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Segmentation of the Blood Vessel and Optic Disc in Retinal Images Using EM Algorithm

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Abstract: *Diabetic retinopathy (DR), glaucoma and hypertension are eye disease which is harmful and causes pressure in eye nerve and finally blindness. With the invention of new systems and the developing of new technologies the research in the medicine field had a great impulse. In particular, the development of the medical imaging field has been revolutionary with the availability of new techniques to acquire and process digital images. This revolution have required of significant innovation in computational techniques for the different aspects of image processing. Retinal image investigation is actually more and more dominant for nonintrusive prognosis approach inside modern day ophthalmology. On this paper, provide a book approach to be able to segment blood vessel and also optic disk inside the fundus retinal photos by making use of EM algorithm. The morphology with the blood vessels and optic disk is actually an essential warning intended for diseases similar to diabetic retinopathy, glaucoma, and also hypertension. Using this method requires seeing that very first action this extraction with the retina vascular tree when using the graph cut approach. The blood vessels details is actually next used to appraisal the placement with the optic disk. The optic disk segmentation is carried out utilizing two choice procedures: Expectation maximization (EM) method and morphological operation.*

Keywords: *EM algorithm, graph cut method, Maxflow algorithm, morphological operation, segmentation.*

I. Introduction

The human eye is usually a important place connected with the skin in which the vascular situation is usually right observed. Retina may be the neural section of the eyes and in addition to fovea and also optic disc, this leading to one of the main highlights of a retinal fundus image.

Presently, there is an increasing interest for establishing automatic systems that screens a huge number of people for vision threatening diseases like Diabetic Retinopathy, Glaucoma and Hypertension to provide an automated detection of the disease.DR is a chronic disease which nowadays constitutes the primary cause of blindness in people of working age in the developed world [1]–[3]. The DR is a micro vascular complication of diabetes, causing abnormalities in the retina and in the worst case blindness. About 10,000 diabetic people worldwide lose the vision each year. There is evidence that retinopathy begins its development at least 7 years before the clinical diagnosis of type 2 diabetes. If the diabetic retinopathy is not detected and the patient does not receive appropriated treatment it is very likely that glaucoma will be followed.

The term of glaucoma refers to a group of diseases characterized by optic neuropathy. These are characterized by structural change and functional deficit (measured by visual field change). Intraocular pressure is used to diagnose glaucoma patients when is not possible visualize the optic nerve and the visual fields cannot be measured. However, even when intraocular pressure is an important risk factor for glaucoma, it is not part of the definition.

Hypertension (HT),is known as high blood pressure or arterial hypertension. HT is rarely accompanied by any symptoms and its identification is usually through screening, or when seeking healthcare for an unrelated problem. Some with high blood pressure report headaches .

Different efforts have worked for the prevention of the blind condition due to a retinopathy, glaucoma. The analysis of retinal images represents a non invasive process to perform the diagnosis and control of patients. Interactive and automatic systems for the analysis of retinal images have been designed. Early models are based on supervised systems. These systems have probed their efficiently in different methods. Unfortunately supervised systems require of high processing time and hand labeled image as part of the training process. Due to the systems have been training using images with specific characteristics the system comprises its performance to image with similar features. The state of the art on retinal image analysis has the need of unsupervised systems that perform the analysis of retinal images without human supervision or interaction.

The optic disc (OD) is usually more important compared to any kind of part of the retina and it is normally spherical in shape.

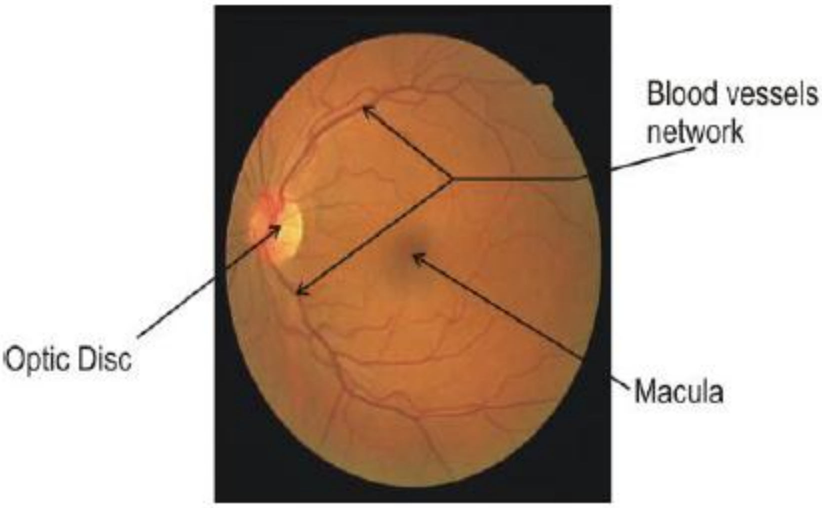

Fig 1: Retina structures: blood vessels, optic disc and macula.

II. Literature Survey

Blood vessel is visible while thin elongated constructions in the retina, with variance wide along with length in which converge in the optic disc. An accurate segmentation of the blood vessels is the first step to extract features and fundamental information to create a diagnosis, evaluate treatments progress and keep control of diseases [4, 5]. Segmentation of our blood vessel with retinal images makes it possible for early on diagnosis. Automating this technique offers several benefits which include reducing subjectivity along with eradicating some sort of careful tiresome process. Guide book diagnosis along with evaluation of the retinal photos is a time consuming along with unreliable process and since the amount of photos increases the study gets quite challenging. As a result it's important to use automatic algorithms regarding evaluation of images. OD(Optic Disc) segmentation comes with a great medical importance in aiding various other retina impression evaluation tasks including vessel monitoring, fovea localization, acceptance of still left along with correct sight last but not least impression registration[6]. Various scientific studies had been performed for the segmentation of bloodstream along with optic disk normally, nonetheless just few these had been related in order to retinal bloodstream.

