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Blood Vessels and Optic Disc Segmentation in Retinal Images Using Normalized Graph Cut Segmentation

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Abstract: The retinal image diagnosis is an important methodology for diabetic retinopathy detection and analysis. Retinal images play a vital role in most of the applications like ocular retinal image operations and human recognition. Also, it is used to detect the diabetes in early stages by evaluating all the retinal blood vessels together. This work introduces a novel algorithm for multi-resolution curvelet transform and normalized graph cut segmentation. It is proposed to detect the blood vessels and optic disc in the retinal images efficiently. The pre-processing stage is performed for image filteration and color contrast enhancement. Then the combined approach for image segmentation and classification are executed using texture, thresholding and morphological operation. This algorithm results in a flexible multi-resolution, local and directional image expansion using contour segments. Finally, Support vector machine(SVM) classifier is employed for the classification task which utilizes feature vectors derived from gray level co-occurrence(GLCM) features.

Key words: Graph cut segmentation · Blood vessel and optical disc segmentation · Curvelet transform

INTRODUCTION

Retinal images are influenced by all the factors that affect the body vasculature in general. The human eye is a unique region of the human body where the vascular condition can be directly observed. In addition to fovea and optic disc, the blood vessels contributes one of the main features of an retinal fundus image and several of its properties are noticeably affected by worldwide major diseases such as diabetes [1], hypertension and arteriosclerosis. Further, certain diseases such as chrorodial neovascularization and retinal artery also make changes in the retinal vasculature. The segmentation of blood vessels in retinal images can be a valuable aid for the detection of diabetic retinopathy and glaucoma diagnosis [2].

An automated segmentation and inspection of retinal blood vessel features as well as the optic disc morphology allows ophthamologist and eye care specialists to perform mass vision screening exams for early detection of retinal disease like diabetic retinopathy and treatment evaluation [3, 4]. This could prevent and reduce vision impairments; age related diseases and many cardiovascular diseases as well as reducing the cost of the screening. Over the past few years, several segmentation techniques have been employed for the segmentation of retinal images under different conditions of illumination, resolution and field of view(FOV) and the overlapping tissue in the retina cause a significant degradation to the performance of automated blood vessel and optic disc segmentations. Thus in our proposed algorithm, efficient segmentation is performed using normalized graph cut segmentation technique [5].

Literature Survey:

- Bhattacharjee R, Chakraborty M, "Exudates, retinal and statistical features detection from diabetic retinopathy and normal fundus images: An automated comparative approach", IEEE transactions on computing and communication systems(NCCCS), 2012.

In this paper, an automated method is designed to extract important features from both normal and diabetic retinopathy (DR) retinal fundus images. The developed method comprises of four basic modules. The preprocessing module performs colour space conversion, Brightness Preserving Dynamic Fuzzy Histogram Equalization (BPDFHE) and De-correlation stretching to

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enhance the contrast of the image based on pixel intensities. In retinal feature extraction module, Optic Disc is segmented by employing logical AND operation of significant bit planes. Retinal vessels are extracted using matched filter response, local entropy thresholding and length filtering techniques. For DR images, exudates are separately extracted using connected components analysis and optic disc elimination. Statistical feature such as exudates area, kurtosis, entropy and Universal Image Quality Index(UIQI) are calculated and tabulated to show distinguishable differences of the features of normal images from that of the DR images. Finally a performance evaluation is carried out in terms of accuracy based on a comparison of exudates area detected by the ground truths and those detected by this automated method.

- Vimala, G.S. Annie Grace, Mohideen, S. Kaja "Automated detection of Optic disc and exudates from retinal images using Clustering algorithm", IEEE International Conference on Intelligent Systems and Control(ISCO), 2013.

Diabetic Retinopathy (DR) is a major cause of blindness. Variation in retinal blood vesselthickness, secretion of Exudates which is a protein leakage in the retina, Hemorrhages are some of the symptoms of Diabetic Retinopathy. It is a kind of disorder which occurs due to high blood sugar level. Since Optic Disc appears as a bright spot in the retinal image, which resembles exudates, it has to be removed from the image. Hence detection of Optic Disc is an essential parameter in retinal analysis. In this paper, an automatic and efficient method ot detect Optic Disc and exudates are proposed. The real time retinal images are obtained from various eye hospitals. The retinal images are pre-processed using the technique of LAB color space image. The preprocessed color retinal images are segmented using Line operator and Fuzzy C Means Clustering technique in order to detect Optic Disc. The outputs are compared and the best methods determined. The exudates are extracted using K-means clustering and finally the classification is done using SVM.

