

# **EXACT DETECTION OF OPTIC DISC IN RETINAL IMAGES USING SEGMENTATION BASED ON LEVEL SET METHOD AND MORPHOLOGICAL OPERATIONS**

*A thesis submitted in partial fulfillment of the requirements  
for the award of degree of*

**Masters of Technology  
In  
Computer Science and Applications**

*Submitted by*

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## CERTIFICATE

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This is to certify that my work presented in this thesis entitled “**Exact detection of optic disc in retinal images using segmentation based on level set method and morphological operations**” in partial fulfillment of the requirement for the award of the degree of **Masters of Technology** in Computer Science and Applications submitted in **School of Mathematics and Computer Applications, Thapar University, Patiala**, is an authentic work carried under supervision and guidance of **Dr. Amit Kumar**. The results embodied in this report have not been submitted to any other university or institute for the award of any degree or diploma.


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Prabhjot Kaur Kohli

## ABSTRACT

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The retinal fundus photograph is widely used in the diagnosis and treatment of various eye diseases such as diabetic retinopathy and glaucoma. Medical image analysis and processing has great significance in the field of medicine, especially in non-invasive treatment and clinical study. Normally fundus images are manually graded by specially trained clinicians in a time-consuming and resource-intensive process. A computer-aided fundus image analysis could provide an immediate detection and characterization of retinal features prior to specialist inspection. Segmentation in eye imaging provides an important role for calculating the geometric shape and size of optic disc and anterior segment and abnormal growth of any region in the eye. It automatically and precisely calculates the values of place, position and area of the contour and structural part of the image required by ophthalmologists. But these methods of segmentation suffer from many problems like optimization, initialization and insufficient results in noisy images. Segmentation in medical imaging is the challenging job for the researchers.

In this thesis we tried to localize the most important region of eye – optic disc using an approach based on level set method of segmentation. The optic disc is the region on the retina at which optic nerve axons enter and leave the eye. Changes in optic disc shape and area may indicate disease processes, particularly glaucoma, and accurate identification of the disk boundary may be used to quantify changes. The proposed algorithm consists of two steps – in first step, preprocessing of image is done using morphology operations and in second step, boundary of optic disc is detected using level set method. These pre-processing operations minimize erroneous boundary detection of optic disc due to blood vessels crossing it. Pre-processing techniques based on morphological operations of dilation, erosion and reconstruction are developed. After pre-processing, the optic disk boundary was determined using level set method.

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### 1.1 Overview

The retinal fundus photograph is widely used in the diagnosis and treatment of various eye diseases such as diabetic retinopathy and glaucoma. Medical image analysis and processing has great significance in the field of medicine, especially in non-invasive treatment and clinical study. Normally fundus images are manually graded by specially trained clinicians in a time-consuming and resource-intensive process. A computer-aided fundus image analysis could provide an immediate detection and characterization of retinal features prior to specialist inspection. With the increasing size and number of medical images of eye, the use of computers in facilitating their processing and analysis has become necessary. In particular, computer algorithms for the delineation of anatomical structures and other regions of interest are a key component in assisting and automating specific radiological tasks. These algorithms, called image segmentation algorithms, play a vital role in numerous biomedical imaging applications such as diagnosis, localization of pathology, study of anatomical structure, treatment planning, partial volume correction of functional imaging data, and computer integrated surgery. Image segmentation remains a difficult task, due to both the tremendous variability of object shapes and the variation in image quality. In particular, medical images are often corrupted by noise, which can cause considerable difficulties when applying classical segmentation techniques. As a result, these techniques either fail completely or require some kind of post processing step to remove invalid object boundaries in the segmentation results. And problem is to tune or optimize the segmentation methods by changing its topology.

In first chapter, segmentation and the various methods, its applications are explained. This chapter also encloses the literature survey. The second chapter holds the techniques used applicable to this research work. The third chapter is about the problem statement and chapter fourth holds the modified algorithm of the former. Fifth chapter encloses the results of the program. Last chapter studies the conclusion and future scope.

## 1.2 Segmentation

Segmentation is the process of partitioning an image into semantically interpretable regions. The purpose of segmentation is to decompose the image into parts that are meaningful with respect to a particular application. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. The result of image segmentation is a set of regions that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic.

### 1.2.1 Applications

The recent developments medical image segmentation are changing the entire outlook of medical diagnosis. The major trend is towards better screening, earlier detection of health threats, individualized planning, less invasive therapeutic procedures by adopting the latest image segmentation methods.

Some of the practical applications of medical image segmentation are:

- Locate tumors, optic disc and other pathologies
- Measure tissue volumes
- Computer-guided surgery
- Diagnosis
- Treatment planning
- Study of anatomical structure

Some other applications are:

- Locate objects in satellite images (roads, forests, etc.)
- Face recognition
- Fingerprint recognition
- Automatic traffic controlling systems
- Machine vision

## 1.2.2 Methods

Several general-purpose algorithms and techniques have been developed for image segmentation.

These are listed below:

- Clustering methods
- Compression-based methods
- Histogram-based methods
- Edge detection methods
- Region growing methods
- Split-and-merge methods
- Partial differential equation-based methods
  - ❖ Parametric methods
  - ❖ Level set methods
  - ❖ [Fast Marching methods](#)
- Graph partitioning methods
- Watershed transformation
- Model based segmentation
- Semi-automatic segmentation
- Segmentation Benchmarking
- Neural networks segmentation

## 1.3 Frequently used methods for segmentation

Several different segmentation techniques could be used to come up with similar results. The methods typically vary in speed, accuracy and robustness. In the following section various segmentation methods are studied:

### 1.3.1 Clustering methods

The K-means algorithm is an iterative technique that is used to partition an image into K clusters.

The basic algorithm is:

- (i) Pick K cluster centers, either randomly or based on some heuristic
- (ii) Assign each pixel in the image to the cluster that minimizes the distance between the pixel and the cluster center
- (iii) Re-compute the cluster centers by averaging all of the pixels in the cluster
- (iv) Repeat steps 2 and 3 until convergence is attained (e.g. no pixels change clusters)

In this case, distance is the squared or absolute difference between a pixel and a cluster center. The difference is typically based on pixel color, intensity, texture, and location, or a weighted combination of these factors K can be selected manually, randomly, or by a heuristic.

This algorithm is guaranteed to converge, but it may not return the optimal solution. The quality of the solution depends on the initial set of clusters and the value of K.

In statistics and machine learning, the k-means algorithm is a clustering algorithm to partition n objects into k clusters, where  $k < n$ . It is similar to the expectation-maximization algorithm for mixtures of Gaussians in that they both attempt to find the centers of natural clusters in the data. The model requires that the object attributes correspond to elements of a vector space. The objective it tries to achieve is to minimize total intra-cluster variance, or, the squared error function. The k-means clustering was invented in 1956. The most common form of the algorithm uses an iterative refinement heuristic known as Lloyd's algorithm. Lloyd's algorithm starts by partitioning the input points into k initial sets, either at random or using some heuristic data. It then calculates the mean point, or centroid, of each set. It constructs a new partition by associating each point with the closest centroid. Then the centroids are recalculated for the new clusters, and algorithm repeated by alternate application of these two steps until convergence, which is obtained when the points no longer switch clusters (or alternatively centroids are no longer changed). Lloyd's algorithm and k-means are often used synonymously, but in reality Lloyd's algorithm is a heuristic for solving the k-means problem, as with certain combinations of starting points and centroids, Lloyd's algorithm can in fact converge to the wrong answer. Other variations exist, but Lloyd's algorithm has remained popular, because it converges extremely quickly in practice. In terms of performance the algorithm is not guaranteed to return a global optimum. The quality of the final solution depends largely on the initial set of clusters, and may, in practice, be much poorer than the global optimum. Since the algorithm is extremely fast, a common method is to run the algorithm several times and return the best clustering found. A drawback of the k-means algorithm is that the number of clusters

k is an input parameter. An inappropriate choice of k may yield poor results. The algorithm also assumes that the variance is an appropriate measure of cluster scatter.

### 1.3.2 Compression based methods

Compression based methods postulate that the optimal segmentation is the one that minimizes, over all possible segmentations, the coding length of the data. The connection between these two concepts is that segmentation tries to find patterns in an image and any regularity in the image can be used to compress it. The method describes each segment by its texture and boundary shape. Each of these components is modeled by a probability distribution function and its coding length is computed as follows:

- (i) The boundary encoding leverages the fact that regions in natural images tend to have a smooth contour. This prior is used by huffman coding to encode the difference chain code of the contours in an image. Thus, the smoother a boundary is, the shorter coding length it attains.
- (ii) Texture is encoded by lossy compression in a way similar to minimum description length (MDL) principle, but here the length of the data given the model is approximated by the number of samples times the entropy of the model. The texture in each region is modeled by a multivariate normal distribution whose entropy has closed form expression. An interesting property of this model is that the estimated entropy bounds the true entropy of the data from above. This is because among all distributions with a given mean and covariance, normal distribution has the largest entropy. Thus, the true coding length cannot be more than what the algorithm tries to minimize.

For any given segmentation of an image, this scheme yields the number of bits required to encode that image based on the given segmentation. Thus, among all possible segmentations of an image, the goal is to find the segmentation which produces the shortest coding length. This can be achieved by a simple agglomerative clustering method. The distortion in the lossy compression determines the coarseness of the segmentation and its optimal value may differ for each image. This parameter can be estimated heuristically from the contrast of textures in an image. For example, when the textures in an image are similar, such as in camouflage images, stronger sensitivity and thus lower quantization is required.

### 1.3.3 Histogram-based methods

Histogram-based methods are very efficient when compared to other image segmentation methods because they typically require only one pass through the pixels. In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are used to locate the clusters in the image. Color or intensity can be used as the measure.

A refinement of this technique is to recursively apply the histogram-seeking method to clusters in the image in order to divide them into smaller clusters. This is repeated with smaller and smaller clusters until no more clusters are formed.

One disadvantage of the histogram-seeking method is that it may be difficult to identify significant peaks and valleys in the image. In this technique of image classification distance metric and integrated region matching are familiar.

Histogram-based approaches can also be quickly adapted to occur over multiple frames, while maintaining their single pass efficiency. The histogram can be done in multiple fashions when multiple frames are considered. The same approach that is taken with one frame can be applied to multiple, and after the results are merged, peaks and valleys that were previously difficult to identify are more likely to be distinguishable. The histogram can also be applied on a per pixel basis where the information result is used to determine the most frequent color for the pixel location. This approach is based on active objects and a static environment, resulting in a different type of segmentation useful in video tracking.

### 1.3.4 Edge detection

Edge detection is a well-developed field on its own within image processing. Region boundaries and edges are closely related, since there is often a sharp adjustment in intensity at the region boundaries. Edge detection techniques have therefore been used as the base of another segmentation technique.

The edges identified by edge detection are often disconnected. To segment an object from an image however, one needs closed region boundaries. The desired edges are the boundaries between such objects.