2.1. Matched Filters

Matched filters were being according to a new link measure between the predicted design sought intended for and also the referenced signal. The idea according to directional 2D harmonized filtration. To further improve retinal vasculature 2D matched harmonized filtration kernel has been designed to convolve using the initial fundus picture. The kernel has been rotated and balanced into often nine as well as a dozen orientations to adjust to into blood vessels regarding a variety of layouts. Many kernel forms are actually researched. Many methods were being additionally planned to spot true blood vessels.

2.2 Tracking Methods

This tracking methods get a steady our blood vessel fragment beginning a point granted sometimes physically as well as instantly according to certain local information. These methods generally look at to get the route which best suits a vessels report model. Sobel edge sensors, gradient operators along with matched filters have been applied to find the vessels along with border. Though these types of methods have been perplexed by our blood vessels bifurcations along with crossings, they might deliver precise sizes of our blood vessels tortuosity along with widths.

2.3. Morphological Processing

In order to part the actual bloodstream within a retinal image statistical morphology can be utilized since the vessels had been the actual behaviour that shows morphological properties these kinds of seeing that connectivity, linearity as well as curvature connected with wrecks different efficiently on the crest collection. Although history behavior furthermore suit such a morphological outline. As a way to discriminate bloodstream coming from different similar set ups, cross curvature evolution as well as linear selection.

2.4. Region Growing Approaches

In region growing approaches, it was regarded in which pixels of more detailed to each other along with having similar bleak levels intensities have been likely to fit into a similar thing. These kinds of approaches generate prospects pixels incrementally in a area starting from any seed products point. The standards employed for segmentation have been value similarity along with spatial proximity.

2.5. Multiscale Approaches

Multiscale approach was performed by varying image resolutions. The main advantage of using these approaches was their efficient computing speed. In these approaches very larger blood vessels were segmented from regions having low resolution and finer vessels were segmented from regions having high resolution. Multiscale analysis of first and second order spatial derivatives of the gray level intensity image was used for the segmentation of blood vessels having different widths, lengths and orientations. A two step region growing procedure was applied in this method. The growth was constrained to regions with low gradient magnitude in the first step. This constraint was relaxed in the second step to permit the borders between regions to be defined.

2.6. Supervised Methods

Recently, several supervised methods focusing on 2D fundus images were explored to obtain better results. Two blood vessel detection methods in digital fundus images based on line operators. The response of the line detector was threshold to attain pixel classification which was unsupervised in the first segmentation method. In the second segmentation method, a feature vector comprising two orthogonal line detectors and target pixel's gray level was used for supervised classification. A pixel based classification method was developed to segment blood vessels. This method classified each pixel of the gray level fundus images as blood vessel component or non-blood vessel component, based on feature vectors of the fundus image. The responses of two dimensional Gabor wavelet transform attained at multiple scales and intensity at each image pixel constitute the feature vectors. Then, Bayesian classifier with Gaussian mixture model [9] was trained to classify these feature vectors. Image ridges were extracted [8] and applied to compile primitives in the form of line elements.

2.7. Adaptive Thresholding Methods

The actual highlights of the particular vasculature have been harnessed by making use of nonlinear orthogonal projections within [10] and a community adaptive thresholding formula was useful for vessels detection. Knowledge-guided adaptive thresholding was working at [11] to help segment vessel system. Multi-threshold probing was put on the particular fundus impression through a confirmation treatment that produces by using any curvilinear framework model. The actual pertinent information regarding items, which includes appearance, color/intensity as well as comparison was included. This usually guides the particular class treatment. Particularly discussed above intended for our blood vessel segmentation can figure effectively to help section the particular important areas of vasculature. Even so, the particular important problems challenging with the above mentioned vessel segmentation strategies usually are

- Extraction of finer blood vessels as the image contrast is especially low around thin vessels
- The presence of lesions as they may be misenhanced and misdirected as blood vessels.

III. Existing System

In the existing system has both pixel control and also tracking solutions. The pixel control solutions can provide a complete removal in the vascular tree in the retinal image given that theyresearch every one of the possible vessel pixels over the total image. On the other hand, these kinds of strategies are usually computationally pricey and also call for specific hardware to become made for significant image dataset. The presence connected with noise and also lesions with some retinal images causes a substantial destruction in the efficiency in the pixel control solutions because enlargement functioning might acquire some noise and also lesions while vessel pixels. This kind of may lead to untrue vessel diagnosis in the identification functioning. In contrast, the pursuing solutions are usually computationally efficient and much quicker compared to the pixel control methods given that they execute vessel segmentation only using pixels in the neighbourhood of the vessel structure and get away from the control of the pixel in the image. In addition, the semiautomated pursuing segmentation methods have to have manual feedback, which usually requires period.

IV. Proposed System

4.1. Blood Vessel Segmentation

Blood Vessel visible as elongated constructions within the retina, along with variance wide and size. As a way to portion the blood vessel in the fundus retinal impression, it has applied the preprocessing technique, which usually consists of an effective adaptive histogram equalization and strong length convert. This particular procedure increases the robustness and the accuracy and reliability on the graph cut technique. Fig. 2 shows the illustration of the vessel segmentation algorithm.