- Barriga, E.S.; Agurto, C.; Echegaray, S.; Pattichis, M.S.; Bauman, W.; Soliz, P. "Localization and Segmentation of Optic Disc in Retinal Images Using Directional Matched Filtering and Level Sets", IEEE transactions on information technology in Biomedicine, Volume: 16, 2012.

The Optic disc (OD) center and margin are typically requisite landmarks in establishing a frame of reference for classifying retinal and optic nerve pathology. Reliable and efficient OD localization and Segmentation are important tasks in automatic eye disease screening. This paper presents a new, fast and fully automatic OD localization and segmentation algorithm developed for retinal disease screening. First, OD location candidates are identified using template matching. The template is designed to adapt to different image resolutions. Then, the vessel characteristics (patterns) on the OD are used to determine OD location. Initialized by the detected OD center and estimated OD radius, a fast, hybrid level-set model, which combines region and local gradient information, is applied to the segmentation of the disk boundary. Morphological filtering is used to remove blood vessels and bright regions other than the OD that affect segmentation in the apillary region. Optimization of the model parameters and their effect on the model performance are considered. The OD location methodology succeeded in 1189 out of 1200 images (99% success). The average mean absolute distance between the segmented boundary and the reference standard is 10% of the estimated OD radius for all image sizes. Its efficiency, robustness and accuracy make the OD localization and segmentation scheme described here in suitable for automatic retinal disease screening in a variety of clinical settings.

Proposed Method: Segmentation of blood vessels in retinal images allows early diagnosis of disease such as diabetic retinopathy. Automating this process provides several benefits including minimizing subjectivity and eliminating a painstaking, tedious task. The low-contrast and narrow blood vessels in retinal images are difficult to be extracted but useful in diagnosis of disease. Motivated by the goals of improving detection of such vessels normalized graph cut method is proposed to segment the blood vessels.

Examination of blood vessels in the eye allows detection of eye diseases such as glaucoma and diabetic retinopathy. Traditionally, the vascular network is mapped by hand in a time-consuming process that requires both training and skill. Automating the process allows consistency and most importantly, frees up the time that a skilled technician or doctor would normally use for manual screening.

While success has been achieved on normal retinal images, on abnormal or diseased images – for which accuracy is more crucial than ever – the algorithms frequently fail. For instance, popular convolution approaches suffer from variable retinal background and low contrast between vessels and surrounding pixels. Thus the proposed method employs various reliable techniques which includes Anisotropic Diffusion Filtering, Image Enhancement using CLAHE Algorithm, curvelet Transform, Normalized Graph cut Segmentation technique and Gray level co-occurrence matrix for achieving higher accuracy and sensitivity.

Contrast Limited Adaptive Histogram Equalization: In contrast limited histogram equalization (CLHE), the histogram is cut at same threshold and then equalization is applied [6].

Contrast limited adaptive histogram equalization (CLAHE) is an adaptive contrast histogram equalization method where the contrast of an image is enhanced by applying CLHE on small data regions called tiles rather than the entire image. The resulting neighboring tiles are then stitched back seamlessly using bilinear interpolation. The contrast in the homogenous region can be limited so that noise application can be avoided [7].

Curvelet Transform: The curvelet transform, a new multiscale transform with the character of anisotropy, was developed from the wavelet transform. It has overcome some inherent limitations of wavelet transform in analyzing signals with dimension higher than 1-D. Curvelet transform yields denoised images with higher PSNR and exhibits better perceptual quality than the ones denoised by wavelet transform [8].

Wavelets generalize the Fourier transform by using a basis that represents both location and spatial frequency. For 2D or 3D signals, directional wavelet transforms go further, by using basis functions that are also localized in orientation. A curvelet transform differs from other directional wavelet transforms [9] in that the degree of localization in orientation varies with scale. In particular, fine-scale basis functions are long ridges; the shape of the basis functions at scale j is 2^ {-j} by 2^ {-j/2} so the fine-scale bases are skinny ridges with a precisely determined orientation.

