Early Proliferation Stage of Detecting Diabetic Retinopathy Using Bayesian Classifier Based Level Set Segmentation

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ABSTRACT : *This article presents Bayesian Classifier which controls the levels set segmentation and it detect the retinal clots at an early stage from the image captured from fundus camera. The classifier is a probabilistic and used for the control of level set contour propagation for the detection of class clot defined, extracting the retinal vessels even with minute deformation due to the clots. The algorithm is tested in MATLAB on fundus images taken at various stages of progression and results which proves the effectiveness of the proposed method.*

Keywords *-Bayesian Classifier, Blood Clots, Contour Propagation, Diabetic Retina, Level set segmentation*

1. INTRODUCTION

A diabetic retinopathy is the most common diabetic eye disease which leads to the blindness because of the changes in the blood vessels of the retina. In this disease, blood vessels may swell, leak fluid and abnormal new growth on the surface of the retina. The retina is the light-sensitive tissue at the back of the eye. A healthy retina is necessary for good vision. Figure 1 shows the diabetic retina with swollen nerves. This makes the vision impaired and lead to permanent blindness at the end stages.

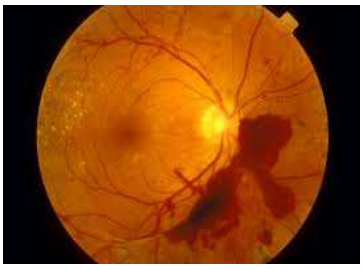

Fig 1: A diabetic retinal image taken from a fundus camera

To detect the diabetic retina at an early stage it is important to adopt an enhanced image processing tool for the detection of even small clots for an early diagnosis. Atul Kumar[2] identified the feature of exudates from the image. On basis of their pixels intensity and frequency it classified into moderate stage of NPDR. Accuracy to the extracting feature is then tested with the perception of the ophthalmologist's. Firstly raw dataset (Fundus Retinal Image) is pre-processed by morphological technique as images are of variant size, colour contrast and resolution. Then adaptive threshold and centroid is calculated by Otsu methodology so the Image boundary is traced. Then optic disk is localised by calculating ROI using Hough Transformation and distant from the image as the intensity of exudate and the optic disk is same in the fundus image. The SVM classifier uses features extracted by combined 2DPCA instead of explicit image features as the input vector Combined 2DPCA is proposed and then for acquiring higher accuracy of classification we can use virtual SVM. N.S.Datta[3] discussed primarily the hardware based issues on early detection of diabetic retinopathy. Software based algorithms for preprocessing, segmentation and classification stages are initially analyzed. Later those techniques were customized and implemented using TMS320C6713 based DSP Kits of Texas instruments with code composer studio for the early detection of diabetic retinopathy through the fundus images of retina. N.Santhi[4] described algorithm to detect the blood vessels effectively by enhancing the retinal image edges using shearlet transform. The directionality feature of the multi structure element makes it an effective tool in edge detection. Morphological operators using multi structure elements are applied to the enhanced image to find the retinal image ridges. By reconstructing the morphological operators, the ridges not belonging to the result unchanged. The remaining ridges belonging to the vessels are determined by using a thresholding method.

Chunming Li[5] proposed a novel region-based method for image Segmentation which is able to deal with intensity inhomogeneities in the segmentation. First, based on the model of images with intensity inhomogeneities, he derived a local intensity clustering property of the image intensities, and define a local clustering criterion function for the image intensities in a neighborhood of each point. This local clustering criterion function is then integrated with respect to the neighborhood center to give a global criterion of image segmentation. In a level set formulation, this criterion defines an energy in terms of the level set functions that represent a partition of the image domain and a bias field that accounts for the intensity inhomogeneity of the image. Therefore, by minimizing this energy, method is able to simultaneously segment the image and estimate the bias field, and the estimated bias field can be used for intensity inhomogeneity correction (or bias correction). The method has been validated on synthetic images and real images of various modalities, with desirable performance in the presence of intensity inhomogeneities. Hafiane,A..Bunyak[6] proposed two forms of deformable models, the parametric form referred as snakes, an explicit parametric representation of the curve is used. This form is compact, robust for image noise and boundary gaps as it constrains the extracted boundaries to be smooth. It restricts the degree of topological adaptability of the model, especially the deformation involves splitting or merging of parts. In contrast the implicit deformable models are designed to handle topological changes naturally. This form is not robust to boundary gaps and suffer from several other deficiencies.