Segmentation methods can also be applied to edges obtained from edge detectors. Lindeberg and Li [23] developed an integrated method that segments edges into straight and curved edge segments for parts-based object recognition, based on a minimum description length (MDL) criterion that was optimized by a split-and-merge-like method with candidate breakpoints obtained from complementary junction cues to obtain more likely points at which to consider partitions into different segments.

### **1.3.5 Partial Differential Equation-based methods**

Using a [partial differential equation](#) (PDE)-based method and solving the PDE equation by a numerical scheme, one can segment the image. Curve propagation is a popular technique in this category, with numerous applications to object extraction, object tracking, stereo reconstruction, etc. The central idea is to evolve an initial curve towards the lowest potential of a cost function, where its definition reflects the task to be addressed. As for most [inverse problems](#), the minimization of the cost functional is non-trivial and imposes certain smoothness constraints on the solution, which in the present case can be expressed as geometrical constraints on the evolving curve.

### **1.3.6 Parametric methods**

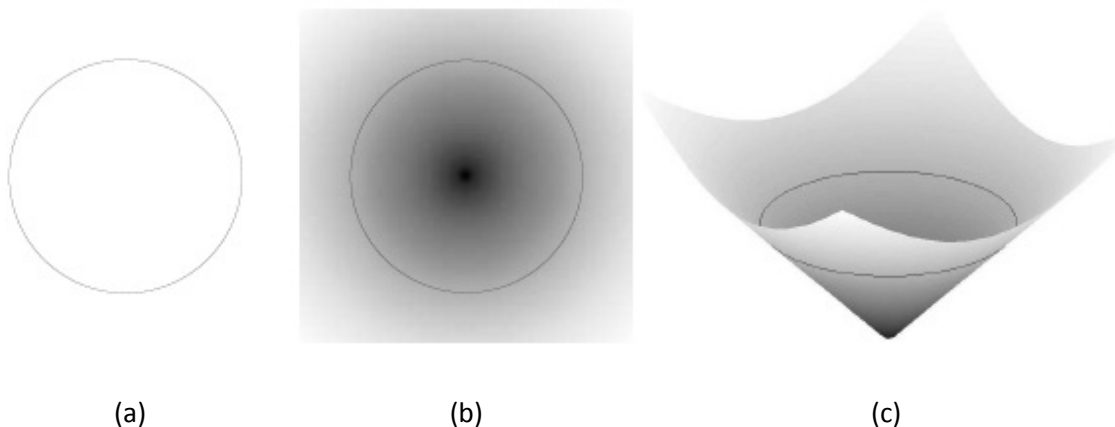
[Lagrangian](#) techniques are based on parameterizing the contour according to some sampling strategy and then evolve each element according to image and internal terms. Such techniques are fast and efficient, however the original "purely parametric" formulation (due to Kass and Terzopoulos in 1987 and known as "[snakes](#)"), is generally criticized for its limitations regarding the choice of sampling strategy, the internal geometric properties of the curve, topology changes (curve splitting and merging), addressing problems in higher dimensions, etc.. Nowadays, efficient "discretized" formulations have been developed to address these limitations while maintaining high efficiency. In both cases, energy minimization is generally conducted using a steepest-gradient descent, whereby derivatives are computed.

### **1.3.7 Level Set segmentation**

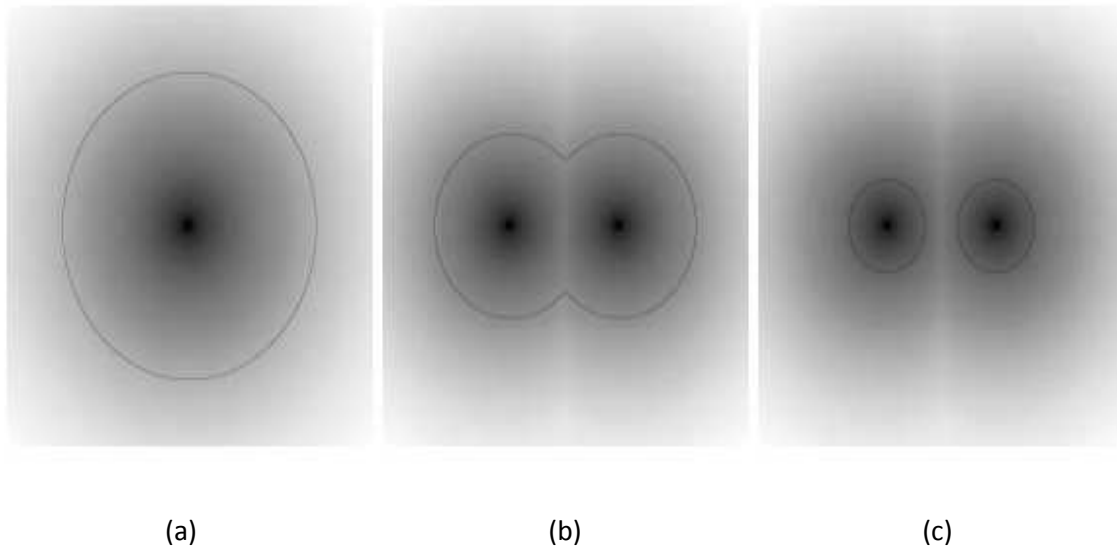
Segmenting images with level set methods was introduced at the end of the 1980's and was based on previous work on moving curvatures. Since then several variants and improvements have come up. Some of the improvements are aimed at speeding up the processing. Other methods have strength related to specific challenges like noise and broken edges.

In the level set method, the curve is represented implicitly as a level set of a 2D scalar function referred to as the level set function which is usually defined on the same domain as the image. The level set is defined as the set of points that have the same function value. Fig1.1 shows an example of embedding a curve as a zero level set. It is worth noting that the level set function is different from the level sets of images, which are sometimes used for image enhancement. The sole purpose of the level set function is to provide an implicit representation of the evolving curve.

Instead of tracking a curve through time, the level set method evolves a curve by updating the level set function at fixed coordinates through time. This perspective is similar to that of an Eulerian formulation of motion as opposed to a Lagrangian formulation, which is analogous to the parametric deformable model. A useful property of this approach is that the level set function remains a valid function while the embedded curve can change its topology. This situation is depicted in Fig 1.1 and 1.2.



**Fig 1.1:** An example of embedding a curve as a level set. ((a) A single curve. (b) The level set function where the curve is embedded as the zero level set (in black). (c) The height map of the level set function with its zero level set depicted in black)



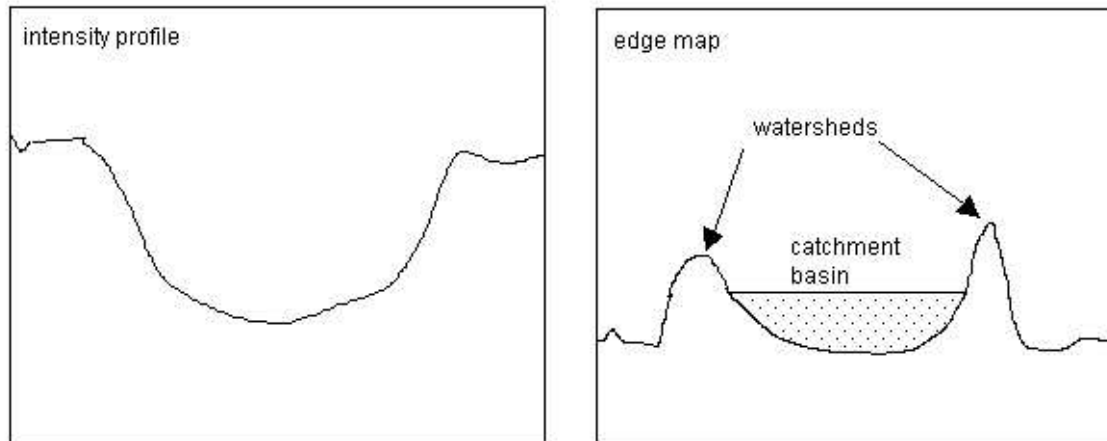
**Fig 1.2:** Zero level set for single and double curves (From Fig. 1.2(a) to Fig. 1.2(c), the zero level set splits into two curves while the level set function still remain a valid function)

### 1.3.8 Fast Marching methods

[Fast marching method](#) has been introduced by James A. Sethian. It has been used in image segmentation in 2006, and this model has been improved (permitting a both positive and negative speed propagation speed) in an approach called Generalized Fast Marching method

### 1.3.9 Watershed segmentation

Watershed segmentation uses the analogy from topography. By interpreting the gradient map of an intensity image as height values we get lines which appear to be ridges. If the contours were a terrain, falling rain would find the way from the dividing lines towards the connected catchments basin. These dividing lines are called watersheds. Figure 1.3 illustrates that steep edges cause high gradients which are watersheds. The edge feature map is not limited to gradient magnitude. Other measures such as texture and intensity can be combined to get the best possible separation of the classes. The homogeneous areas of the image cause low edge feature values and forms the catchments basins. There might be an idea to truncate values below a given threshold to reduce the number of regions detected.



**Fig 1.3** Watershed segmentation simplified to one dimension.

## 1.4 Morphology

Morphology word is derived from the Greek word *morphē*, meaning shape or form. Morphology is a broad set of image processing operations that process images based on shapes. An essential part of the morphological operations is the structuring element used to probe the input image. A structuring element is a matrix consisting of only 0's and 1's that can have any arbitrary shape and size. Morphological operations apply a structuring element to an input image, creating an output image of the same size. Dilation and erosion are basic morphological processing operations. Both dilation and erosion are produced by the interaction of a structuring element with the pixels of interest in the input image.

## 1.5 Related Work

A method for segmentation for retina images using level set and GVF methods was proposed by F. Mendels et al. in 1999. Both the methods detected the boundaries of blood vessels without any distortion. The optic disc is a significant anatomical landmark in the retina. Various ophthalmic pathologies, especially glaucoma, are noticeable by changes in the shape, pallor, or depth of the optic disk region. Accurate identification of the outer boundary of the optic disk may allow ophthalmologists to quantitatively assess changes in the optic disc over time. Initial formulations of active contours suffered from a need for good initialization, and an inability to move into small

concavities. A gradient vector flow (GVF) based snake was introduced to address these limitations. In this formulation, a more general external force was defined which gave a directional field that accounted for boundary proximity, but with a larger range of attraction. This decreased the sensitivity to initial conditions. An alternative approach to boundary detection is offered by level-set theory. In this, a desired propagating boundary is considered as the zero level set of a higher dimensional function [1].

Sinthanayothin et al. in 1999 identified the location of the optic disc using the variance of intensity between the optic disc and adjacent blood vessels. The optic discs were located by identifying the area with the highest variation in intensity of adjacent pixels. Blood vessels were identified by means of a multilayer perceptron neural net, for which the inputs were derived from a principal component analysis (PCA) of the image and edge detection of the first component of PCA [2].