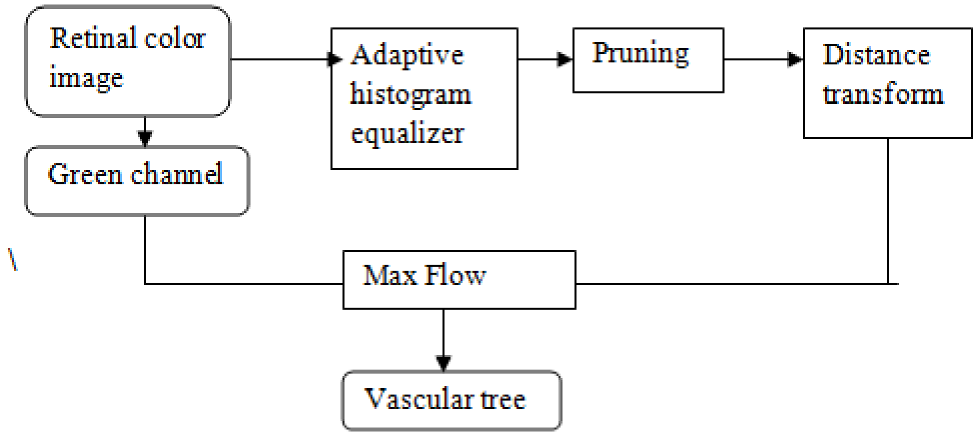

Fig 2 segmentation algorithm

4.1.1 Preprocessing

Apply a contrast enhancement process to the green channel image similar to the work presented in [20]. The intensity of the image is inverted, and the illumination is balanced. The resulting image is further enhanced by adaptive histogram equalizer, given by:

$$I_{\text{Enhanced}} = \left(\sum_{p' \in R(p)} \frac{s\left(I\left(p\right) - I\left(p'\right)\right)}{h^2} \right)^r \cdot M \tag{1}$$

where I is the green channel of the fundus retinal color image, p denotes a pixel, and p′ is the neighborhood pixel around p. p′∈ R(p) is the square window neighborhood with length h. s(d) = 1if d > 0, and s(d) = 0 otherwise with d = s (I (p) − I (p′)). M = 255 value of the maximum intensity in the image. r is a parameter to control the level of enhancement. Increasing the value of r would also increase the contrast between vessel pixels and the Bg as seen in Fig. 3. The experimental values ofthe window length was set to h = 81 and r = 6.

A binary morphological open process is applied to prune the enhanced image, which remove all the unwanted pixels in Fig.3(d). This method also reduces the false positive, since the enhanced image will be used to construct the graph for segmentation.

The distance transform algorithm is used to create distance map image which calculate the direction and the magnitude of the vessel gradient, Fig. 3(e) and (f) shows the distance map of the entire image and a sample vessel with arrows representing the direction of the gradients, respectively. From the sample vessel image, we can find the center line with the brightest pixels,which are progressively reduced in intensity in the direction of the edges (image gradients). The arrows in Fig. 3(f) are referred to as vector field, which are used to construct the graph in the next sections.

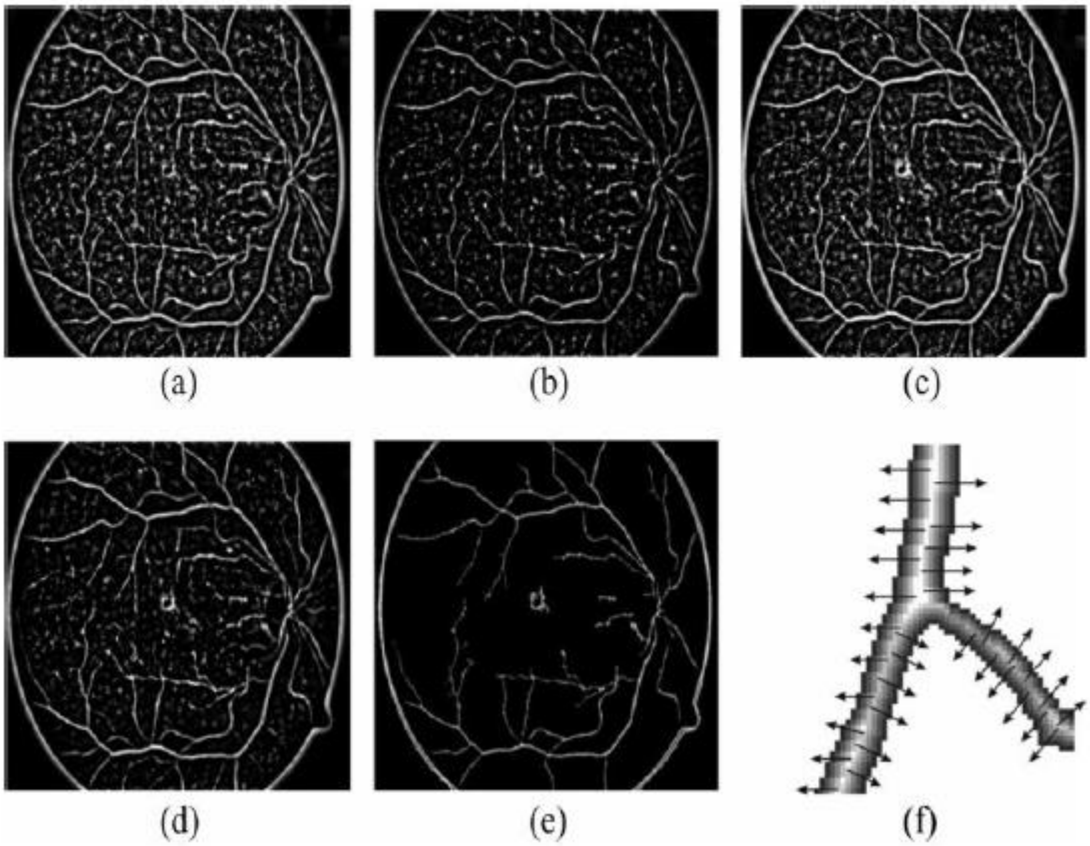

Fig.3. Preprocessing. (a) $h = 45$, $r = 3$, (b) $h = 45$, $r = 6$, (c) $h = 81$, $r =3$, (d) $h = 81$, $r = 6$, (e) distance map, and (f) sample of avessel with arrows indicating the vessel gradients.