Curvelets are an appropriate basis for representing images (or other functions) which are smooth apart from singularities along smooth curves, where the curves have bounded curvature, i.e. where objects in the image have a minimum length scale [10]. This property holds for cartoons, geometrical diagrams and text. As one zooms in on such images, the edges they contain appear increasingly straight. Curvelets take advantage of this property, by defining the higher resolution curvelets to be more elongated than the lower resolution curvelets [11]. However, natural images (photographs) do not have this property; they have detail at every scale. Therefore, for natural images, it is preferable to use some sort of directional wavelet transform whose wavelets have the same aspect ratio at every scale.

When the image is of the right type, curvelets provide a representation that is sparser than other wavelet transforms. This can be qualified by considering the best approximation of a geometrical test image that can be represented using only n wavelets and analyzing the approximation error as a function of n. For a fourier transform, the squared error decreases only as O(1/n^{1/2}) [12]. For a wide variety of wavelet transforms, including both directional and non-directional variants, the squared error decreases as O(1/n). The extra assumption underlying the curvelet transform allows it to achieve O({log(n))}^3/{n^2}).

Efficient numerical algorithms exist for computing the curvelet transform of discrete data. The computational cost of a curvelet transform is approximately 10-20 times that of an FFT and has the same dependence of O(n^2log(n)) for an image of size n.

Curvelet Construction: To construct a basic curvelet and provide a tilting of the 2-D frequency space, two main ideas should be followed:

- Consider polar coordinates in frequency domain.
- Construct curvelet elements being locally supported near wedges.

The number of wedges is $N_j = 4\text{-}2^{[j/2]}$ at the scale 2^{-j}, i.e, it doubles in each second circular ring.

Let $\xi(\xi 1, \xi 2)^T$ be the variable in frequency domain and $r{=}\xi 1)^2{+}(\xi 2)^2)^{1/2}$, $\omega{=}\arctan(\xi 1/\xi 2)$ be the polar coordinates in the frequency domain.

To construct a basic curvelet with compact near a "basic wedge", the two windows W and $\tilde{V}_{Nj}$ need to have compact support.

Here, we can simply take W(r) to cover (0, ∞) with dilated curvelets and $\tilde{V}_{Nj}$ such that each circular ring is covered by the translations of $\tilde{V}_{Nj}$.

Then the admissibility yields;

$$\sum_{j=-\infty}^{\infty} | W(2^{-j} r^2 = 1, r \in (0,\infty)$$

Foe tilting a circular ring into N wedges, where N is an arbitrary positive integer, we need a 2π-periodic non negative window $\tilde{V}_N$ with support inside $[\frac{-2\pi}{N}, \frac{2\pi}{N}]$ such that $\sum_{i=0}^{N-1} (\tilde{V}_N)^2 (\omega - \frac{2\pi l}{N})$, for all ω ∈ [0,2π]. $\tilde{V}_N$ can be simply constructed as 2π-periodizations of a scaled window $V(\frac{N\omega}{2\pi})$. Then, it follows that;

$$\sum_{l=0}^{N_j-1} |2^{\frac{3j}{4}} \hat{\phi}_{j,0,0}(r, \omega - \frac{2\pi l}{N_j})|^2 = |W(2^j r|^2 \sum_{l=0}^{N_j-1} \tilde{V}_{N_j}^2 (\omega - \frac{2\pi l}{N}) = |W(2^{-j} r)|^2$$

For a complete covering of the frequency plane including the region around zero, we need to define a low pass element that is supported on the unit circle and where we do not consider any rotation.

$$W_0{}^2(r)^2 := 1 - \sum_{j=0}^{\infty} W(2^{-j} r)^2$$

Principle Component Analysis: Principle component analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. PCA is the simplest of the true eigenvector-based multivariate analyses. Often, its operation can be thought of as revealing the internal structure of the data in a way that explains the variance in the data. PCA is mathematically defined as an orthogonal linear transformation that transforms the data to a new coordinate system such that the greatest variance by some projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate and so on.