In 2001 T. Walter and J. C. Klein presented algorithms to detect optic disc and vessels in fundus images. In order to detect optic disc, first optic disc was localized and then the contours of the optic disc is detected by applying the classical watershed transformation. The proposed vascular tree detection algorithm consisted of contrast enhancement, application of the morphological top hat transform and then a post-filtering step [3].

Tony F. Chan and Luminita A. Vese 2001 proposed a new method of active contour without edges for detection of an object in an image, based on curve evolution. The method detected objects whose boundaries were not necessarily defined by gradient or with very smooth boundaries, for which the classical active contour models were not applicable. Two approaches were used; Mumford–Shah functional for segmentation and level sets. The proposed method did not require to smoothen the initial image, the locations of boundaries were very well detected and preserved and it was not based on an edge-function to stop the evolving curve on the desired boundary. The model automatically detected interior contours starting with only one initial curve having position of the initial curve anywhere in the image, and it did not necessarily require to surround the objects to be detected [4].

In 2003 Adam Hoover and Michael Goldbaum, proposed a method for optic nerve detection based upon an algorithm called fuzzy convergence. This algorithm identified the optic nerve as the focal point of the blood vessel network. Fuzzy convergence uses the endpoints of the blood vessel segments to help find the solution. The method used the convergence of the blood vessel network

as the primary feature for detection, in conjunction with the brightness of the nerve as a secondary method [5].

Jean-Francois Aujol et al. in 2003 proposed method that used level set formulation for segmentation of textured images. A wavelet packet transform was used to analyze the textures. The level sets evolved according to wavelet coefficients and allowed multiple junctions [6].

Principal component analysis (PCA) has been used by Chutatape and Li in 2004 to differentiate the optic disc from other main features in retinal images. A modified active shape model (ASM) was proposed to detect the optic disk boundary in retinal images. A fundus coordinate system was established to provide a better description of the features in the retinal images [7].

Chunming Li et al. in 2005 proposed a new level set formulation that completely eliminated the need of the re-initialization. The proposed level set method can be easily implemented by using simple finite difference scheme. It was computationally more efficient than the traditional level set methods. The level set function no longer required to be initialized as a signed distance function. The model employed region-based initialization of level set function, which was not only computationally more efficient than computing signed distance function, but also allowed for more flexible applications [8].

Park et al. in 2006 used the repeated thresholding technique to find the brightest particle, then used the roundness of the object to detect optic disk features, finally localized the optic disk by using the Hough transform [9].

Yuping Wang and Chuangyin Dang in 2007 developed an evolutionary algorithm (EA) based on the level-set evolution and Latin square design. Latin squares lead to crossover operator which can generate a set of uniformly scattered offspring around their parents, has the ability to search locally, and can explore the search space. The level set of the objective function was evolved using the crossover operator and mutation operator [10].

Localization of optic disc in colour digital fundus has been presented by S.Sekhar et al. in 2008. This was attained by using morphological operations followed by Hough transform. The morphological processing was done to isolate the brightest area in the image which provided with the circular region of interest i.e. optic disk. The circular Hough transform used on the image gradient then detected the contour of the optic disk corresponding to the optical disk within the circular region of interest [11].

Kaihua Zhang et al. in 2009, proposed region-based active contour model (ACM) for image segmentation which was implemented with a new level set method named Selective Binary and Gaussian Filtering Regularized Level Set (SBGFRLS) method. It first selectively penalized the level set function to be binary, and then used a Gaussian smoothing kernel to regularize it [12].

Cybele Ciofolo et al. in 2009, proposed an automatic method for the segmentation of multiple structures with competitive level sets driven by fuzzy control. Several contours evolved simultaneously toward previously defined anatomical targets. A fuzzy decision system combined the a priori knowledge provided by an anatomical atlas with the intensity distribution of the image and the relative position of the contours. The combination automatically determined the directional term of the evolution equation of each level set. This directed to a local expansion or contraction of the contours, in order to match the boundaries of their respective targets. Each level set evolution was dependent on the intensity distribution of the volume, the distance to other evolving contours, and the distance to a target label registered from an atlas [13].

Xiu-Fen Ye in 2010 proposed two new level set models, two-phase level-set and multiphase level-set models. The texture images extracted by the GMRF model were combined into the proposed level-set models [14].

The study of Mohamed Ben Salah et al. in 2010 investigated level set multiphase image segmentation by kernel mapping and piecewise constant modeling of the image data thereof. A kernel function mapped implicitly the original data into data of a higher dimension which made the piecewise constant model applicable. The method used an active curve objective functional containing an original term which referenced the image data transformed via a kernel function. Functional minimization was carried out by iterations of two consecutive steps: curve evolution and mean shift update of the regions parameters [15].

Hui Gao and Oksam Chae in 2010 proposed active contour tracking algorithms which used single level set method and coupled level set method. The single level set method tracking was used for root segmentation and handled the complex image conditions as well as the root branching problem. The coupled level set method tracking was formulated for crown segmentation which separated the touching teeth and created the virtual common boundaries between them. Furthermore, the variational level set method was improved in several aspects: gradient direction was introduced into the level set framework to prevent catching the surrounding object boundaries; in addition to the shape prior, intensity prior was introduced to provide adaptive shrinking or expanding forces in order to deal with the topological changes [16].

Primary segmentation using the spiral scanning technique was performed by Dirk Smeets et al. in 2010. Also the speed image was obtained by statistical pixel classification algorithm with supervised learning. An initialization for the level set algorithm was obtained using spiral scanning technique and the speed image guides the propagation of the level set [17].

Bo Liu et al. in 2010 projected a method in which the energy function was formulated with level set approach and was based on the difference between the actual and estimated probability densities of the intensities in different regions. The energy function was minimized to complete the segmentation process [18].

In 2010 Anusha Achuthan proposed an approach for region segmentation in CT images which contained regions demonstrating the characteristics of intra- region intensity variations and having high similarity in intensity distributions with the adjacent regions. In the proposed approach wavelet energy was used to represent the region information and was embedded with level set model to formulate the segmentation [19].

In 2011 Bing NanLi proposed a new fuzzy level set algorithm for auto- mated medical image segmentation. The initial level set function was given by fuzzy clustering. The controlling parameters of level set evolution were also estimated by results fuzzy clustering [20].

In 2011 Yunjie Chen et al. proposed a variational level set method, in which bias field estimation was done before quantitative analysis of magnetic resonance (MR) images for images with intensity inhomogeneities. The objective function defined first, clustered image pixel in small region and the cluster centers then estimated the bias within the small region. The objective functions were integrated over the entire domain with local Gaussian distribution of fitting energy and analyzed the data [21].

This chapter discusses the various techniques employed for the purpose of detection of optic disc in retinal imaging, relevant to this thesis. These will be:

- Level Set Method of Segmentation
- Eye Imaging
- Morphology

#### **2.1 Level Set method of segmentation**

In recent time, a considerable amount of work on geometric active contours, i.e., active contours implemented via level set methods, has been proposed to address a wide range of image segmentation problems in image processing and computer vision. Segmenting images with level set methods was introduced at the end of the 1980's by Sethian and Osher [22] in the context of modeling propagating fronts described by a number of physical phenomena and was based on previous work on moving curvatures. Since then several variants and improvements have come up. Some of the improvements are aimed at speeding up the processing. Other methods have strength related to specific challenges like noise and broken edges.

In level set method, the curve is represented implicitly as a level set of a 2D scalar function referred to as the level set function, which is usually defined on the same domain as the image. The level set is defined as the set of points that have the same function value. The advantage of the level set method is that one can perform numerical computations involving curves and surfaces on a fixed Cartesian grid without having to parameterize these objects (this is called the Eulerian approach). Also, the level set method makes it very easy to follow shapes that change topology, for example when a shape splits in two, develops holes, or the reverse of these operations. The existing active contour models can be broadly classified as either parametric active contour models or geometric active contour models according to their representation and implementation. In particular, the

parametric active contours are represented explicitly as parameterized curves in a Lagrangian framework, while the geometric active contours are represented implicitly as level sets of a two-dimensional function that evolves in an Eulerian framework. Geometric active contours models are based on curve evolution theory and level set method. The basic idea is to represent contours as the zero level set of an implicit function defined in a higher dimension, usually referred as the level set function, and to evolve the level set function according to a partial differential equation (PDE). This approach presents several advantages over the traditional parametric active contours.

First, the contours represented by the level set function may break or merge naturally during the evolution, and the topological changes are thus automatically handled. Second, the level set function always remains a function on a fixed grid, which allows efficient numerical schemes. Early geometric active contour models are typically derived using a Lagrangian formulation which uses a certain evolution PDE of a parametrized curve. Compared with pure PDE driven level set methods, the variational level set methods are more convenient. Chan and Vese [4] proposed an active contour model using a variational level set formulation. By incorporating region-based information into their energy functional as an additional constraint, their model has much larger convergence range and flexible initialization. In implementing the traditional level set methods, it is numerically necessary to keep the evolving level set function close to a signed distance function. Re-initialization, a technique for periodically re-initializing the level set function to a signed distance function during the evolution, has been extensively used for maintaining stable curve evolution and ensuring usable results. In this thesis we used level-set without re-initialization proposed by Chunming Li et.al [8].

### 2.1.1 Traditional level set method

In level set formulation of active contours, the active contour is denoted by  $C$ , are represented by the zero level set

$$c(t) = \{(x, y) \mid \phi(t, x, y) = 0\} \quad (2.1)$$

of a level set function  $\phi(t, x, y)$ . The evolution equation of the level set function  $\phi$  can be written in the following form:

$$\frac{\partial \phi}{\partial t} + F|\nabla \phi| = 0 \quad (2.2)$$

which is called level set equation. The function  $F$  is called the speed function. For image segmentation, the function  $F$  depends on the image data and the level set function  $\phi$ . In this method of level set problems are the level set function can develop shocks, very sharp and flat shape during the evolution, To avoid these problems, a common numerical scheme is used that is to initialize the function  $\phi$  as a signed distance function before the evolution, and then reshape the function  $\phi$  to be a signed distance function periodically during the evolution.

The re-initialization method is to solve the following re-initialization Equation

$$\frac{\partial \phi}{\partial t} = \text{sign}(\phi_0)(1 - |\nabla \phi|) \quad (2.3)$$

where  $\phi_0$  is the function to be re-initialized, and  $\text{sign}(\phi)$  is the sign function. But problem is there if  $\phi_0$  is not smooth or  $\phi_0$  is much steeper on one side of the interface than the other, the zero level

set of the resulting function  $\phi$  can be moved incorrectly from that of the original function. For removing this limitation we use new approach of Level Set Evolution without Re-initialization by Chunming Li et.al [8].

