma detection. The method has a great potential to be used for large scale population based glaucoma screening.

Detecting glaucoma in time is critical. The symptoms of the glaucoma disease occur when it is in advanced stage. Hence, glaucoma is called the silent thief of sight. Detecting the disease in time is very important. In this thesis, an optic disc and optic cup segmentation is used to identify the glaucoma disease in time. In optic disc and optic cup segmentation, super pixel classification for glaucoma screening is proposed. In optic disc segmentation, histograms and centre surround statistics are used to classify each super pixel as disc. The segmented optic cup and optic disc is then used to compute the cup to disc ratio for glaucoma screening. From the cup to disc ratio, analysis is performed to identify whether the given image is glaucomatous or not.

II. RELATED WORKS

This section reviews representative state - of - art fundus retinal image are defined as the optic disc, fovea and blood vessels to the retina and its localization and segmentation is an important task in an automated retinal image disease analysis system.

Matched Filtering digital imaging using a fundus camera is widely considered an integral part of medical examination in ophthalmology. Standard fundus images contain various regions which can be useful for diagnosis, such as the macula, which is usually examined in connection with age-related macular degeneration the optic disc for examination of glaucoma and vascular structures, which are mostly evaluated in the context of diseases affecting the circulatory system. Several pathologies affecting the retinal vascular structures due to diabetic retinopathy can be found in fundus images using precisely segmented blood vessels. Moreover, automatic retinal vessel segmentation algorithms can be useful in the evaluation of other diseases, such as arteriolar narrowing and vessel tortuosity due to hypertensive retinopathy or glaucoma .Furthermore, vessel diameter, bifurcations and crossovers can be effectively measured on the segmented blood vessel tree to test for other cardiovascular diseases .A precise and accurate detection of the vascular tree in fundus images can provide several useful features for the diagnosis of various retinal diseases.

However, retinal blood vessel segmentation can have a considerable impact on other applications, particularly when used as a preprocessing step for higher-level image analysis. For example, an accurate detection of the blood vessel tree can be used in registering time series fundus images locating the optic disc or fovea detecting retinal nerve fiber layer or in the field of biometric identification. Owing to the wide range of applications, and because the segmentation of retinal vessels is one of the most challenging tasks in the field of retinal image analysis retinal vessel tree segmentation at a wide range of blood vessel sizes in high-resolution color fundus images. In method is based on matched filtering (MF) in combination with minimum error thresholding technique.

Two-dimensional matched filtering the two-dimensional MF locally exploits the correlation between local image areas and 2D masks developed according to the appearance of typical blood vessel segments of different widths (diameters) and orientations. These masks were created by measuring numerous perpendicular cross-sectional intensity profiles of retinal vessels in the images from the HRF database. The cross-sectional profiles were heuristically classified into five classes of differing blood vessel thicknesses to achieve a reliable and precise detection of all possible blood vessel segments with an acceptable width resolution. Thus, 250 profiles were manually selected per blood vessel width class from all images in the database. For each width class, all its cross-sectional profiles were centered and then averaged in order to obtain a smoothed intensity profile for that class.

The resulting averaged profiles cover a range of blood vessel diameters from 5 to 22 pixels, measured at a full-width at half-maximum of the cross-sectional profiles. The shape of the particular intensity profiles smeared by plain parallel back projection along the vessel axis thus represents pieces of retinal blood vessel structures from the thinnest blood vessels through thicker structures to the thickest ones, which appear with central light reflection. The corresponding mask sizes are 14 × 14, 22 × 22, 24 × 24, 26 × 26 and 32 × 32 pixels. Hence, the particular width classes cover all types of blood vessels in a common fundus image. Particular kernels were then rotated into the angular direction j = 0,…, 165 degrees, with the angular step of 15 degrees in order to cover all possible directions of blood vessel segments. The bilinear interpolated pixel values for individual positions, which do not fit the image lattice during mask rotation.

The square shape of the 2D kernels was utilized as a compromise between signal-to-noise ratio (low for masks with short length) and maximal possible length of blood vessel segment fulfilling a condition of piecewise parallel edges. Each kernel is then convolved with the preprocessed input image G (i, j).It will obtain a number of 60 (5 × 12) parametric images (MFRk, j(i, j) – matched filter responses) related to the corresponding width class and orientation of blood vessel segments.