Independent Component Analysis: Independent component analysis (ICA) is a computational method for separating a multivariate signal into additive subcomponents. This is done by assuming that the subcomponents are non-Gaussian signals and that they are statistically independent from each other. ICA is a special case of blind source separation. Using ICA mean and illumination of the image is calculated. It also finds the independent components (also called factors, latent variables or sources) by maximizing the statistical independence of the estimated components.

Normalized Graph Cut Segmentation: The gradient of an image measures how it is varying and it offers two bits of information, in which the one is, direction of the gradient implies the direction in which the image is changing most promptly and the other is magnitude of the gradient implies how fast the image is changing. To explain this, assume an image like a terrain, in which at each point we are given a height, rather than intensity. For any point we are given in the terrain, the direction would be the direction uphill. When we take a very small step uphill, the magnitude of the gradient would implies how fast how our height increases. As the gradient has both magnitude and direction, it is easy to encode the information in a vector. The direction of the vector and its length provides the gradient direction and magnitude of the gradient respectively. At every image location, the direction is represented with a different vector, because the gradient may be different at every location.

$$\nabla V = \left(\frac{\partial V}{\partial x}, \frac{\partial V}{\partial y} \right)$$

It begins with the calculation of the gradient at an image location. Then it is shown that the thing which is calculated actually encodes the gradient magnitude and direction. The partial derivative of the image in x direction and y direction is combined to form the gradient vector, which can be given as:

$$\frac{\partial I(x,y)}{\partial x} = \lim_{\Delta x \to 0} \frac{I(x+\Delta x, y) - I(x,y)}{\Delta x}$$

When we take the partial derivatives of I with respect to x we are determining how fast the image intensity changes as x changes. For a continuous function, V (x, y) can be written as:

The maxow/mincut is the problem which occurs between the source and sink nodes in directed graphs can be solved by using the graph-based approach. Hence, a s-t graph is generated to take advantage of this. The pixels in the image is equal to the set of nodes and the every pixel is connected with the neighborhood(d=4.8).

The process of apportioning a directed or undirected graph into disjoint sets is known as normalized graph cut. The concept of optimality of such cutes is usually introduced by associating energy to each cut. Problems occurred in this kind have been well considered within the field of graph theory but can for graphs with more than only a few nodes be extremely difficult. Nevertheless, ever since it became apparent that many low-level vision problems can be posed as finding energy minimizing cuts in graphs these techniques have received a lot of attention in the computer vision community. Graph cut methods have been successfully applied to stereo, image restoration, texture syntheses and image segmentation.

Consider a graph A={X, Y, Z} is given. Here, X represents the graph nodes, Y its edges and Z the affinity matrix, which links a weight to each edge in Y. The division of X into two subdivisions P and Q is done by a cut on a graph such that

$P \cup Q = X$

Min-cut formulation is the most simple and best known graph cut method. It is the cut that divides A into disjoints segments such that the sum of the weights connected with the edges among the different segments is decreased.

Mostly every pixel in the image is noticed as a node in a graph, edges are designed between nodes with weights corresponding to how similar two pixels are assumed some degree of resemblance, as well as the distance among them. A challenge to reduce the number of edges in the graph only pixels within a smaller, prearranged neighborhood X of each other are measured. The sink and the source and the two terminal nodes does not resemble to any pixel in the image. Instead are observed as signifying the object and background. Edges are designed among the sink and source and every further non-terminal nodes, where the equivalent weights are defined using models for the object and background.

This segmentation is done be a partition in such a way that, due to the description of image-pixel similarity, alike pixels that are closer will be in same partition. Moreover, by means of the terminal weights, pixels should be divided in such a way so they end up in the same partition as the terminal node equivalent to the model.

GLCM Features (Gray Level Co-Occurrence Matrix): GLCM which is also known as gray-level spatial dependence matrix, is a arithmetical method. This method considers the three-dimensional relation of pixels. 3-D relation can be defined as the pixel of interest and its immediate right pixels, but the other 3-D relation can also be specified. Every component in the (P, Q) in the subsequent GLCM is the addition of number of times that the pixel with value P arisen in the indicated 3-D relationship to a pixel with value Q in the input image.