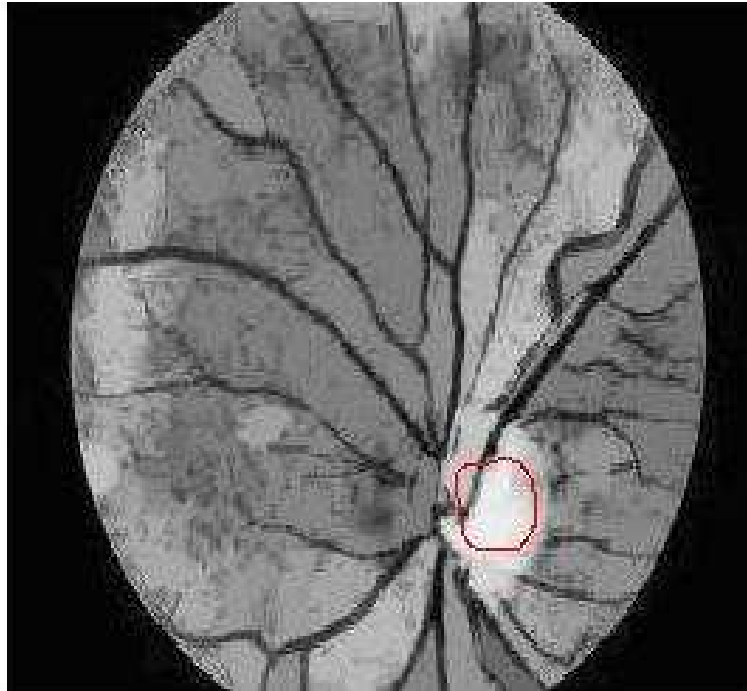


Fig 2.1 Active contour after 80 iterations

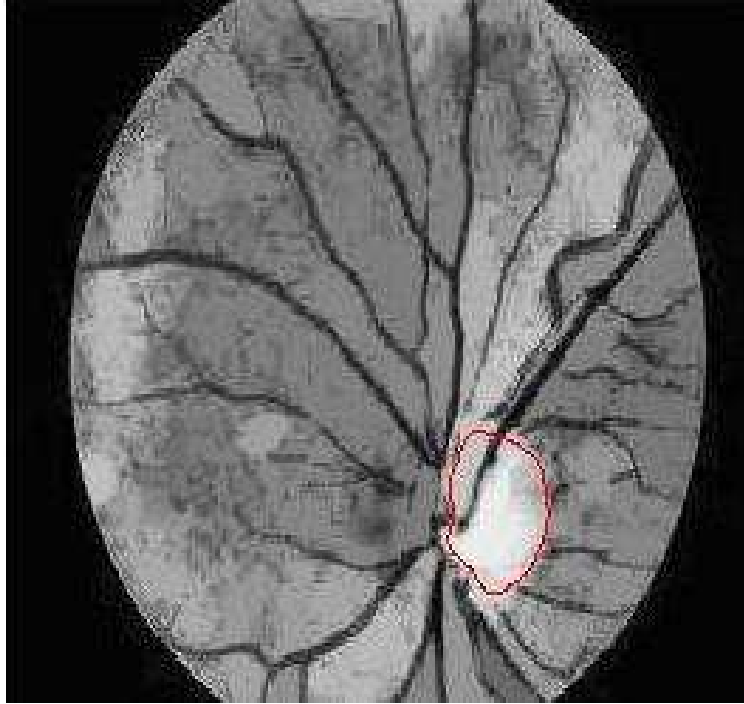


Fig 2.2 Active contour after 300 iterations (Final contour)

### 2.1.2 Level Set evolution without Re-initialization

We know that active contours are dynamic curves that move toward the object boundaries. Therefore we define an external energy that can move towards the edges. If  $I$  be the image, then edge indicator function ( $g$ ) is defined by:

$$g = \frac{1}{1 + |\nabla G_\sigma * I|^2} \quad (2.4)$$

where  $G_\sigma$  is the Gaussian kernel with standard deviation  $\sigma$ . We define an external energy for a function  $\phi(x, y)$  as below:

$$E_g^{\lambda, \nu}(\phi) = \lambda L_g(\phi) + \nu A_g(\phi) \quad (2.5)$$

where  $\lambda > 0$  and  $\nu$  are constants, and the terms  $L_g(\phi)$  and  $A_g(\phi)$  are defined by

$$L_g(\phi) = \int_{\Omega} g\delta(\phi)|\nabla\phi|dxdy \quad (2.6)$$

and,

$$A_g(\phi) = \int gH(-\phi)dxdy \quad (2.7)$$

respectively, where  $\delta$  is the univariate Dirac function, and  $H$  is the Heaviside function.

Now, the following total energy functional

$$E(\phi) = \mu P(\phi) + E_{g, \lambda, \nu}(\phi) \quad (2.8)$$

The external energy  $E_{g, \lambda, \nu}$  drives the zero level set toward the object boundaries, while the internal energy  $\mu P(\phi)$  penalizes the deviation of  $\phi$  from a signed distance function during its evolution. The energy functional  $A_g(\phi)$  introduced to speed up curve evolution. The coefficient  $\nu$  of  $A_g$  can be positive or negative, depending on the relative position of the initial contour to the object of interest. For example, if the initial contours are placed outside the object, the coefficient  $\nu$  in the weighted area term should take positive value, so that the contours can shrink faster. If the initial contours are placed inside the object, the coefficient  $\nu$  should take negative value to speed up the expansion of the contours. By calculus of variations, the Gateaux derivative of the functional  $E$  in can be written as

$$\frac{\partial E}{\partial \phi} = -\mu[\Delta\phi - \text{div}(\frac{\nabla\phi}{|\nabla\phi|})] - \lambda\delta(\phi)\text{div}(g\frac{\nabla\phi}{|\nabla\phi|}) - \nu g\delta(\phi) \quad (2.9)$$

where  $\Delta$  is the Laplacian operator, Therefore, the function  $\phi$  that minimizes this functional satisfies the Euler-Lagrange equation  $\frac{\partial E}{\partial \phi} = 0$ . The gradient flows of the energy function  $\lambda E_g(\phi)$  and  $\nu A_g(\phi)$  are responsible for driving the zero level curve towards the object boundaries.

This new approach of active contours has shown good results on medical images like ultrasound, CT and MRI. In this research work, we have tested this approach on retinal imaging. It does not show good results on eye images. The problem is solved by preprocessing eye images with morphological operations and then using this level set algorithm.

## 2.2 Eye Imaging

Ophthalmologists use ophthalmic (or eye) photography to study the eye and diagnose potential problems with vision. Ophthalmic (or eye) photography is a specialized branch of medical imaging that uses specific imaging equipment to photograph, scan or otherwise image the eye.

### 2.2.1 Uses of Eye Imaging

- (i) **Documentation:** To create a permanent record of ocular conditions that can be referred to over time.
- (ii) **Diagnostics:** To provide diagnostic information that will lead to accurate diagnoses of eye conditions and guide treatment decisions.
- (iii) **Research:** Eye photographs are used extensively in basic scientific research and clinical trials that investigate new treatments for debilitating eye diseases.

### 2.2.2 Conditions Photographed

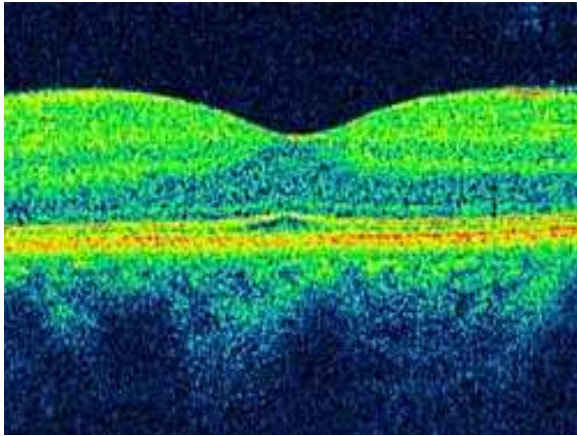
- (i) **Retina:** Age-related macular degeneration (AMD), diabetic retinopathy (DR), glaucoma, vein and artery occlusions, central serous retinopathy (CSR), aftereffects of traumatic injuries, choroidal nevi (freckles) and tumors
- (ii) **Anterior segment:** Aftereffects of traumatic injuries, iris and conjunctival nevi (freckles) and tumors, corneal abnormalities such as deposits, ulcers and injuries

## 2.3 Types of Eye Imaging

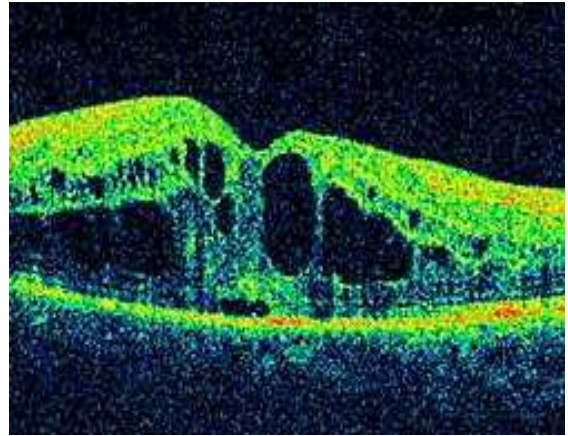
Various types of eye imaging that are used by ophthalmologists for examining different features of eye and analyze problems related to eye are described below.

### 2.3.1 Optical Coherence Tomography (OCT)

Optical coherence tomography (OCT) is an optical signal acquisition and processing method. It captures micrometer-resolution, three-dimensional images from within optical scattering media (e.g., biological tissue). Optical coherence tomography is an interferometric technique, typically employing near-infrared light. The use of relatively long wavelength light allows it to penetrate into the scattering medium. Optical coherence tomography (OCT) systems are employed in diverse applications, notably in ophthalmology where it can be used to obtain detailed images from within the retina.



(a)

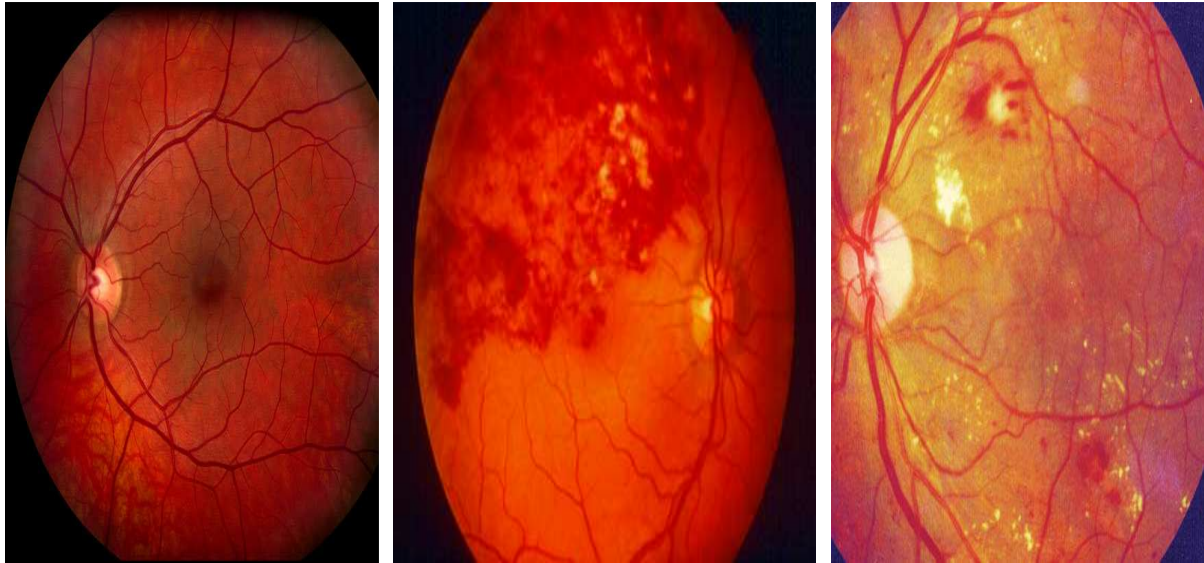


(b)

Fig. 2.3(a) Normal OCT scan showing human retina in cross-section (b) OCT scan showing macular edema (swelling).