4.1.2 Graph Construction for Vessel Segmentation

The graph cut is usually an energy-based object segmentation method. The actual method is seen as a good optimisation procedure meant to limit the energy generated from provided picture information. This particular energy identifies the connection among area pixel components in the picture.

Table 1. Weight of the edges in the graph

Edge	weight	for
{p, q}	$B_{\{p,q\}}$	$\{p,q\} \in N$
{p, S} (Foreground)	$\lambda \cdot R_p(Fg)$	$p \in P, p \notin F \cup B$
	K	$p \in F$
	0	$p \in B$
{ p, T} (Background)	$\lambda \cdot R_p(Bg)$	$p \in P, p \notin F \cup B$
	0	$p \in F$
	K	$p \in B$

A graph G (ν, ϵ) is defined as a set of nodes (pixels) ν and a set of undirected edges ϵ that connect these neighboring nodes. The graph included two special nodes; a foreground (Fg) terminal (source S) and a Bg terminal (sink T). ϵ includes two types of undirected edges: neighborhood links (n-links) and terminal links (t-links). Each pixel p ∈ P (a set of pixels) in the graph presents two t-links {p, S} and {p, T} connecting it to each terminal, while a pair of neighboring pixels {p, q} ∈ N (number of pixel neighbors) is connected by an n-link [21]. Thus:

$$\epsilon = N \bigcup_{p \in P} \{\{p,S\},\{p,T\}, \nu = P \cup \{S,T\}\}. \tag{2}$$

An edge e ∈ ϵ is assigned a weight (cost)We>0.A cut is defined by a subset of edges C ∈ ϵ,where G (c) = ν, ϵ\C〉 separating the graph into Fg. The max-flow algorithm is used to cut the graph and find the optimal segmentation. Table 1 assigns weight to the edges ϵ in the graph [21], where:

$$K = 1 + \max_{p \in P} \sum_{\{p,q\}} B_{p,q}, \tag{3}$$

and F and B represent the subsets of pixels selected as the Fg and Bg, respectively. Thus, F⊂P and B⊂ P such that FUB=null set. Bp,q defines the discontinuity between neighboring pixels, and its value is large when the pixel intensities. λ > 0 is a constant coefficient, which will define in the energy formulation of the graph.

The graph cut technique is used in our segmentation because it allows the incorporation of prior knowledge into the graph formulation in order to guide the model and find the optimal segmentation. Let us assume A = (A1, Ap. . . AP) is a binary vector set of labels assigned to each pixel p in the image, where Ap indicate assignments to pixels p in P . Therefore, each assignment Ap is either in the Fg or Bg. Thus, the segmentation is obtained by the binary vector A and the constraints imposed on the regional and boundary proprieties of vector A are derived by the energy formulation of the graph defined as :

$$E(A) = \lambda \cdot R(A) + B(A) \tag{4}$$

where the positive coefficient λ indicates the relative importance of the regional term (likelihoods of Fg and Bg) RA against the boundary term (relationship between neighborhood pixels) BA .The regional or the likelihood of the Fg and Bg is given by:

$$R(A) = \sum_{p \in P} R_p(A_p) \tag{5}$$

and the boundary constraints are defined as :

$$B(A) = \sum_{p,q \in N} B_{p,q} \cdot \phi(A_p, A_q) \tag{6}$$

Where φ (Ap, Aq) = 1 for Ap = Aq and 0 otherwise,

$$B_{p,q} = \exp\left(-\frac{(I_p - Iq)^2}{2\sigma^2}\right) \cdot \frac{1}{\mathrm{dist}(p,q)}. \tag{7}$$

Rp (Ap) specifies the assignment of pixel p to either the Fg or the Bg.Bp,q defines the discontinuity between neighboring pixels, and its value is large when the pixel intensities Ip and Iq are similar and close to zero when they are different. The value of Bp,q is also affected by the Euclidean distance dist(p,q) between pixels p and q.

4. 2. Optic Disk Segmentation

The optic disk segmentation starts by defining the location of the optic disk. This process used the convergence feature of vessels into the optic disk to estimate its location. The disk area segmented using two different automated methods (Expectation maximization method and morphological operation).Both methods use the convergence feature of the vessels to identify the position of the disk.

4.2.1 Expectation and Maximization Method

Expectation–maximization (EM) algorithm is an iterative method for finding maximum likelihood or maximum a posteriori(MAP) estimates of parameters , where the model depends on unobserved latent variables. The EM iteration alternates between performing an expectation (E) step, which creates a function for the expectation of the log-likelihood evaluated using the current estimate for the parameters, and maximization (M) step, which computes parameters maximizing the expected log-likelihood found on the *E* step. These parameter-estimates are then used to determine the distribution of the latent variables in the next E step.