Autocorrelation, Contrast, Correlation, Cluster prominence, Cluster shade, Dissimilarity energy, Entropy, Homogeneity, Maximum probability, Sum of squares, Sum average, Sum variance, Sum entropy, Difference variance, Difference entropy, Information measure of correlation, inverse difference normalized. These are the features of GLCM found in our research work.

Rearrange all the features into the matrix and store it as a database. (Few Image training) Rest of the images will be tested.

Support Vector Machine Classification: The use of Support Vector Machine (SVM) is to divide the task, using feature vectors designed from gray level co-occurrence (GLCM) features. The consequences of such a classification are estimated with the use of precision, sensitivity and specificity. The formulation for SVM classification is given as,

SV Classification:

$$\min_{f,\xi i} \| f \| k^2 + C\sum_{i=1}^{l} \xi_I \quad y_i f(x_i) \geq 1 - \xi_i \text{ for all i.}$$

$$\xi_i > 0$$

SVM Classification, Testing Formulation: Variables ξi are called slack variables and they measure the error made at point (x_i, y_i). Training SVM becomes quite challenging when the number of training points is large. A number of methods for fast SVM training and testing have been proposed.

SVM Classifier:

- Training
- Testing

An SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier. Contrast between Trained database and testing input image. The classification of the class is done based on the hidden layer of the SVM classifier. The majority opinion of the features are used for further classification.

Sensitivity: Sensitivity relates to the test's ability to identify a condition correctly. Consider the example of a medical test used to identify a disease. Sensitivity of the test is the proportion of people known to have the disease, who test positive for it.

Mathematically, this can be expressed as:

Sensitivity = $\frac{No.\,oftruepositives}{No.\,oftruepositives + No.\,offalsenegatives}$

Specificity: Specificity relates to the test's ability to exclude a condition correctly. Consider the example of a medical test for diagnosing a disease. Specificity of a test is the proportion of healthy patients known not to have disease, who will test negative for it.

Mathematically, this can also be written as:

$$Specificity = \frac{No.\,oftruenegatives}{No.\,oftruenegatives + No.\,offalsepositives}$$

Accuracy: Accuracy is also defined as a statistical measure of how well a binary classification test correctly identifies or excludes a condition. That is, the accuracy is the proportion of true results (both true positives and true negatives) in the population. To make the context clear by the semantics, it is often referred to as the "Rand Accuracy". It is a parameter of the test.

$$Accuracy = \frac{No.\,oftruepositives + No.\,oftruenagatives}{No.\,oftruepositives + falsepositives + falsenegatives + truenegatives}$$

A test with perfect discrimination (no overlap in the two distributions) has a ROC curve that passes through the upper left corner (100% sensitivity, 100% specificity). Therefore the closer the ROC curve is to the upper left corner, the higher the overall accuracy of the test (Zweig & Campbell, 1993).

Proposed Algorithm: The main aim of the project is to segment the blood vessel and optic disc in fungus retinal images. Segmentation of blood vessels and optic disc in retinal images allow early diagnosis, automating this process provides several benefits including minimizing subjectivity and eliminating a painstaking, tedious task. The results and comparison with alternative methods show that our method achieved exceptional performance in segmenting the blood vessel and optic disk.

STEP 1: The basic step in segmentation in which a retinal image is given as input for processing of the image.

STEP 2: The given input color image is converted into green channel image to identify the blood vessels and optic disc more clearly.

STEP 3: The Curvelet transform is applied for denoising and a suitable threshold value is set to remove noises from the image. Anisotropic diffusion is done in order to reduce image noises without removing significant parts of the image that are important for interpretation.

STEP 4: The image restoration is done to get a clear image which will be helpful for the segmentation process carried out by normalized graph cut method.

STEP 5: PCA is the simplest of the true eigenvector-based multivariate analyses. Often, its operation can be thought of as revealing the internal structure of the data in a way that best explains the variance in the data. Illumination and contract is improved by using PCA method. Mean adjustment is done by using ICA analysis, Independent Component Analysis attempts to decompose a multivariate signal into non-gaussian signals.

Fig. 5 shows the illuminated image using PCA which helps in calculating mean of the image.

