



STRATIFIED SAMPLING VOXEL CLASSIFICATION FOR SEGMENTATION OF OCT IMAGES USING NORMALIZED GRAPH CUT SEGMENTATION WITH MFCM CLUSTERING

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ABSTRACT

One of the ocular disorder is age related macular degradation(AMD) which is a factor caused mainly due to ageing or glaucoma. OCT images provides a non-invasive and contactless method which provides access to monitor the progression of disease. Automated detection is implemented only for accurate segmentation. This paper provides an improvised algorithm for automated detection of retinal detachment thereby enabling easier diagnosis. The main problem with OCT images is that it is corrupted by speckle noise which makes the analyse difficult. In our algorithm, pre-processing use Adaptive median filter for denoising followed by image enhancement. Modified fuzzy-c means clustering (MFMC)graph cut is used for segmentation the abnormalities can be obtained from the datasets enabling automated evaluation. Classification is executed using texture, thresholding, and morphological operation. This approach reduces the false positives and increases the accuracy.

Keywords: Age related macular degradation, Modified fuzzy C-means clustering, Optical coherence tomography, retinal detachment.

I. INTRODUCTION

Around the world about 3 million people are affected by ocular disease. One of such disease is age related macular degradation(AMD). This may be mainly due to glaucoma or aging which can lead to blindness of the victim. AMD results in retinal detachment or swollen retinal layer. In such case, the retinal fluids enter beneath the affected area resulting is poor eyesight. The affected area is diagnosed by surgery or laser treatment. In laser treatment, the detached layers are subjected to head and a bond made between the layers recovering the original position. OCT image provides a non-invasive imaging technique with microscopic resolution. The main problem in OCT is that it is affected by speckle noise which degrades the image contrast with grainy and low intensity features [1] and [6]. In order to remove speckle noise several filters such as median filter [2] and [3], anisotropic diffusion filter [4], bilateral filter [5] have been used. Pre-processing involves denoising and image enhancement. Most of the algorithm use filter window which suppresses the speckle noise level in homogeneous areas but smoothens the image in nonhomogeneous areas like edges and boundaries. The main aim of noise

reduction is to remove the noise without losing much detail contained in an image. However, due to the presence of the speckle noise, imaging contrast is reduced making the boundaries between highly scattering structures in tissue difficult to differentiate. As a result, this inevitably affects human interpretation of the images as well as the future development of computer assisted OCT techniques for accurate quantification.

II. METHODOLOGY

2.1 Pre-Processing

The Pre-Processing stage equalizes the uneven illumination associated with OCT images and also removes noise present in the image. Segmentation stage clusters the image into two distinct classes (blood vessel) while the Disease Classifier stage was used to distinguish between candidate blood vessel and other information. In this paper, adaptive median filter is used for denoising of the image. The simplest and best investigated diffusion method for smoothing images is to apply a linear diffusion process. We shall focus on the relation between linear diffusion filtering and the convolution with a Gaussian and analyse its smoothing properties for the image as well as its derivatives and look over the fundamental properties of the Gaussian scale-space which is induced by linear diffusion filtering. The OCT input is shown in Fig 1.1.