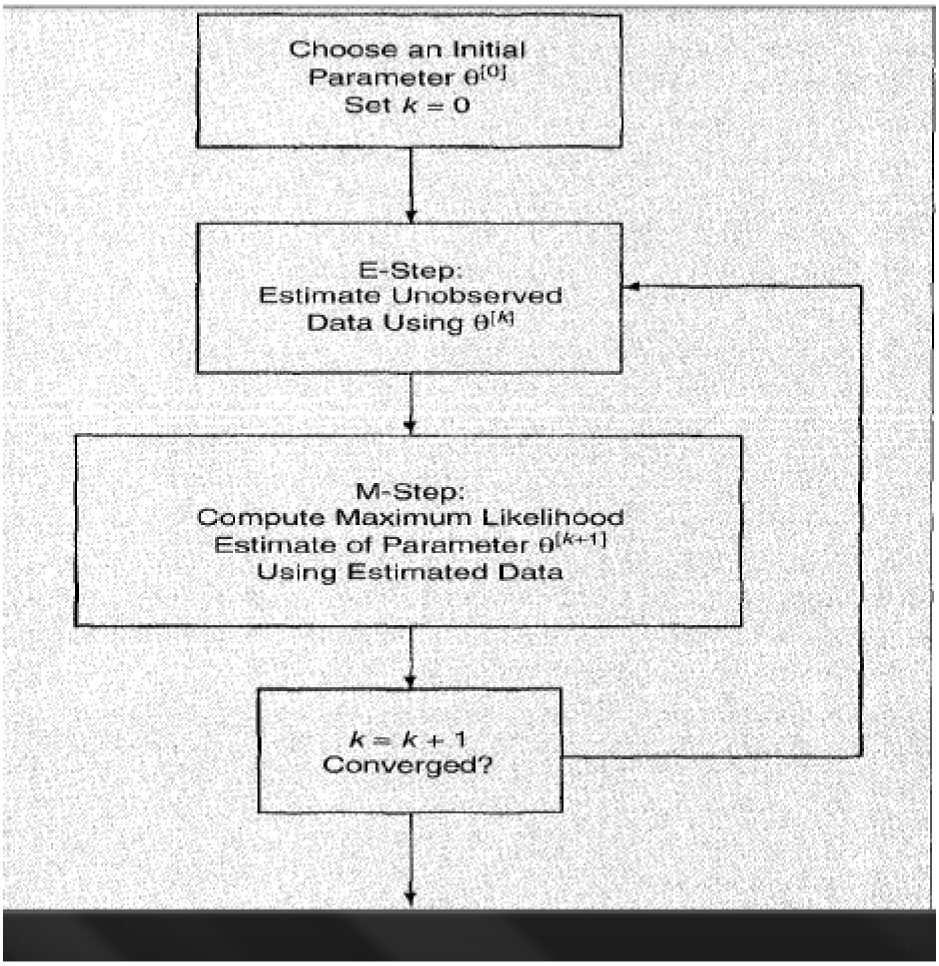

Fig 4: An overview of the EM algorithm.

Given a statistical model which generates a set X of observed data, a set of unobserved latent data or missing values Z, and a vector of unknown parameters ɵ , along with a likelihood function , the maximum likelihood estimate (MLE) of the unknown parameters is determined by the marginal likelihood of the observed data:

$$L(\boldsymbol{\theta}; \mathbf{X}, \mathbf{Z}) = p(\mathbf{X}, \mathbf{Z}|\boldsymbol{\theta}) \tag{8}$$

$$L(\boldsymbol{\theta}; \mathbf{X}) = p(\mathbf{X}|\boldsymbol{\theta}) = \sum_{\mathbf{Z}} p(\mathbf{X}, \mathbf{Z}|\boldsymbol{\theta}) \tag{9}$$

However, this quantity is often intractable (e.g. if Z is a sequence of events, so that the number of values grows exponentially with the sequence length, making the exact calculation of the sum extremely difficult).
The EM algorithm seeks to find the MLE of the marginal likelihood by iteratively applying the following two steps:
Expectation step (E step): Calculate the expected value of the log likelihood function, with respect to the conditional distribution of Z given X under the current estimate of the parameters $ɵ^{(t)}$:

$$Q(\boldsymbol{\theta}|\boldsymbol{\theta}^{(t)}) = \mathrm{E}_{\mathbf{Z}|\mathbf{X},\boldsymbol{\theta}^{(t)}}\left[\log L(\boldsymbol{\theta}; \mathbf{X}, \mathbf{Z})\right] \tag{10}$$

Maximization step (M step): Find the parameter that maximizes this quantity:

$$\boldsymbol{\theta}^{(t+1)} = \underset{\boldsymbol{\theta}}{\arg\max}\ Q(\boldsymbol{\theta}|\boldsymbol{\theta}^{(t)}) \tag{11}$$

Note that in typical models to which EM is applied:

- The observed data points X may be discrete (taking values in a finite or countably infinite set) or continuous (taking values in an uncountablyinfinite set). There may in fact be a vector of observations associated with each data point.
- The missing values (aka latent variables) Z are discrete, drawn from a fixed number of values, and there is one latent variable per observed data point.
- The parameters are continuous, and are of two kinds: Parameters that are associated with all data points, and parameters associated with a particular value of a latent variable (i.e. associated with all data points whose corresponding latent variable has a particular value).

However, it is possible to apply EM to other sorts of models.