Sau Dan Lee[7] used naives bayes classification of uncertain data with a pdf. The key solution is to extend the class conditional probability estimation in the Bayes model to handle pdf's. Extensive experiments on UCI datasets show that the accuracy of naïve bayes model can be improved by taking into account the uncertainty information. In the proposed method a level set segmentation used for the retinal image segmentation. The problem is normally solved by iterative methods which obtain the current pixel position using the boundary at the previous time step. Therefore, it may be required to specify an initial guess to start the iterative process. A contour is implicitly represented by the zero level kept as initial value and evolved according to a motion equation. To move the contour put on chain rule in order to derivative inside and outside function. Level set evolution is used to deduct for finding the abnormal clots. The Bayesian risk is formed by false positive and false negative fractions in a hypothesis test finally it is s used find the iterative level set function from the derived function. Therefore results show faster convergence and efficiency in detected the minute clots.

2. MATERIAL AND METHODS

Image processing techniques as level set segmentation can be used for the retinal image segmentation due to the fact that the contours area propagation and the speed of propagation both are controllable.

2.1 Methodology

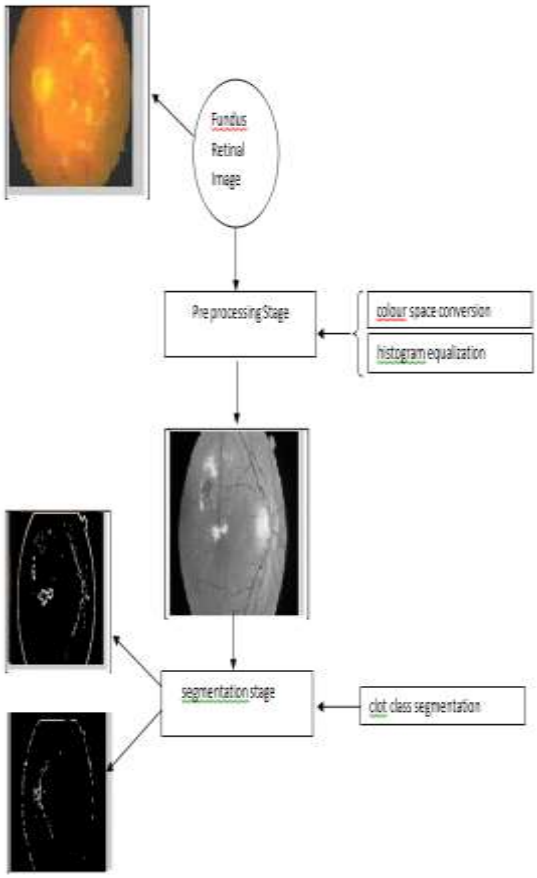

Fig 2 Pre processing and Image Segmentation

2.2 Level set segmentation

In a level set method the level set surface has to be moved. In order to move the velocity field F is defined, shows how contour points move in time. The movement is based on the application specific physics such as the time, position, normal,

curvature and most importantly the image gradient magnitude. The figure3 expresses the method of the level set algorithm. Consider two conical surfaces as shown.

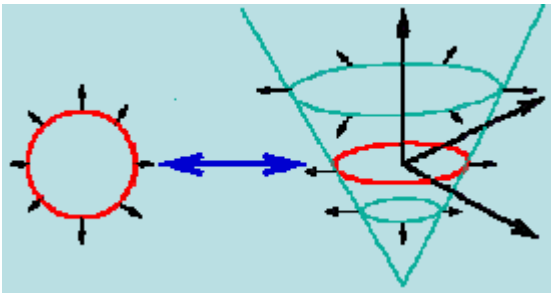

Fig 3. The contour propagation method for the level set segmentation.

In the figure 3 shows the curve is moved up by setting the level set function $\emptyset$ (x,y,t) so that it rises, falls and expands through the blue colour defined constrained space. After declaring the dependent parameters it is important to build an initial value of the level set function

$\emptyset$(x,y,t=0) …(1)

which is based on the initial contour position. The next step is to adjust the $\emptyset$ over time to time, such that the contour at time t is defined as

$\emptyset$(x(t),y(t),t=0 …(2)

Formulation of the level set

During the formulation of the level function the importance is given to the constraints involved in the propagation of the curve. The first constraint is the level set value of a point on the contour with motion x(t) must always be zero.

$\emptyset$(x(t),t=0) …(3)

Upon application of the chain rule.

$\emptyset_t$+delta(x(t),t).x'(t)=0 … (4)

Since the value of F supplies the speed in the outward normal direction

X'(t).n=F, where n=delta($\emptyset$) / | delta($\emptyset$)| …..(5)

Hence the equation for the evolution of the curve is

$\emptyset_t$+ F| delta($\emptyset$)| =0 ….(6)

2.3 Bayesian classifier application to Level set segmentation

A Bayes classifier is a simple probabilistic classifier based on applying Bayes' theorem (from Bayesian statistics) with strong (naive) independence assumptions. A more descriptive term for the underlying probability model would be "independent feature model". In simple terms, a naive Bayes classifier assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature.