### 2.3.2 Color Fundus (Retinal) Photography (CFP)

The Fundus, or inner lining, of the eye is photographed with specially designed cameras through the dilated pupil of the patient. The painless procedure produces a sharp view of the retina, the retinal vasculature, and the optic nerve head (optic disc) from which the retinal vessels enter the eye. Color Fundus Photography is used to record the condition of these structures in order to document the presence of disorders and monitor their change over time.



(a)

(b)

(c)

Fig. 2.4 Color fundus photographs of eye (a)Normal Retina (b)Retinal Vein Occlusion (c)Diabetic Retinopathy in Retina

### 2.3.3 Fluorescein Green Angiography

Angiography is a diagnostic test used by ophthalmologists to photograph structures in the back of the eye and is especially useful in finding damage to the blood vessels, which nourish the retina. There are two types of angiography: fluorescein and indocyanine green (ICG). Fluorescein angiography is used primarily to study blood circulation in and just beneath the surface of the retina. The purpose of either type of angiography is to determine whether there are irregularities in the circulatory system of the retina. Several serious eye disorders, such as diabetic retinopathy, affect retinal circulation and are usually studied with the fluorescein procedure.

### 2.3.4 Indocyanine Green (ICG) Angiography

ICG angiography is better for photographing the deeper choroidal vessels. The problems, such as age-related macular degeneration, are caused by leakage from the deeper choroidal blood vessels. In these cases, the ICG procedure can provide additional information, which may not be available through a fluorescein angiography.

### **2.3.5 Fundus Auto Fluorescence (FAF)**

Fundus Auto fluorescence (FAF) imaging is a diagnostic technique for documenting the presence of fluorophores in the human eye. Fluorophores are chemical structures that possess fluorescent properties when exposed to light of an appropriate wavelength. Fluorescence occurs when these molecules absorb electromagnetic energy, which excites them to a higher energy state and triggers the emission of light at wavelengths longer than the excitation source. FAF is used to record fluorescence that may occur naturally in the eye or accumulate as a byproduct of a disease process. Optic nerve drusen, astrocytic hamartomas, lipofuscin pigments in the retina, and the aging crystalline lens are all believed to exhibit natural fluorescence.

### **2.3.6 Corneal Topography**

Corneal topography, also known as photokeratoscopy or videokeratography, is a non-invasive medical imaging technique for mapping the surface curvature of the cornea, the outer structure of the eye. Since the cornea is normally responsible for some 70% of the eye's refractive power, its topography is of critical importance in determining the quality of vision. The three-dimensional map is therefore a valuable aid to the examining ophthalmologist or optometrist and can assist in the diagnosis and treatment of a number of conditions; in planning refractive surgery such as LASIK and evaluation of its results; or in assessing the fit of contact lenses.

### **2.3.7 Slit-Lamp Photography**

Slit-lamp photography is the photography of the structures of the eye with a specially designed horizontally mounted microscope. The primary illumination for the microscope is produced by a light which can be adjusted from a very broad pattern to a very narrow slit of light. It is from this slit of light that the Slit-lamp derives its name. The slit can be used to isolate structures in the eye. The photograph above illustrates the use of a narrow slit of light to identify the surfaces of the cornea and lens of the eye.

### **2.3.8 External Photography**

External photography is the term used by ophthalmic photographers to describe pictures of the eye made with conventional cameras. The pictures look familiar to a person uninitiated in the more esoteric images made with fundus or slit lamp cameras, even though both of these cameras can also photograph the "external" (rather than internal) eye. External photographs of patient faces are used by general ophthalmologists and ophthalmic-plastic surgeons to document skin types as well as lesions and morphological abnormalities of the skull, eye lids and surrounding areas. Neuro-ophthalmologists use pictures of the head and shoulders, face and eyes to document nerve anomalies.

### **2.3.9 Optic Nerve Head Analysis**

Optic nerve head analysis is used for precise optic nerve head imaging. It is primarily for patients with, or suspected of having, glaucoma.

### **2.3.10 Endothelial Cell-Layer Photography**

Endothelial cell-layer photography is for high-magnification of all corneal layers. Endothelial cell-layer photography enables endothelial cell counts.

## **2.4 Retinal Photography**

Retinal or color fundus photography documents the retina, the neurosensory tissue in our eyes which translates the optical images we see into the electrical impulses that our brain understands. Retinal photography is the creation of a photograph of the interior surface of the eye, including the retina, optic disc, macula, and posterior pole (i.e. the fundus). Ophthalmologists use the retinal photography to follow, diagnose, and treat eye diseases. Retinal photographs are used by optometrists, ophthalmologists, and trained medical professionals for monitoring progression of a disease, diagnosis of a disease (combined with retinal angiography), or in screening programs, where the photos can be analyzed later.

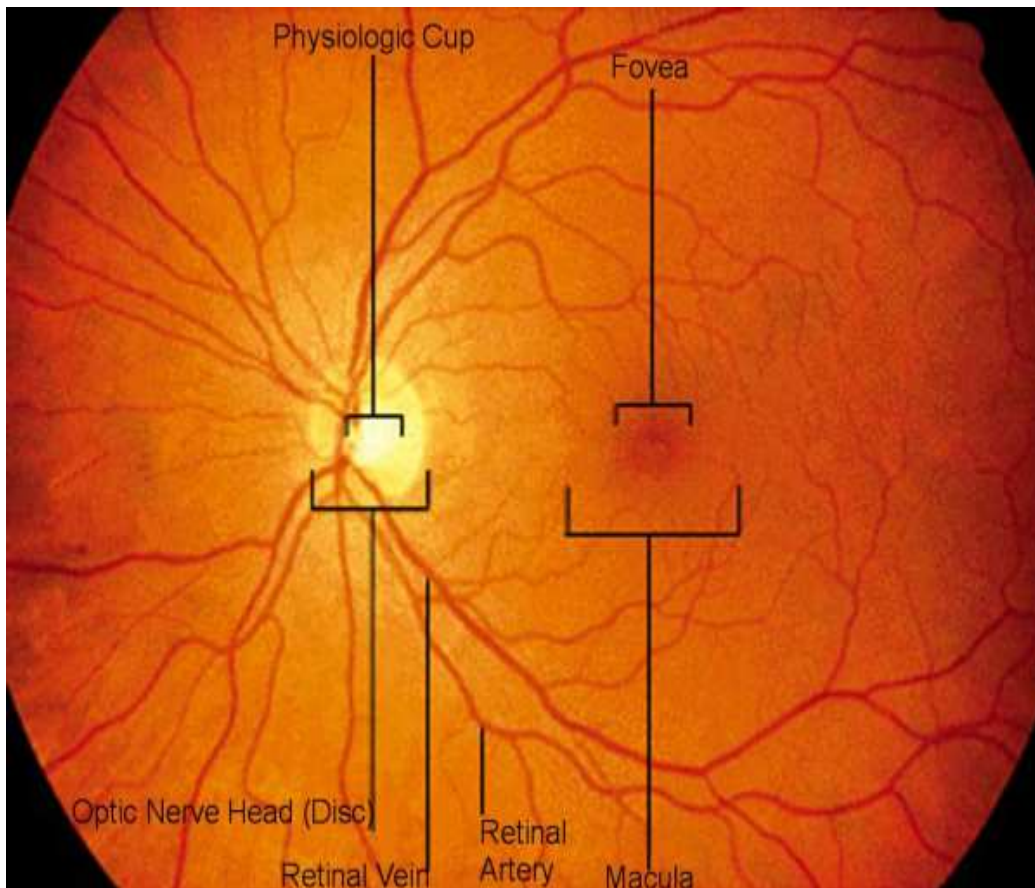


Fig. 2.5 Retinal imaging of eye

Retinal (fundus) photography is performed by a fundus camera, which basically consists of a specialized low power microscope with an attached camera. Its optical design is based on the indirect ophthalmoscope. Fundus cameras are described by the angle of view - the optical angle of acceptance of the lens. An angle of 30°, considered the normal angle of view, creates a film image 2.5 times larger than life. Wide angle fundus cameras capture images between 45° and 140° and provide proportionately less retinal magnification. A narrow angle fundus camera has an angle of view of 20° or less.

#### 2.4.1 Applications

Retinal photographs have following applications:-

- (i) Retinal photograph is used to detect and evaluate symptoms of [retinal detachment](#) or eye diseases such as [glaucoma](#). Cupped optic discs are seen in [glaucoma](#).
- (ii) In patients with [headaches](#), the finding of swollen [optic discs](#), or [papilledema](#), on retinal photography is a key sign, as this indicates raised [intracranial pressure](#) (ICP) which could be due to [hydrocephalus](#), [benign intracranial hypertension](#) (aka pseudotumor cerebri) or [brain tumor](#), amongst other conditions.
- (iii) In patients with [diabetes mellitus](#), regular fundus examinations (once every 6 months to 1 year) are important to screen for [diabetic retinopathy](#) as visual loss due to diabetes can be prevented by retinal laser treatment if retinopathy is spotted early.
- (iv) In [arterial hypertension](#), hypertensive changes of the retina closely mimic those in the brain, and may predict [cerebrovascular accidents](#) (strokes).

## 2.5 Anatomy of eye

The human eye is the organ which gives us the sense of sight. The eye allows us to see and interpret the shapes, colors, and dimensions of objects by processing the light they reflect or emit. The eye is able to detect bright light or dim light, but it cannot sense an object when light is absent. Several structures compose the human eye. Among the most important anatomical components are the following components.