The motivation is as follows. If know the value of the parameters ɵ , I can usually find the value of the latent variables Z by maximizing the log-likelihood over all possible values of Z , either simply by iterating over Z or through an algorithm such as the Viterbi algorithm for hidden Markov models. Conversely, if know the value of the latent variables Z ,find an estimate of the parameters ɵ fairly easily, typically by simply grouping the observed data points according to the value of the associated latent variable and averaging the values, or some function of the values, of the points in each group. This suggests an iterative algorithm, in the case where both ɵ and Z are unknown:

- First, initialize the parameters ɵ to some random values.
- Compute the best value Z for given these parameter values.
- Then, use the just-computed values of Z to compute a better estimate for the parameters ɵ. Parameters associated with a particular value of Z will use only those data points whose associated latent variable has that value.
- Iterate steps 2 and 3 until convergence.

The algorithm as just described monotonically approaches a local minimum of the cost function, and is commonly called hard EM. The k-means algorithm is an example of this class of algorithms.

However, one can do somewhat better: Rather than making a hard choice for Z given the current parameter values and averaging only over the set of data points associated with a particular value of Z one can instead determine the probability of each possible value of Z for each data point, and then use the probabilities associated with a particular value of Z to compute a weighted average over the entire set of data points. The resulting algorithm is commonly called soft EM, and is the type of algorithm normally associated with EM. The counts used to compute these weighted averages are called soft counts (as opposed to the hard counts used in a hard-EM-type algorithm such as k-means). The probabilities computed for Z are posterior probabilities and are what is computed in the E step. The soft counts used to compute new parameter values are what are computed in the M step.

Speaking of an expectation (E) step is a bit of a misnomer. What are calculated in the first step are the fixed, data-dependent parameters of the function *Q*. Once the parameters of *Q* are known, it is fully determined and is maximized in the second (M) step of an EM algorithm.

Although EM iteration does increase the observed data (i.e. marginal) likelihood function there is no guarantee that the sequence converges to a maximum likelihood estimator. For multimodal distributions, this means that an EM algorithm may converge to a local maximum of the observed data likelihood function, depending on starting values. There are a variety of heuristic or meta heuristic approaches for escaping a local maximum such as random restart (starting with several different random initial estimates $\theta^{((t)}$), or applying simulated annealing methods.

There are other methods for finding maximum likelihood estimates, such as gradient descent, conjugate gradient or variations of the Gauss–Newton method. Unlike EM, such methods typically require the evaluation of first and/or second derivatives of the likelihood function.

4.2.2 Morphological Operation

Binary images may perhaps include many defects. Particularly, the binary regions produced by uncomplicated thresholding are usually distorted by means of sound along with surface Morphological picture finalizing pursues our aims regarding taking away these types of defects by means of human resources with the kind along with structure in the picture. Most of these tactics could be lengthy to grayscale images. Morphological picture processing is an accumulation of non-linear operations relevant to the design or maybe morphology regarding features within the picture. Morphological operations rely just around the comparative placing our order regarding pixel values, not really on their statistical values, along with therefore are especially suitable for our finalizing regarding binary images. Morphological operations may also be placed on greyscale images so that the gentle exchange functions are usually unknown and therefore the complete pixel values are usually regarding no or maybe modest attention. Morphological technique probe a graphic that has a small shape or maybe template known as a structuring element. The particular structuring element is put by any means probable destinations in the picture and it's compared with our corresponding area regarding pixels. Many operations examination if these components “fit" within the area, and some examination regardless of whether the item "hits" or maybe intersects our area. A morphological function over a binary picture creates a new binary picture that the pixel includes a non zero value provided that our examination is productive at that position in the input picture. The structuring element is a small binary picture, a small matrix regarding pixels, each and every that has a value regarding zero or maybe one: The particular matrix dimensions identify the size of our structuring element. The particular design regarding ones along with zeros specifies they shape of your structuring element. An origin of our structuring element is usually considered one of its pixels, while usually the origins could be exterior our structuring element. One common process should be to have got odd dimensions in the structuring matrix and also the origins understood to be our centre in the matrix Structuring aspects participate in morphological picture finalizing exactly the same role while convolution kernels in linear picture selection. When a structuring element is positioned inside a binary picture, every one of its pixels is usually from the corresponding pixel in the area under the structuring element. The structuring element is said to fit the image if, for each of its pixels set to 1, the corresponding image pixel is also 1. Similarly, a structuring element is said to hit, or intersect, an image if, at least for one of its pixels set to 1 the corresponding image pixel is also 1. Zero-valued pixels of the structuring element are ignored, i.e. indicate points where the corresponding image value is irrelevant.

Fundamental operations

Erosion and dilation

Erosion with small (e.g. 2×2 - 5×5) square structuring elements shrinks an image by stripping away a layer of pixels from both the inner and outer boundaries of regions. The holes and gaps between different regions become larger, and small details are eliminated:

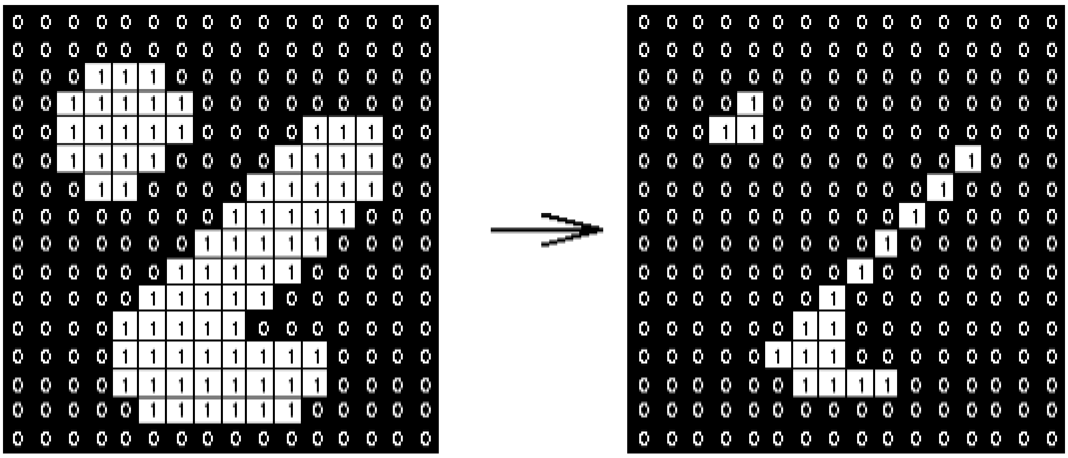

Fig 5: Erosion: a 3×3 square structuring element

Larger structuring elements have a more pronounced effect, the result of erosion with a large structuring element being similar to the result obtained by iterated erosion using a smaller structuring element of the same shape. If s1 and s2 are a pair of structuring elements identical in shape, with s2twice the size of s1, then:

$$f \ominus s_2 \approx (f \ominus s_1) \ominus s_1. \tag{12}$$

Erosion removes small-scale details from a binary image but simultaneously reduces the size of regions of interest, too. By subtracting the eroded image from the original image, boundaries of each region can be found: b = f− (f ɵ s) where f is an image of the regions, s is a 3×3 structuring element, and b is an image of the region boundaries.

The dilation of an image f by a structuring element s produces a new binary image g with ones in all locations (x,y) of a structuring element's origin at which that structuring elements hits the input image f, i.e. g(x,y) = 1 if s hits f and 0 otherwise, repeating for all pixel coordinates (x,y). Dilation has the opposite effect to erosion. It adds a layer of pixels to both the inner and outer boundaries of regions.

Results of dilation or erosion are influenced both by the size and shape of a structuring element. Dilation and erosion are dual operations in that they have opposite effects.

Let f^c denote the complement of an image f, i.e., the image produced by replacing 1 with 0 and vice versa, formally duality is written as

$$f \oplus s = f^c \ominus s_{rot} \tag{13}$$

where srot is the structuring element s rotated by 180 . If a structuring element is symmetrical with respect to rotation, then srot does not differ from. If a binary image is considered to be a collection of connected regions of pixels set to 1 on a background of pixels set to 0, then erosion is the fitting of a structuring element to these regions and dilation is the fitting of a structuring element (rotated if necessary) into the background.

V. Results

method	TPR	FPR	Accuracy
Mendanocca[3]	0.7258	0.0209	0.9492
Hoovr[2]	0.6766	0.338	0.9324
Chaudhuri[6]	0.7335	0.0218	0.9484
Zhang[21]	0.7526	0.0221	0.9510
Our method	0.8717	0.0364	0.9513

For the vessel segmentation method, tested the algorithm In public dataset, DRIVE with a total of 8 images. The optic disk segmentation algorithm was tested on DRIVE consisting of 8 images in total. The performances of both methods are tested against a number of alternative methods.

To facilitate the performance comparison between our method and alternative retinal blood vessels segmentation approaches, parameters such as the true positive rate (TPR), the false positive rate (FPR), and the accuracy rate (ACC) are derived to measure the performance of the segmentation [5]. The ACC is defined as the sum of the true positives (pixels correctly classified as vessel points) and the true negatives (nonvessel pixels correctly identified as nonvessel points), divided by the total number of pixels in the images. The TPR is defined as the total number of true positives, divided by the number of blood vessel pixels marked in the ground true image. The FPR is calculated as the total number of false positives divided by the number of pixels marked as nonvessel in the ground true image. It is worth mentioning that a perfect segmentation would have an FPR of 0 and a TPR of 1. Our method and all the alternative methods used first expert hand-labeled images as a performance reference.

Most of the alternative methods use the whole image to measure the performance. In [5], all the experiments are carried out on the field of view (FOV) without considering the performance in the dark area outside the FOV. The method in [3] measures the performance on both the whole image and the FOV. The dark Bg outside the FOV in the retinal image is easy to segment. It is an advantage in measuring the true negatives pixels when the whole image is considered. It has calculated the percentage of pixels outside the FOV in the images for the two datasets, which represents approximately 25% of the pixels in the whole image. However, it does not affect all the measurement metrics, except when the true negative value is involved (e.g.,ACC). On the other hand, most of the methods use the whole image to measure their performance, making the comparison fair.

VI. Conclusion

It presented a novel technique intended for arteries along with optic computer segmentation within the fundus from the retinal photographs, the process could be utilized to help nonintrusive diagnosis within modern day ophthalmology because morphology from the blood vessel along with the optic disc is an significant signal intended for diseases similar to diabetic retinopathy, glaucoma, along with hypertension. The method takes seeing that primary step the actual removal from the retina vascular tree when using the graph cut technique. This blood vessel information will be then utilized to calculate the placement from the optic disc. In order to segment the actual blood vessel within the EM algorithm along with morphological preprocessing in to the graph cut approach. The task in addition entails comparison development, adaptive histogram equalization, binary opening, along with distance convert intended for preprocessing..EM algorithm is an iterative method for finding maximum likelihood or maximum a posteriori(MAP) estimates of parameters , where the model depends on unobserved variables. The Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image. This pursues the goals of removing these imperfections in segmented image using EM algorithm. This method provides more accuracy and less time consuming.

References

[1]. K. Fritzsche, A. Can, H. Shen, C. Tsai, J. Turner, H. Tanenbuam,C. Stewart, B. Roysam, J. Suri, and S. Laxminarayan, “Automated model based segmentation, tracing and analysis of retinal vasculature from digital fundus images,” in State-of-The-Art Angiography, Applications and Plaque Imaging Using MR, CT, Ultrasound and X-rays.Boca Raton,FL, USA: CRC Press, 2003, pp. 225-298.