STEP 6: The blood vessels are segmented by using normalized graph cut method. A normalized graph cut is the process of partitioning a directed or undirected graph into disjoint sets. The concept of optimality of such cuts is usually introduced by associating energy to each cut.

STEP 7: The optic disc is segmented by using EM algorithm and by morphological process consisting of dilation and erosion.

RESULT

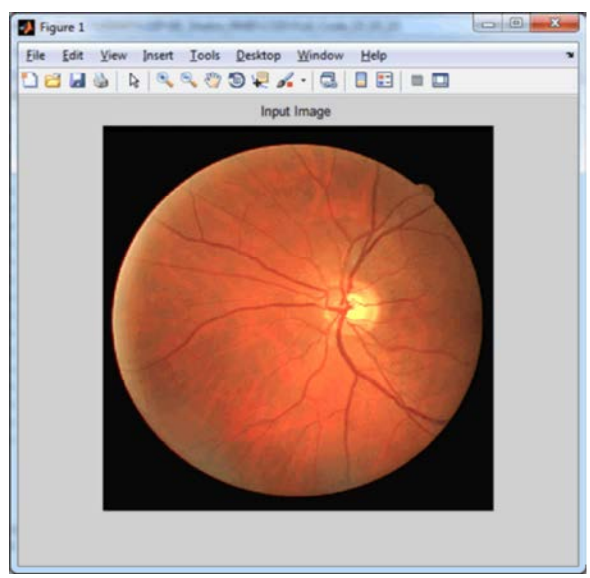

Fig 1: Input Image

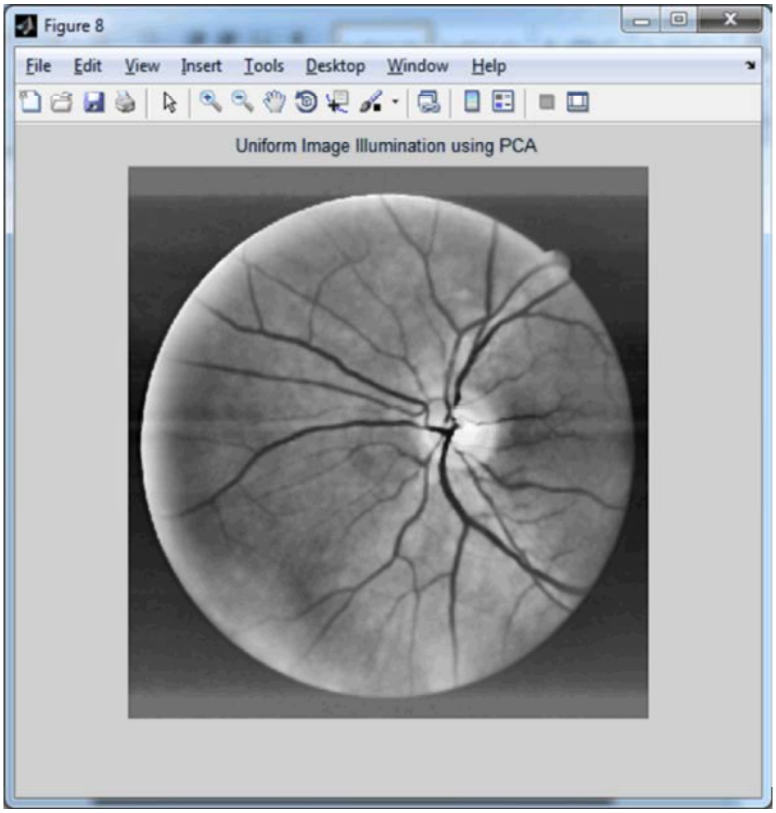

Fig. 4: Uniform Illuminated Image

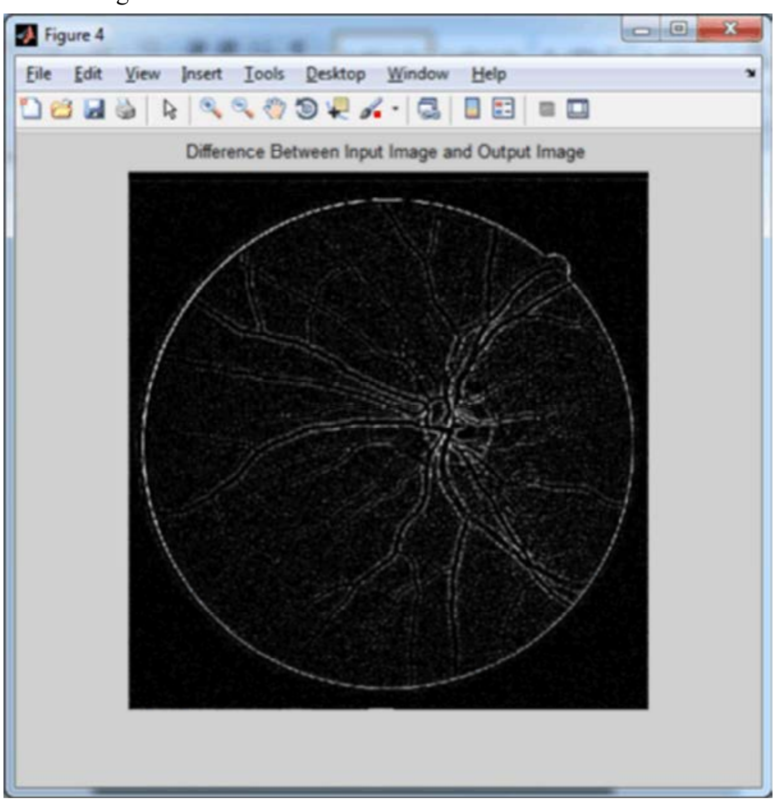

Fig. 5: Difference Between Input And Output Image