A Bayesian classifier model as per the theorem is given as

$$p(C_j|d) = \frac{p(d|C_j)\ p(C_j)}{p(d)} \ldots (7)$$

The classifier could be in simple given as

$$\text{posterior} = \frac{\text{prior} \times \text{likelyhood}}{\text{evidence}} \ldots (8)$$

$p(C_j|d)$is the probability of the instance d being in class Cj.

$p(d|C_j)$is the probability of generating instance d given in class Cj.

$p(C_j)$is the probability of occurrence of class Cj.

p(d) is the probability of instance d occurring.

Assuming that we have two classes C1 and C2 where

C1= normal dimension retinal blood vessels and C2=abnormal dimension retinal blood vessels suspected to be a retinal blood clot. The classifier can be used to propagate the curve in a level set segmentation algorithm to classify the normal retinal blood vessels and abnormal retinal clots at an early stage. The level set function propagation vector can be unified in the form

$\emptyset_s$ = $\emptyset_t$+ F| delta($\emptyset$)|

Here the $\emptyset_s$ is the contour propagator function traversing through the retinal pixel image. The level set function $\emptyset_s$ can be enhanced by forming a likelihood model using a Bayes classifier for contouring the curves around the retinal clots as given in equation below.

Assuming contour $\emptyset_s$ to be travelling in a direction with possible next pixel given by

$$\emptyset_{s1}, \emptyset_{s2}, \dots \emptyset_{sn}$$

The classifier can hence be given as

$$\emptyset_{s1}, \emptyset_{s2}, \dots \emptyset_{sn} = \text{aargmax } p(C1, C2) \prod_{i=1}^{n} p(C1 = \emptyset_s | C2 = \emptyset_s) \dots (9)$$

3. Results and Discussion

The proposed algorithm is implemented in MATLAB and the results are analyzed for cases like end stage proliferation and beginning of the proliferation stage. Figure 4 shows the original input image converted to gray scale image .The application of a Bayesian classifier aided in detection of the blood vessels with a cluster of blood clots. The cots with clustering of 0.15 mm were successfully detected . Some of the clots above the cluster with 0.03 mm dimensions were also detected suggesting the effectiveness of the algorithm for the macular clot detection.

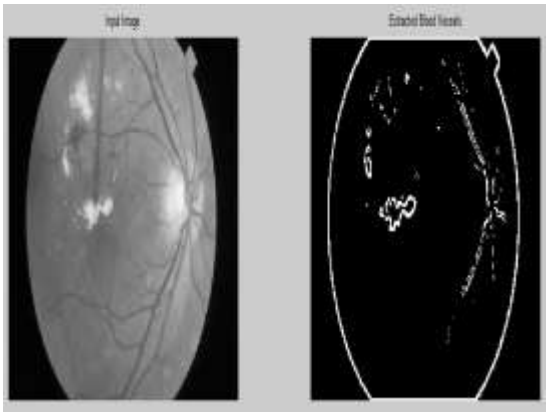

Fig 4: Extracted blood vessels for the end proliferative stage

Figure 5 shows the early stage proliferation of the diabetic retina. The algorithm showed the efficiency in detected the clots of size 0.02mm near the optic disc which was about to proliferate to the next stage. Clots with minute dimensionality at the micro macular vessels were detected at two places.

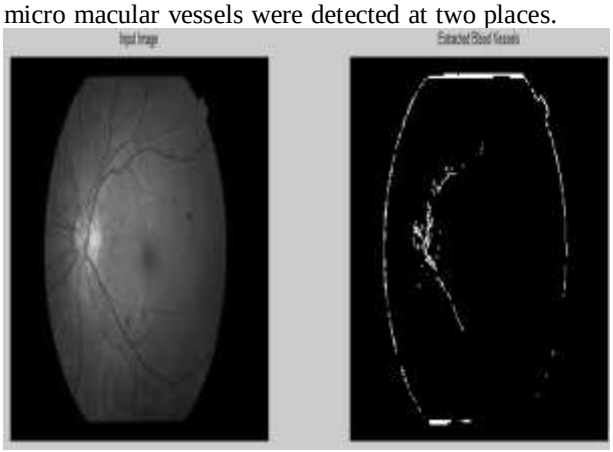

Fig 5: Extracted blood vessels for the start of proliferative stage

4. Conclusion

The accurate extraction of the retinal blood clots can provide much help for diagnosis of diabetic retinopathy diseases. Even though many techniques and algorithms have been developed, there is still room for improvement in finding the minute blood clots in segmentation methodologies. In this paper, we have presented a Bayesian classifier to detection of the blood vessels with a cluster of blood clots. The proposed method has been tested on real retinal image databases and the experimental results have been compared with those of other methods. Since the developed algorithm detected in micro level clots information into account, it can result in very good performance in the detection of early stage of proliferation of the diabetic retinal eye. The result demonstrates that the proposed method outperforms other methods by deducting the minute clots in early proliferation stage.

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