[2]. A. Hoover, V. Kouznetsova, and M. Goldbaum, “Locating blood vessels in retinal images by piecewise threshold probing of a matched filter response,” IEEETrans.Med.Imag.,vol.19,no.3,pp.203-210,Mar.2000.

[3]. A. M. Mendonca and A. Campilho, “Segmentation of retinal blood vessels by combining the detection of centerlines and morph ological reconstruction,” IEEE Trans. Med. Imag., vol. 25,no.9,pp.1200-1213,Sep.2006.

[4]. J. Soares, J. Leandro, R. Cesar, H. Jelinek, and M. Cree, “Retinal vessel segmentation using the 2-D gabor wavelet and supervised classification,”IEEE Trans. Med. Imag., vol. 25, no. 9,pp.1214-1222,Sep.2006.

[5]. J. Staal, M. D. Abramoff, M. Niemeijer, M. A. Viergever, and B. van Ginneken, “Ridge-based vessel segmentation in color images of the retina,”IEEE Trans. Med. Imag., vol. 23, no. 4, pp.501-509,Apr.2004.

[6]. S. Chaudhuri, S. Chatterjee, N. Katz, M. Nelson, and M. Goldbaum, “Detection of blood vessels in retinal images using two-dimensional matched filters,” IEEE Trans. Med. Imag., vol.8,no.3,pp.263-269,Sep.1989.

[7]. F.Zana and J.-C. Klein,“Segmentation of vessel-like patterns using mathematical morphology and curvature evaluation,” IEEE Trans. Image Process., vol. 10, no. 7, pp. 1010-1019, Jul. 2001.

[8]. L. Xu and S. Luo, “A novel method for blood vessel detection from retinal images,”Biomed.Eng.Online,vol.9,no.1,pp.14,2010.

[9]. M. E. Martinez-Perez, A. D. Hughes, S. A. Thom, A. A. Bharath, and K. H. Parker, “Segmentation of blood vessels from red-free and fluorescein retinal images,” Med. Image Anal., vol. 11, no. 1, pp. 47-61, 2007.

[10]. L. Zhou, M. S. Rzeszotarski, L. J. Singerman, and J. M. Chokreff, “The detection and quantification of retinopathy using digital angiograms,”IEEE Trans. Med. Imag., vol. 13, no. 4, pp. 619-626, Dec. 1994.

[11]. C. Sinthanayothin, J. F. Boyce, H. L. Cook, and T. H. Williamson, “Automated localisation of the optic disk, fovea, and retinal blood vessels from digital colour fundus images,” Brit. J. Ophthalmol., vol. 83, no. 8,pp. 902-910, 1999.

[12]. R. Chrastek, M. Wolf, K. Donath, H. Niemann, D. Paulus, T. Hothorn,B. Lausen, R. Lammer, C. Y. Mardin, and G. Michelson, “Automated segmentation of the optic nerve head for diagnosis of glaucoma,” Med.Image Anal., vol. 9, no. 1, pp. 297-314, 2005.

[13]. J. Lowell, A. Hunter, D. Steel, A. Basu, R. Ryder, E. Fletcher, and L. Kennedy, “Optic nerve head segmentation,” IEEE Trans. Med. Imag.,vol. 23, no. 2, pp. 256-264, Feb. 2004.

[14]. D. Welfer, J. Scharcanski, C. Kitamura, M. D. Pizzol, L. Ludwig, and D. Marinho, “Segmentation of the optic disk in color eye fundus images using an adaptive morphological approach,” Comput. Biol. Med., vol. 40, no. 1, pp. 124-137, 2010.

[15]. A. Aquino, M. E. Geg úndez-Arias, and D. Marín, “Detecting the optic disk boundary in digital fundus images using morphological, edge detection, and feature extraction techniques,” IEEE Trans. Med. Imag., vol. 29, no. 11, pp. 1860-1869, Nov. 2010.

[16]. V. Kolmogorov and Y. Boykov, “What metrics can be approximated by geo-cuts, or global optimization of length/area and flux,” in *Proc. 10th IEEE Int. Conf. Comput. Vis.*, 2005, vol. 1, pp. 564–571.

[17]. J. V. Soares, J. J. Leandro, R. M. Cesar, H. F. Jelinek, and M. J. Cree,“Retinal vessel segmentation using the 2-D gabor wavelet and supervised classification,” IEEE Trans. Med. Image., vol. 25, no. 9, pp. 1214-1222,Sep. 2006.

[18]. A. Salazar-Gonzalez, Y. Li, and D. Kaba, “Mrf reconstruction of retinal images for the optic disk segmentation,” in *Health Information Science*.New York, NY, USA: Springer-Verlag, 2012, pp. 88–99.

[19]. A. G. S. Gonzalez, “Structure analysis and lesion detection from retinal fundus images,” Ph.D. dissertation, Dept. Comput. Sci., Brunel Univ.West London, U.K., 2011.

[20]. D. Wu, M. Zhang, and J. Liu, “On the adaptive detection of blood vessels in retinal images,” *IEEE Trans. Biomed. Eng.*, vol. 53, no. 2, pp. 341–343, Feb. 2006.

[21]. Zhang, L. Zhang, L. Zhang, and F. Karray, “Retinal vessel extraction by matched filter with first-order derivative of gaussian,” *Comput. Biol.Med.*, vol. 40,no.4,pp.438–445,2010.