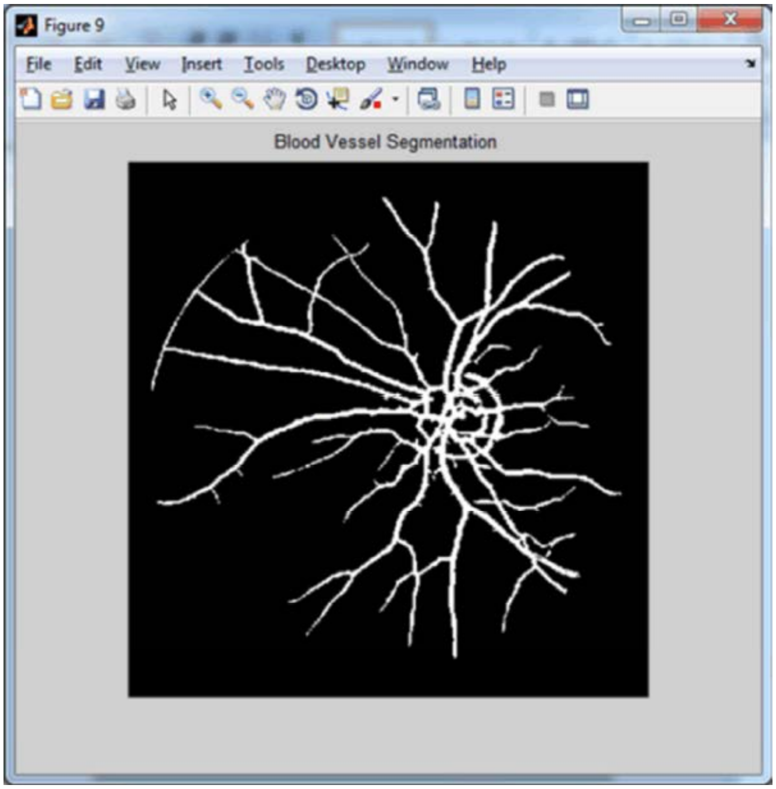

Fig. 6: Blood vessel

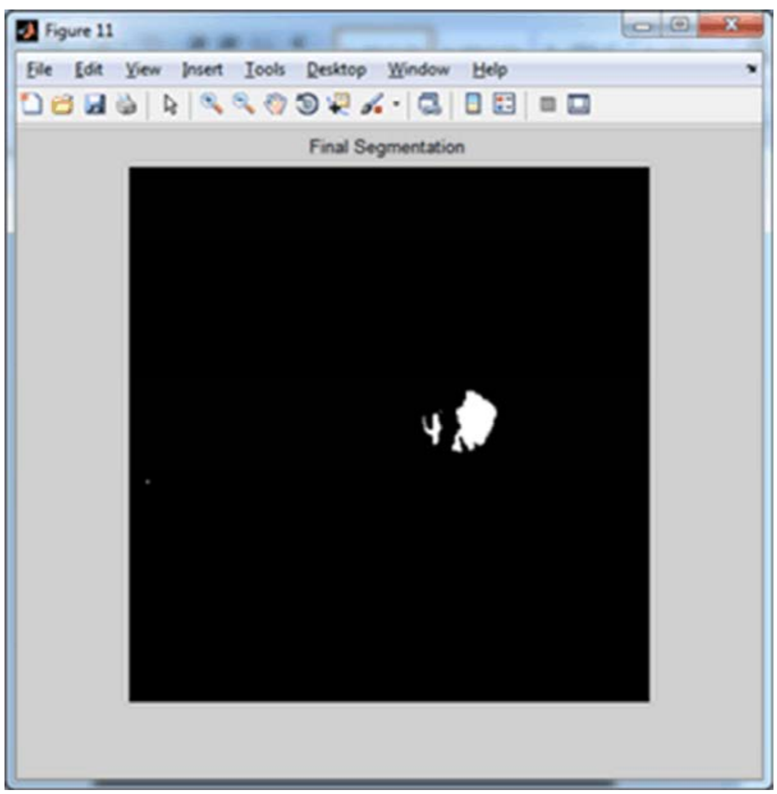

Fig. 7: Optic Disc

Fig. 8: SVM

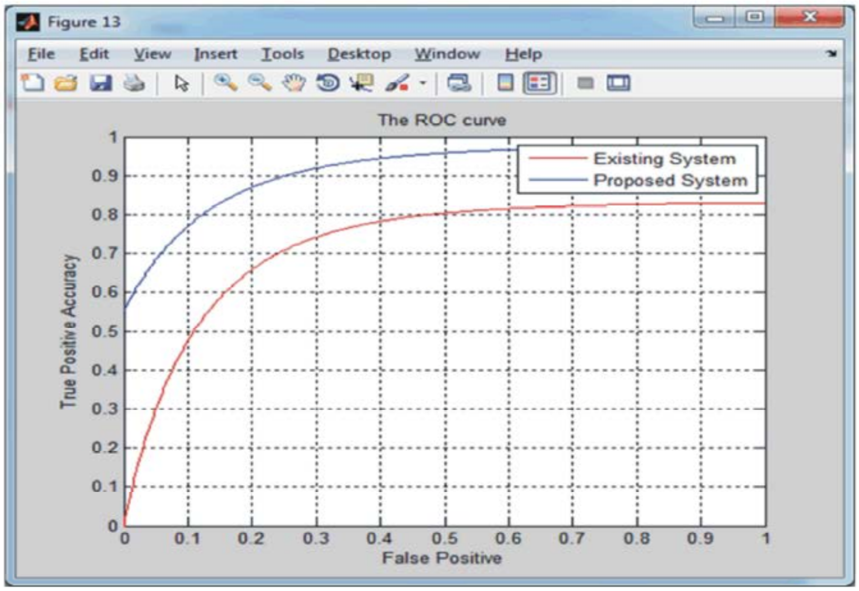

Fig. 9: Graph

CONCLUSION

The paper incorporates prior knowledge of blood vessels to perform the segmentation and it can be applied on retinal images from multiple sources and under different conditions without a need for training. Furthermore, the proposed method addresses one of the main issues in medical image analysis which is the "overlapping tissue segmentation". Since the blood vessels converse into the optic disc area and lead to false identifications of blood vessels, proper segmentation of vessels may not be achieved in the existing method. To achieve good segmentation results, the normalized graph cut technique is performed. It eliminates vessels in the optic disc area without any modification of the image structures before segmenting the optic disc. On the other hand the EM algorithm and morphological process incorporates vessels using local intensity characteristic to perform the optic disc segmentation. Thus this paper can be applied in other medical image analysis applications to overcome the overlapping tissue segmentation.

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