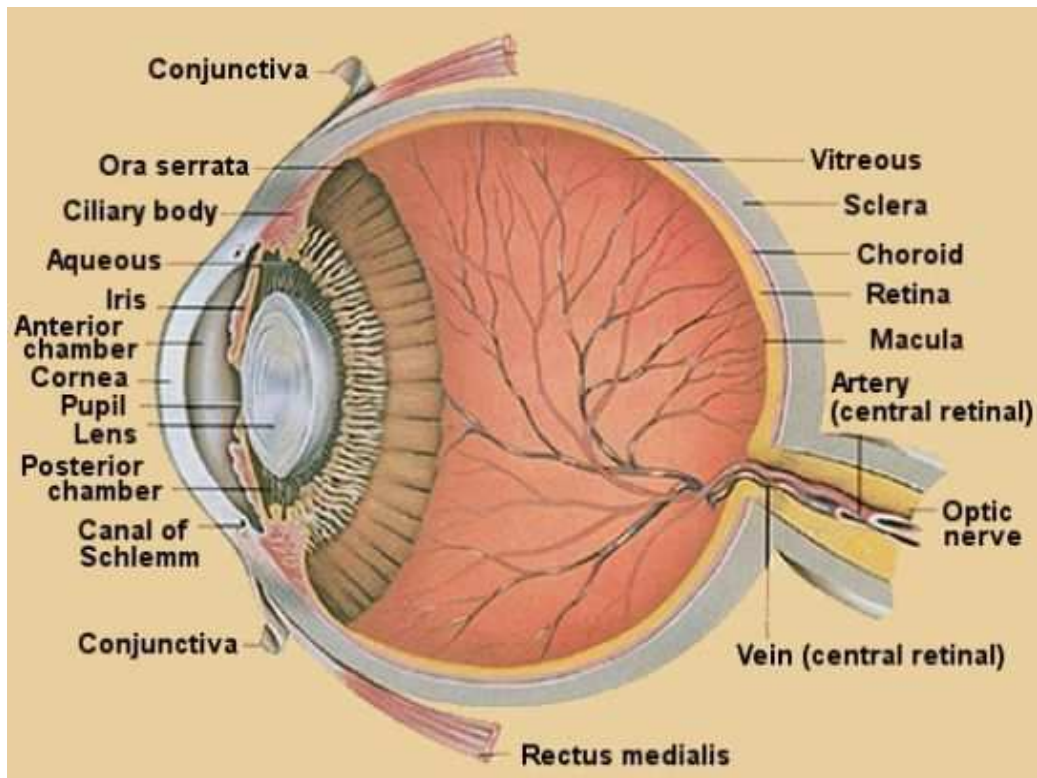


Fig 2.6 Anatomy of eye

**Aqueous Humour:** The aqueous humour is a jelly-like substance located in the anterior chamber of the eye

**Choroid:** The choroid layer is located behind the retina and absorbs unused radiation.

**Ciliary Muscle:** The ciliary muscle is a ring-shaped muscle attached to the iris. It is important because contraction and relaxation of the ciliary muscle controls the shape of the lens.

**Cornea:** The cornea is a strong clear bulge located at the front of the eye (where it replaces the sclera - that forms the outside surface of the rest of the eye). The front surface of the adult cornea has a radius of approximately 8mm. The cornea contributes to the image-forming process by refracting light entering the eye.

**Fovea:** The fovea is a small depression (approx. 1.5 mm in diameter) in the retina. This is the part of the retina in which high-resolution vision of fine detail is possible.

**Hyaloid:** The hyaloid diaphragm divides the aqueous humour from the vitreous humour.

**Iris:** The iris is a diaphragm of variable size whose function is to adjust the size of the pupil to regulate the amount of light admitted into the eye. The iris is the coloured part of the eye (illustrated in blue above but in nature may be any of many shades of blue, green, brown, hazel, or grey).

**Lens:** The lens of the eye is a flexible unit that consists of layers of tissue enclosed in a tough capsule. It is suspended from the ciliary muscles by the zonule fibers.

**Optic Nerve:** The optic nerve is the second cranial nerve and is responsible for vision. Each nerve contains approx. one million fibers transmitting information from the rod and cone cells of the retina.

**Papilla:** The papilla is also known as the "blind spot" and is located at the position from which the optic nerve leaves the retina.

**Pupil:** The pupil is the aperture through which light - and hence the images we "see" and "perceive" - enters the eye. This is formed by the iris. As the size of the iris increases (or decreases) the size of the pupil decreases (or increases) correspondingly.

**Retina:** The retina may be described as the "screen" on which an image is formed by light that has passed into the eye via the cornea, aqueous humour, pupil, lens, then the hyaloid and finally the vitreous humour before reaching the retina. The retina contains photosensitive elements (called rods and cones) that convert the light they detect into nerve impulses that are then sent onto the brain along the optic nerve.

**Sclera:** The sclera is a tough white sheath around the outside of the eye-ball. This is the part of the eye that is referred to by the colloquial terms "white of the eye".

**Visual Axis:** A simple definition of the visual axis is a straight line that passes through both the centre of the pupil and the centre of the fovea. However, there is also a stricter definition (in terms of nodal points) which is important for specialists in optics and related subjects.

**Vitreous Humour:** The vitreous humour (also known as the "vitreous body") is a jelly-like substance.

**Zonules:** The zonules (or "zonule fibers") attach the lens to the ciliary muscles.

## 2.6 Morphology

Morphology is a broad set of image processing operations that process images based on shapes. Morphological operations apply a structuring element to an input image, creating an output image of the same size. In a morphological operation, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors. By choosing the size and shape of the neighborhood, you can construct a morphological operation that is sensitive to specific shapes in the input image. The most basic morphological operations are dilation and erosion. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries. The number of pixels added or removed from the objects in an image depends on the size and shape of the structuring element used to process the image. In the morphological dilation and erosion operations, the state of any given pixel in the output image is determined by

applying a rule to the corresponding pixel and its neighbors in the input image. The rule used to process the pixels defines the operation as dilation or erosion. The various morphological operations are discussed below:

## Dilation

In dilation the value of the output pixel is the maximum value of all the pixels in the input pixel's neighborhood. In a binary image, if any of the pixels is set to the value 1, the output pixel is set to 1.

$$(I \oplus G)(x, y) = \max_{(z_x, z_y) \in G, (x-z_x, y-z_y) \in I} \{I(x-z_x, y-z_y) + \bar{I}(x-z_x, y-z_y) \cdot G(z_x, z_y)\} \quad (2.10)$$

To dilate an image, use the imdilate function. The imdilate function accepts two primary arguments:

- (i) The input image to be processed (grayscale, binary, or packed binary image).
- (ii) A structuring element object, returned by the strel function, or a binary matrix defining the neighborhood of a structuring element.

## Erosion

The value of the output pixel is the minimum value of all the pixels in the input pixel's neighborhood. In a binary image, if any of the pixels is set to 0, the output pixel is set to 0.

$$(I \ominus G)(x, y) = \min_{(z_x, z_y) \in G, (x+z_x, y+z_y) \in I} \{I(x+z_x, y+z_y) + \bar{I}(x+z_x, y+z_y) \cdot G(z_x, z_y)\} \quad (2.11)$$

To erode an image, use the imerode function. The imerode function accepts two primary arguments:

- (i) The input image to be processed (grayscale, binary, or packed binary image).
- (ii) A structuring element object, returned by the strel function, or a binary matrix defining the neighborhood of a structuring element.

## Structuring Element

An essential part of the dilation and erosion operations is the structuring element used to probe the input image. A structuring element is a matrix consisting of only 0's and 1's that can have any arbitrary shape and size. The pixels with values of 1 define the neighborhood. Two-dimensional, or flat, structuring elements are typically much smaller than the image being processed. The center pixel of the structuring element, called the origin, identifies the pixel of interest - the pixel being processed. The pixels in the structuring element containing 1's define the neighborhood of the structuring element. These pixels are also considered in dilation or erosion processing.

## Reconstruction

Morphological reconstruction can be thought of conceptually as repeated dilations of an image, called the marker image, until the contour of the marker image fits under a second image, called the mask image. In morphological reconstruction, the peaks in the marker image spread out or dilate. Morphological reconstruction processes one image, called the marker, based on the characteristics of another image, called the mask. The high points, or peaks, in the marker image specify where processing begins. The processing continues until the image values stop changing.

$$I_{rec} = \max\{I(x, y), ((I \oplus G) \ominus G)\} \quad (2.12)$$

Morphological reconstructions are based on morphological dilation, but note the following unique properties:

- (i) Processing is based on two images, a marker and a mask, rather than one image and a structuring element.
- (ii) Processing is based on the concept of connectivity, rather than a structuring element.
- (iii) Processing repeats until stability; i.e., the image no longer changes.

## **Opening**

The definition of a morphological opening of an image is erosion followed by dilation, using the same structuring element for both operations. Morphological opening is used to remove small objects from an image while preserving the shape and size of larger objects in the image.

## **Closing**

The morphological closing of an image is the reverse: it consists of dilation followed by erosion with the same structuring element.

### PROBLEM STATEMENT

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MATLAB code and algorithm proposed by Li et al [8] for active contour without re-initialization is explained in this chapter.

#### 3.1 Algorithm

The algorithm employed for Level Set evolution without Re-initialization is as follows.

**Step 1:-** Firstly the image was read with help of `imread` command. This command is inbuilt command in matlab processing toolbox. The image to be read should not be of compressed .tiff file format because it is not acceptable in matlab.

**Step 2:-** Now the matrix values are converted into more uniform and simple form so as to make further calculation easy by using following mathematical formula

$$f = I_x.^2 + I_y.^2 \quad (3.1)$$

**Step 3:-** After this image is filtered with the help of Gaussian filter. The Gaussian filter is the basic filter. Generally Gaussian filter is used to remove the noise from the image so as to make the image more sharp and smooth. The Gaussian filter smoothens or blurs an image by performing a convolution operation with a Gaussian filter kernel.

**Step 4:-** Now preprocessed image is further processed and its gradient is calculated. Now this gradient image is used to calculate the edges of the image. For calculation of edges, function defined below is used

$$g = \frac{1}{1+f} \quad (3.2)$$

**Step 5:-** In this step all Parameters are defined which change the topology of the contour. By topology of contour we mean speed, stability etc.

**Epsilon-** The parameter in the definition of smoothed Dirac function refer equation 2.6

**Timestep-** In implementing the proposed level set method, the time step  $\tau$  can be chosen significantly larger than the time step used in the traditional level set methods. Using larger time step can speed up the evolution, but may cause error in the boundary location if the time step is chosen too large. There is a tradeoff between choosing larger time step and accuracy in boundary location. Usually, I use  $\tau \leq 10.0$  for the most images.

**Lambda-** Coefficient of the weighted length term  $L_g(\phi)$  refer equation 2.5, which is responsible for driving the zero level curve towards the object boundaries.