The magnitudes of the parametric images thus correspond to the degree of correlation between particular masks and the local areas in the image. The maximum filter response indicates the mask best matching the width and orientation of blood vessel segment contained in the respective image area. Non-existence of blood vessel in the area is indicated by a relatively low value of the filter response.

Thresholding and Post processing the resulting parametric image is threshold in order to obtain a binary representation of the vascular tree. The blood vessels are considered as a foreground (objects) and remaining parts as a background of the image, whereas only pixels inside the FOV are considered. The method utilized for thresholding belongs to the class of minimum error thresholding methods. These methods assume that the image can be formally characterized by mixture densities of foreground and background pixels

$$q(r) = Q(T)\, qf(r) + [1 \quad Q(T)]\, qb(r) \qquad \textit{(Equation 1)}$$

In this equation, q(r), r = 0,…,R, where R is the maximum luminance value in the image, is referred to as a probability mass function (QMF). The terms qf(r), $0 \leq r \leq T$, and qb(r), $T + 1 \leq r \leq R$, where T is the threshold value, are thus the QMFs of the foreground and background pixels, respectively. The QMF q(r) can be simply estimated from one-dimensional image histogram by normalizing it to the total number of samples.

DRIVE and STARE databases DRIVE and STARE databases were included into analysis in order to compare the proposed method with the state-of-the-art methods, since they have not been so far evaluated using the new HRF database. Owing to the low-resolution images in DRIVE and STARE databases, it is unsuitable to test all designed filtration masks for five width classes. It was experimentally determined, that applying only two of them is adequate to get acceptable results. The kernels were obtained heuristically from the profiles for 'width 1' and 'width 2' by down sampling corresponding masks with factor. Evaluation on the DRIVE and STARE was performed using the test sets of these databases, each containing 200 images with gold standard segmentations provided by the first human observer.

Adaptive Thresholding after vessel pixels are emphasized by Gabor filtering, they must be classified as vessel or non vessel. Hoover applied local region-based threshold probing, which produce good results because the particular information of retinal vessel network is used. In this approach, combine this region-based thresholding with the multiscale structure to achieve adaptive thresholding. The following outlines the major steps of the implementation:

1. Binarize the image with a single threshold F
2. Thin the thresholded image
3. Erase all branch points in the thinned image
4. All remaining endpoints are placed in the probe queue and are used as a starting point for tracking
5. Track the region with threshold F
6. If the region passed testing, F=F - 1, go to 5

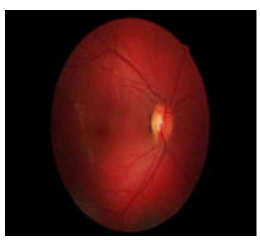
Line Strength Features the retinal vasculature is composed of arteries and veins appearing as piecewise linear features, with variation in width and their tributaries visible within the retinal image. The concept of employing line operators for detection of linear structures in medical images is introduced in which is modified and extended in to incorporate the morphological attributes of retinal blood vessels. The average grey level is measured along lines of a particular length passing through the pixel under consideration at different orientations. The line with the highest average gray value is marked. The line strength of a pixel is calculated by computing the difference in the average gray values of a square sub-window centered at the target pixel with the average gray value of the marked line. The calculated line strength for each pixel is taken as pixel feature vector.

Detection of Vascular Intersection Crossovers vascular intersections and crossovers are the most appropriate representation in registration process because they exist in every retinal image, and do not move except in some diseases. If a vascular tree is one-pixel wide, the branching points can be detected and characterized efficiently from the vascular tree. Morphological thinning is applied to the vascular tree in order to get one-pixel wide vascular tree. In order to save computational time, a 3 x 3 neighborhood window is used to probe and find the branching points. If the number of vascular tree in the window is great than 3, it is a branch point. Then an 11 x 11 neighborhood is applied through a detected branching points in order to eliminate the small intersections consider only the boundary pixels of a 11 x 11 square. If the number of vascular tree on the boundary is greater than 2 mark it as an intersection / crossover.

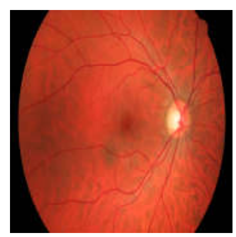
III. METHODS

A. Image possession

In this work, we have constructed a dataset of 200 images for the training and evaluation of our proposed method. This image dataset was acquired using a Canon CR-1 with a 45 degree field of view. Each image was captured using 24 bit per pixel (standard RGB) at 760 x 570 pixels. Of the 200 images in the dataset, 90 are of patients with no pathologies (normal) and the remaining images contain pathologies (such as micro aneurysms, hemorrhages and glaucoma) that can obscure or confuse the blood vessel appearance in varying positions of the image (abnormal) [6]. This selection is made for two reasons. First, most of the referenced methods have only been tested against normal images which are easier to distinguish. Second, some level of success with abnormal vessel appearances must be established to recommend clinical usage. (See Fig. 1 for an example of both a normal and an abnormal retinal image). As can be seen, a normal image consists of blood vessels, optic disc, fovea and the background, but the abnormal image also has multiple artifacts of distinct shapes and colors caused by different diseases.



(a)



(b)

Fig. 1. Digital retinal images. a) a normal image from our image dataset shows blood vessels, optic disc and fovea components, b) an abnormal image with exudate and hemorrhage lesions

B. Pixel-level learning dataset construction

In this work, the image pixels of the retinal images are considered as objects represented by their feature vectors, so that we can apply statistical classifiers in order to classify the image pixels. Here, we assume a binary multi-dimensional classification approach to distinguish the vessel pixels from other anatomical-pathological structures and artifacts, which we refer to collectively as non-vessels [7]. Our chosen data for the learning stage consists of typical pixels, which are representative of our classification problem [8]. To make-up such a dataset, examples, including vessels and non-vessels are labeled manually and then used to train and test the classifiers (Fig. 2). The obtained labeled examples feature vectors are mapped into the feature space and their labels are utilized to obtain that subspace which correspond to our two different classes i.e. vessel and non-vessel.

(a) (b)

Fig. 2. Manual blood vessel segmentation. a) A typical normal image, b) manually segmented vessels

C. Line Strength Features

The retinal vasculature is composed of arteries and veins appearing as linear features, with variation in width and their tributaries visible within the retinal image. The concept of employing line operators for detection of linear structures in medical images is introduced in which is modified and extended in to incorporate the morphological attributes of retinal blood vessels [9]. The average grey level is measured along lines of a particular length passing through the pixel under consideration at different orientations. The line with the highest average gray value is marked. The line strength of a pixel is calculated by computing the difference in the average gray values of a square sub-window centered at the target pixel with the average gray value of the marked line.

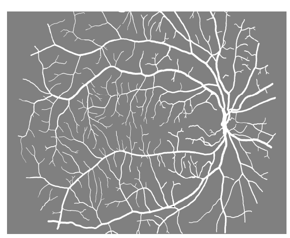


Fig. 3. Line strength vector retinal image

IV. PROPOSED SYSTEM

Automatically locating the accurate vascular pattern is very important in implementation of vessel screening system. An automated vessel screening system to facilitate the specialists is an application of consumer electronics [10]. Our proposed method segments the blood vessels from retinal images with great accuracy as compared to previous techniques. In proposed method, the monochromatic RGB retinal image is taken as an input and 2-D Gabor Filter is used to enhance the vascular pattern especially the thin and less visible vessels are enhanced using Gabor Filter.Vessels segmentation binary mask is created by threshold the enhanced retinal image. The blood vessels are marked by the masking procedure which assigns one to all those pixels which belong to blood vessels and zero to non vessels pixels.

This gives us the enhanced vascular pattern for the retinal image. Histogram for the enhanced retinal image is calculated. Maximum values occur for the grayish background while the vessel corresponds to values a slight greater than the background values as they are of bright color. An adaptive threshold technique is used that selects this point which separates the vessels from the rest of image. Automatically locating the accurate vascular pattern is very important in implementation of vessel screening system. An automated vessel screening system to facilitate the specialists is an application. In this proposed method segments the blood vessels from retinal images with great accuracy as compared to previous techniques. In proposed method, the monochromatic RGB retinal image is taken as an input is used to enhance the vascular pattern especially the thin and less visible vessels are enhanced using Gabor Filter.