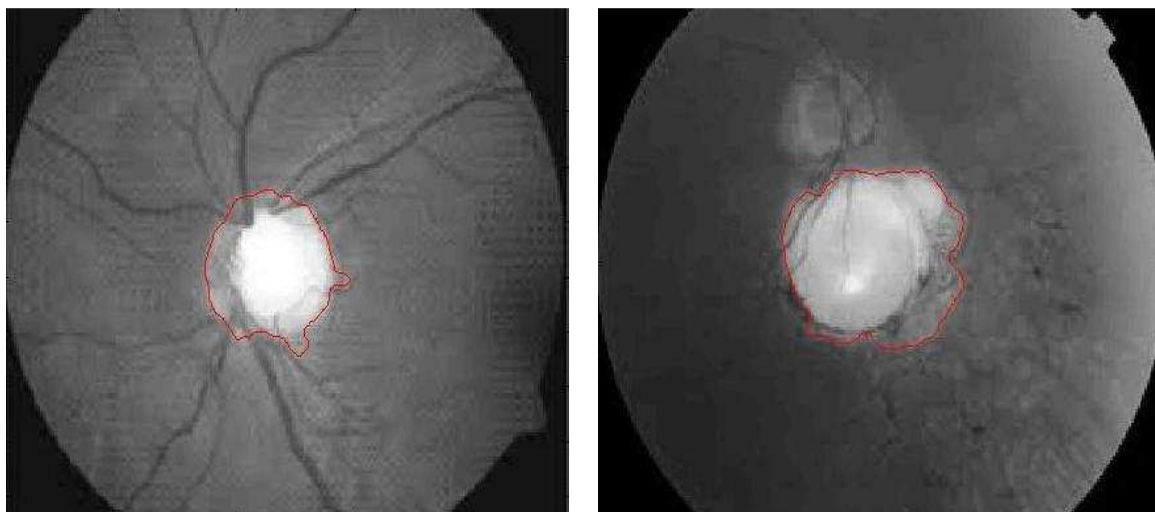
**Alpha-** Coefficient of the weighted area term  $A_g(\phi)$  in equation 2.5 can be positive or negative depending on the relative position of the initial contour to the object of interest. For example, if the initial contours are placed outside the object, the coefficient  $v$  in the weighted area term should take positive value, so that the contours can shrink faster. If the initial contours are placed inside the object, the coefficient  $v$  should take negative value to speed up the expansion of the contours.

**Step 6:-** Initialization of contour, means starting shape of contour which depends upon the region. Mainly we can start it from the centre of optic disc in retinal image because in retinal images nerve of retina make many edges so if we start from outside of optic disc then it might stop on other edges while not on edges of optic disc. So in this we can start from center by making a polygon by mouse click inside the optic disc using this command. It creates a polygon and it is this value that is given to contour function.

**Step 7:-** In this step we give all parameters and the initial contour to the evolution function. This evolution function updates the level set function according to the level set evolution equation given in Equation 2.2. The simple idea of the curve evolution is to reduce the set of vertices of the polygon to a subset of vertices containing important information about the original contour.

**Step 8:-** The step 7 repeats until we do not get final contour. The repetition depends on the number of iterations given.

**Step 9:-** In the last step, final contour will display after all iterations. The updated value from evolution function is given to the function contour and at end of the iterations it gives us final contour.



(a)

(b)

Fig. 3.1 Results with the algorithm stated as problem statement

The above results reveal that the algorithm stated in problem statement has detected inaccurate boundary of optic disc in retinal images. In accordance with the problems aroused in above algorithm the changes are made in the proposed algorithm to detect exact boundary of optic disc useful for ophthalmologists.

## CHAPTER 4

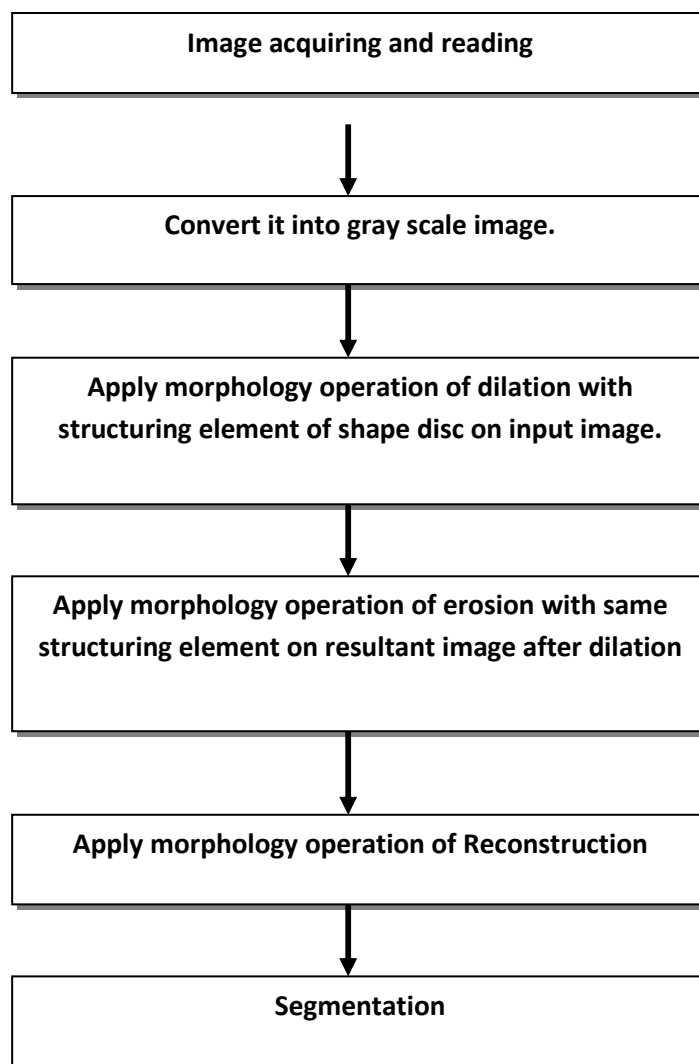
### PROPOSED METHODOLOGY

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Chunming Li's MATLAB code for active contour without re-initialization is used and modified to get better results. The modification that has been done in the algorithm is described in this chapter.

#### 4.1 Block diagram

The proposed algorithm is explained below with the help of block diagram.



**Fig 4.1** Blocks diagram of the proposed algorithm

## **4.2 Changes made in Algorithm**

The following steps explain the modifications made to the Level Set Method for the inclusion of Morphological Operations.

**Step 1:-** The image is acquired and converted to a grayscale equivalent, and dilation operation is performed to increase the luminescence level of regions with sizes equal to that of the structuring element.

**Step 2:-** Erosion operation is performed to reduce the enhanced regions to increase the sharpness of the image by restoring the boundary size of the optic disc.

**Step 3:-** Morphological reconstruction is performed to include the maximum information from the original and the eroded forms.

**Step 4:-** Level set method for segmentation is applied to the image thus generated to obtain the fine boundary of optic disc in the retinal image by final contour.

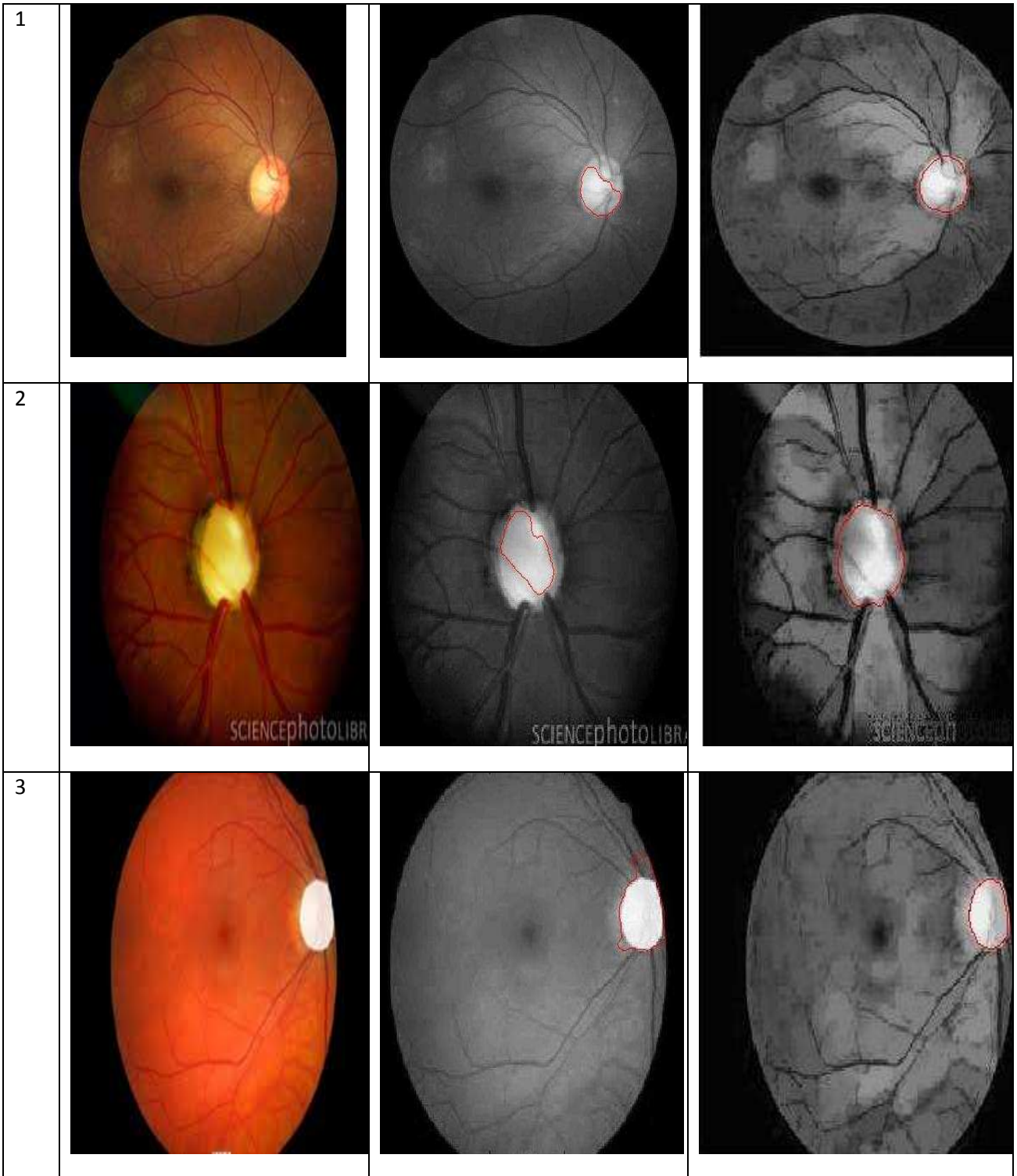
This chapter studies the results produced by the various segmentation techniques, and compares these to understand the quality of the results produced, and the effect parameterization has on these results.