Vessels segmentation binary mask is created by threshold the enhanced retinal image. The blood vessels are marked by the masking procedure which assigns one to all those pixels which belong to blood vessels and zero to non vessels pixels.This gives us the enhanced vascular pattern for the retinal image. Histogram for the enhanced retinal image is calculated. SFS (sequential forward selection) approach the interaction among features is taken into account. From the available set of features, the feature with the highest area under the curve (AUC) is selected. Maximum values occur for the grayish background while the vessel corresponds to values a slight greater than the background values as they are of bright color. An adaptive threshold technique is used that selects this point which separates the vessels from the rest of image. Propose a novel and precise method for accurate retinal vessel tree segmentation at a wide range of blood vessel sizes in high-resolution colour glaucoma fundus images. In this method Interactive evolutionary computation Algorithm (IECA) in combination with minimum error threshold technique and to use novel vessel segmentation approach to efficiently locate and extract blood vessels in color retinal images. More to the point, this study is concerned with developing fast methods while achieving high accuracy. Supervised methods requiring suitable pre-labeled training datasets and with efficient training time can be easily adjusted to new populations.

An accurate detection of the blood vessel tree can be used in registering time series glaucoma fundus images. Retinal vessel tree segmentation at a wide range of blood vessel sizes in high-resolution color glaucoma fundus images. Otsu’s method is used to automatically perform clustering based image threshold or the reduction of a gray level image. Comparable blood vessel followed by Interactive evolutionary computation Algorithm (IECA) to diagnosis of different diseases.

Image Preprocessing retina images are then preprocessed in order to bring the intensity values of each image into a particular range.

Generation of Super pixels the training images after preprocessing are represented by small regions called super pixels. The generation of the feature vector for each super pixel makes the process computationally efficient as compared to feature vector generation for each pixel.Feature extraction module.

Feature Generation image based features which are used to distinguish between the retinal area and the cup disc. The image-based features reflect textural, greyscale, or regional information and they were calculated for each super pixel of the image present in the training set. In testing stage, only those features will be generated which are selected by feature selection process.

Feature Selection due to a large number of features, the feature array needs to be reduced before classifier construction. This involves features selection of the most significant features for classification.

Classifier Construction in conjunction with manual annotations, the selected features is then used to construct the binary classifier. The result of such a classifier is the super pixel representing either the "Glaucoma" or "not."

Image Post processing is performed by morphological filtering so as to determine the retinal area boundary using super pixels classified by the classification model.

A. Threshold along with post privilege

The resulting parametric image is threshold in order to obtain a binary representation of the vascular tree. The blood vessels are considered as an objects and remaining parts as a background of the image, whereas only pixels inside the FOV are considered [11]. The method utilized for threshold belongs to the class of minimum error threshold methods .These methods assume that the image can be formally characterised by mixture densities of foreground and background pixels. Other threshold methods, specifically standard Multi Otsu method and the method based on the evaluation of local entropy from co-occurrence matrix, were tested as well.

The results from all threshold algorithms were evaluated and compared using the images from HRF database and it was found that the Kittler minimum error threshold technique is the most reliable for our segmentation task. Finally, morphological cleaning of the binary image by deleting the unconnected objects with pixel area less than selected value (generally determined in heuristic manner to 200 pixels) is applied to remove subtle artifact that are not connected to the blood vessel tree. An example of the binary representation of blood vessels is shown in Fig. 4 and the corresponding morphologically cleaned image.

(a) (b)

Fig. 4. Corresponding morphologically cleaned image

B. Otsu's method

In computer vision and image processing, Otsu's method is used to automatically perform clustering-based image threshold or the reduction of a gray level image to a binary image [12]. The algorithm assumes that the image to be threshold contains two classes of pixels or bi-modal histogram (e.g. foreground and background) then calculates the optimum threshold separating those two classes so that their combined spread (intra-class variance) is minimal. The extension of the original method to multi-level threshold is referred to as the Multi Otsu method.

In Otsu's method we exhaustively search for the threshold that minimizes the intra-class variance (the variance within the class), defined as a weighted sum of variances of the two classes:

$$\sigma_w^2(t) = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t) \quad (1)$$

Weights ω_i are the probabilities of the two classes separated by a threshold t and σ_i^2 variances of these classes. Otsu shows that minimizing the intra-class variance is the same as maximizing inter-class variance:

$$\sigma_b^2(t) = \sigma^2 - \sigma_w^2(t) = \omega_1(t)\omega_2(t)\left[\mu_1(t) - \mu_2(t)\right]^2 \quad (2)$$

This is expressed in terms of class probabilities ω_i and class means μ_i.