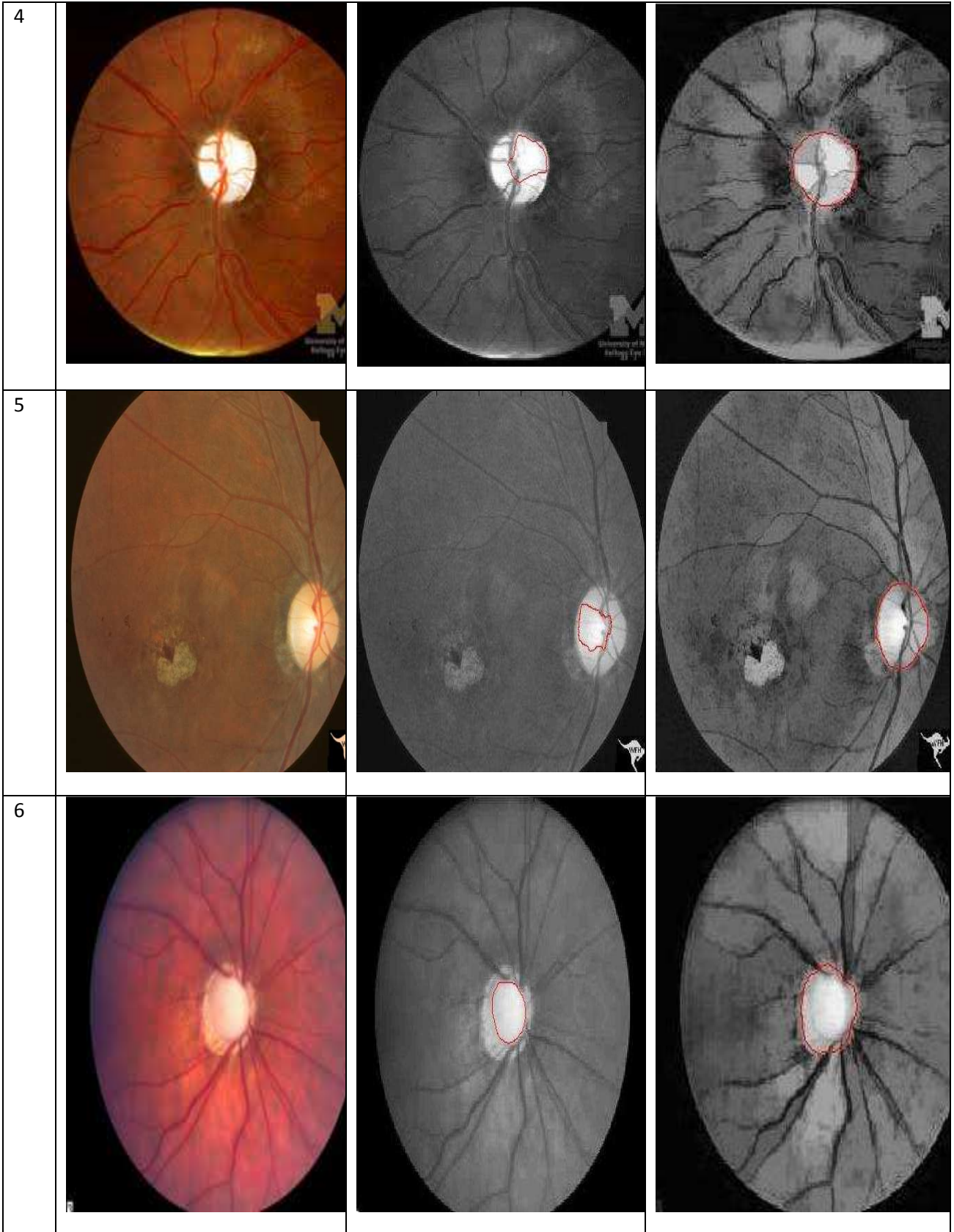
**5.1 Analysis of results using existing Algorithm [8] and proposed Algorithm**

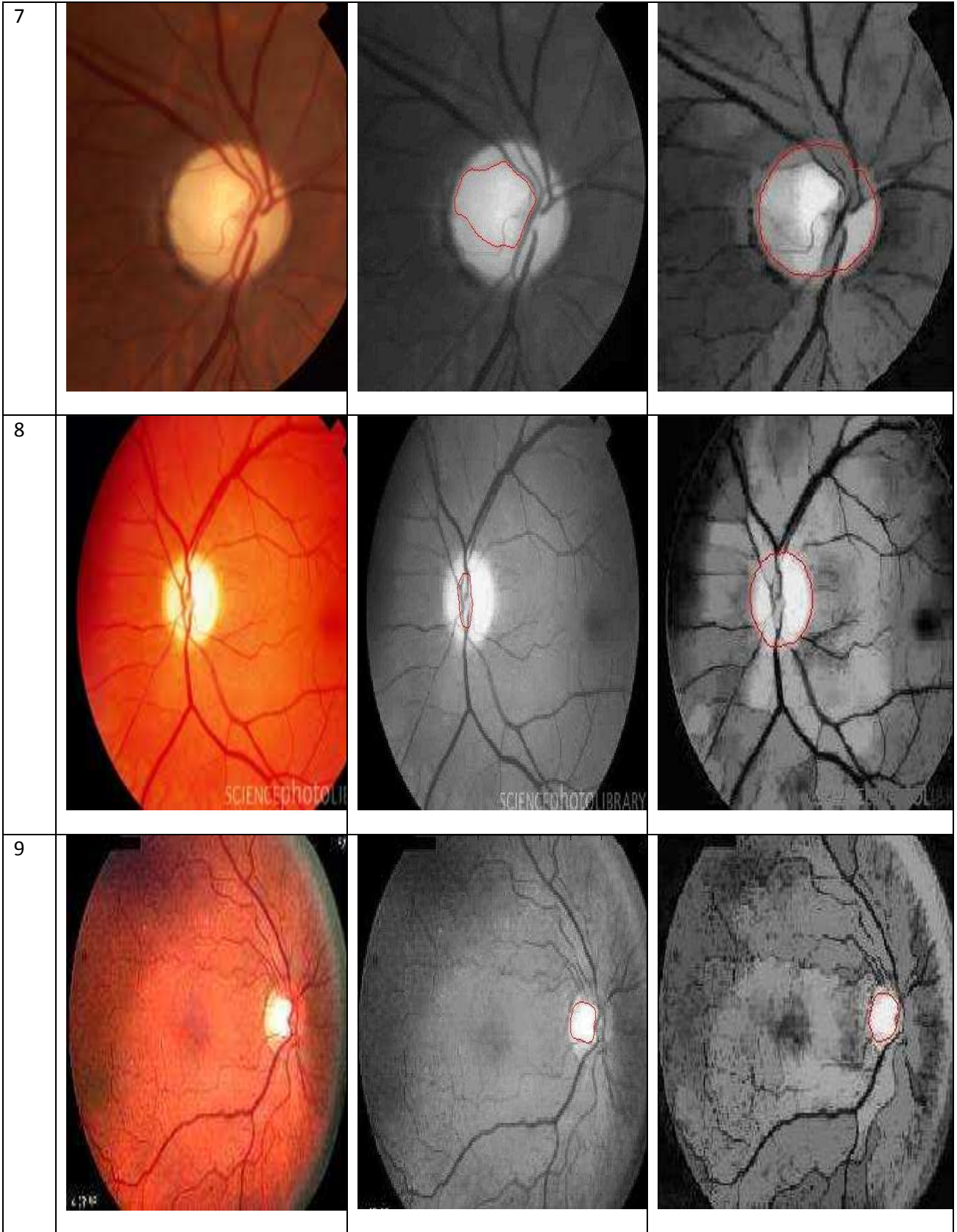
Segmentation generated by the level set method with and without morphological operations is studied with different parameters and compared for the results produced.

**Table 5.1** Comparison of results of two Algorithms

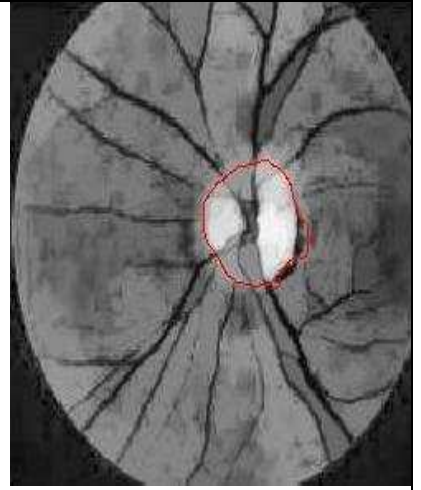
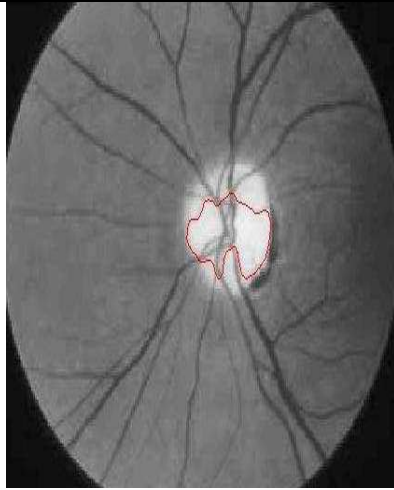
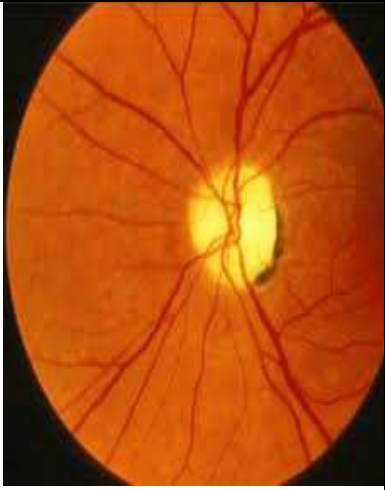
<b>S.N o.</b>	<b>Original Image</b>	<b>Results with Algorithm proposed by Chunming Li et al.[8]</b>	<b>Results with Proposed Algorithm</b>
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## 5.2 Discussion of Results

The results indicate that a level set evolution without re-initialization can be used in conjunction with a pre-processed fundus image to extract an accurate boundary for the optic disk region. Pre-processing is an essential step for accurate convergence, and will be needed for any general problem which requires boundary detection in the presence of small occluding objects.

The proposed algorithm processes images 80% of the time with considerable accuracy, but as detailed in the above diagrams, deficiencies are detected in exceptional cases, which make up only a small proportion of the sample size. As revealed in table 5.1, images from 1-8 show precise results while image 9 and image 10 did not show accurate detection of boundary of optic disc using the proposed algorithm.

### CONCLUSION AND FUTURE SCOPE

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#### 6.1 Conclusion

In this thesis, a computer-assisted retinal image analysis system for the localization of optic disc in color digital fundus images has been presented. This is achieved by means of morphological processing followed by the level set method without re-initialization. The proposed algorithm has segmented the exact boundary of optic disc in retinal images. It segmented the different retinal images without the need of tuning the contour parameters. Overall, morphological pre-processing provided optimized results that were least sensitive to initial conditions and which captured subtle details of the disc boundary. The boundaries of optic disc extracted by this technique can be used by clinical ophthalmologists for clinical use.

#### 6.2 Future Scope

Automated analysis of fundus images requires segmentation of the image into regions such as optic disk, fovea, vessels, and background retina. The technique described here can form part of this segmentation process.

The success of the proposed algorithms can be accredited to the employment of the morphological operations for preprocessing of retinal images. Further pre-processing techniques should be used on the proposed algorithms. Such techniques could contribute to further improvements on the algorithms, resulting in more robust and more precise detection that eventually can be accepted for the clinical purposes.

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