The class probability $\omega_1(t)$ is computed from the histogram as t:

$$\omega_1(t) = \Sigma_0^t p(i) \quad (3)$$

While the class mean $\mu_1(t)$ is:

$$\mu_1(t) = \left[\Sigma_0^t p(i)\, x(i)\right] / \omega_1 \quad (4)$$

Where $x(i)$ is the value at the center of the i th histogram bin. Similarly, you can compute $\omega_2(t)$ and μ_t on the right-hand side of the histogram for bins greater than t.

(a) (b)

Fig. 5. Digital retinal images threshold

a) Gray Level Original image, b) Threshold using Otsu's Method

The class probabilities and class means can be computed consistency. This idea yields an effective algorithm.

V. ANALYSIS IMAGE MATCHED ALGORITHM

Interactive evolutionary computation or aesthetic selection is a general term for methods of evolutionary computation that use human evaluation. Usually human evaluation is necessary when the form of fitness function is not known or the result of optimization should fit a particular user preference [13].

The number of evaluations that IECA can receive from one human user is limited by user fatigue which was reported by many researchers as a major problem. In addition, human evaluations are slow and expensive as compared to fitness function computation. Hence, one-user IECA methods should be designed to converge using a small number of evaluations, which necessarily implies very small populations. Several methods were proposed by researchers to speed up convergence, like interactive constrain evolutionary search or fitting user preferences using a convex function. IECA human-computer interfaces should be carefully designed in order to reduce user fatigue.

The segmented disc and cup boundary, the cup to disc ratio (CDR) is computed as CDR=VCD/VDD.Glaucoma breaks the nerves in the disk region, so that the area of optic cup increases. In order to find out the cup to disc ratio, first we extract the images of cup and disc separately. The computed CDR is used for glaucoma screening. When it is greater than a threshold, it is glaucomatous, otherwise healthy.

IECA is defined as a genetic algorithm that uses human evaluation. These algorithms belong to a more general category of Interactive evolutionary computation. The main application of these techniques include domains where it is hard or impossible to design a computational fitness function, for example, evolving images, various artistic designs and forms to fit a user's aesthetic preferences. Interactive computation methods can use different representations, as in traditional genetic algorithms and genetic programming.

VI. CONCLUSION

Interactive evolutionary computation or aesthetic selection is a general term for methods of evolutionary computation that use human evaluation. Usually human evaluation is necessary when the form of fitness function is not known or the result of optimization should fit a particular user preference.

In this proposed using Otsu's methods based colored retinal image blood vessel segmentation technique using identified the glaucoma disease. Vessel segmentation mask is created and refined using Otsu's method and morphological operator respectively through the cup disc. The problem with retinal images is that the visibility of vascular pattern is usually not good .So, it is necessary to enhance the vascular pattern. In this thesis, vessels are enhanced and sharpened prior to their detection.

Canny Edge Detection using in contrast to conventional approaches that are based on visual features, method provides an interactive mechanism to bridge the gap between the visual features and the human perception. A retinal blood vessel was associated with two measures of executive function, which is more typically affected early in vascular cognitive impairment. To essentially knowledge, this is the first study showing an association between generalized retinal vessel reduction and cognitive function in healthy individuals without cognitive impairment. In healthy individuals with normal represent through blood vessel, central retinal line equivalent may serve as a non-invasive indicator of early micro vascular changes subtly affecting executive function. Further work considering more high-level semantics in the proposed approach is in progress.

The number of evaluations that IECA can receive from one human user is limited by user fatigue which was reported by many researchers as a major problem. In addition, human evaluations are slow and expensive as compared to fitness function computation. Hence, one-user IECA methods should be designed to converge using a small number of evaluations, which necessarily implies very small populations. Several methods were proposed by researchers to speed up convergence, like interactive constrain evolutionary search or fitting user preferences using a convex function. IECA human computer interfaces should be carefully designed in order to reduce user fatigue.

In further work planning to enhance this methodology more effective. The proposed approach does not involve exact and effective preprocessing algorithm for retinal image improvement. In the future works involves basic noise and blur removal approach.

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