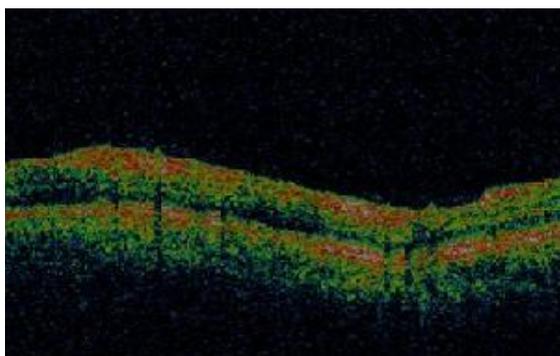


Fig 1.1. Input Image

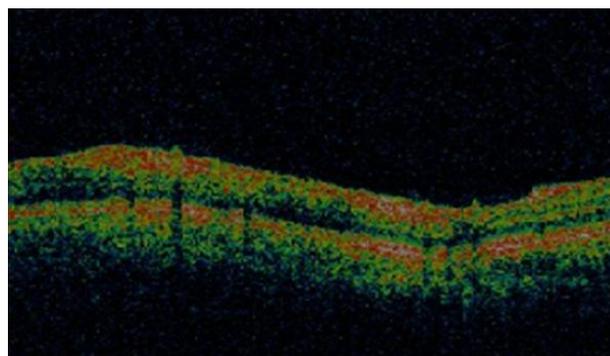


Fig 1.2 Adaptive Median Filter Output

The image is denoised by means of adaptive bilateral filter as shown in Fig 1.2

III. IMAGE ENHANCEMENT

In general, to improve the contrast of the image adaptive histogram equalization(AHE) is used. It is a computerized technique. In this technique, several histograms are computed which are different sections of the image. These images are used to redistribute the enhanced pixel values of the image. Hence, the local contrast of the image is increased along with improvised property detail of the image. The main problem with AHE is that it overamplifies the homogeneous regions of the image. To overcome this problem contrast limited adaptive histogram equalization(CLACHE) technique is used which prevents overamplification. It is important to preserve the boundary properties of the image since the region of interest should be highlighted and it is used to find the difference between the normal and abnormal retinal layers. For inner and outer boundary detection methods such as active counters were used [8] which required more processing time. In this paper, intensity

thresholding based enhancement is used. This focuses mainly on every pixel which holds the information which is obtained from the filtered output.

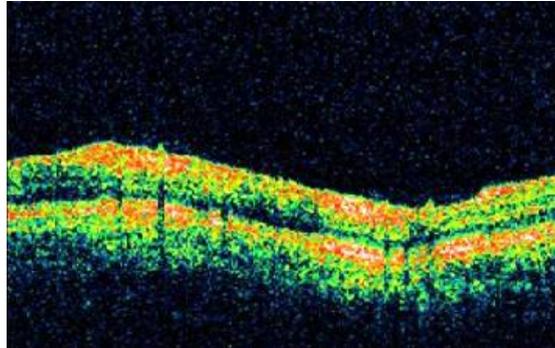


Fig 2.1 Enhanced Image

IV. SEGMENTATION

Eyes with abnormalities have changes in the structure of blood vessel. Segmentation of blood vessels in OCT image[10] enables diagnosis at early stage. by automating this process the subjectivity can be minimised. This also avoids the painstaking procedure converts the tedious task into a simpler one. Previous approaches provides better result hence, improvising the techniques to be a quicker and easier is the main goal of image processing. Abnormalities in blood vessels cause discontinuities in boundaries of the retinal layers. The robustness of the algorithms in the presence of blood vessel artifacts[11],[12],[13] can decrease the quality of the image. The gradient of an image measures how it is changing. It provides the magnitude and direction of the image. The magnitude of the gradient shows how fast the image is changing, while the direction of the gradient shows the direction in which the image is changing most rapidly. To illustrate this, assume the image as like a terrain, in which at each point we are given a height instead of intensity. Any point in the terrain is the direction of the gradient that would be the direction uphill. For a small step, uphill, the magnitude of the gradient would tell us how rapidly our height increases. Since the gradient has a direction and a magnitude, the information can be encoded in a vector. The length of this vector provides the magnitude of the gradient, while its direction gives the gradient direction. The gradient may be different at different location so, we represent it with a different vector at every image location. Initially the computation of the gradient at an image location is shown. Then the computation which actually encodes the gradient direction and magnitude is shown. The gradient vector can be formed by combining the partial derivatives of the image along the x and y direction. We can represent this as:

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

To have a clear idea, we review the partial derivatives. When we consider the partial derivative of I with respect to x , then the rapid change of image intensity with respect to changes in x can be determined. The direction of the gradient can be found by the following formula:

$$\theta = \tan^{-1} \left[\frac{g_y}{g_x} \right]$$

Image gradients are commonly used for edge detection. After the computation of gradient image, the pixel with large gradient value is assigned to be the edge pixel. The direction of the edges is perpendicular to that of the gradient and hence can be traced. In this paper, we use canny edge detector for edge detection. A graph-based approach makes use of efficient solutions of the maxow/mincut problem between source and sink nodes in directed graphs. The set of nodes is equal to the set of pixels in the image. Every pixel is connected with its neighbourhood pixel. A directed or undirected graph is partitioned to disjoint sets which is known as normalised graph cut segmentation. By associating energy to each cut the concept of optimality of the cuts is introduced. Based on the degree of variability of neighbouring group of pixels in the image, the segmentation criterion can be adjusted. Hence it is an adaptive technique but cannot be used for small contours efficiently. 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. Image restoration, texture synthesis and image segmentation are some of the areas where graph cut method has been successfully implemented. We can segment the retinal layers of the OCT image as shown in fig 3.1

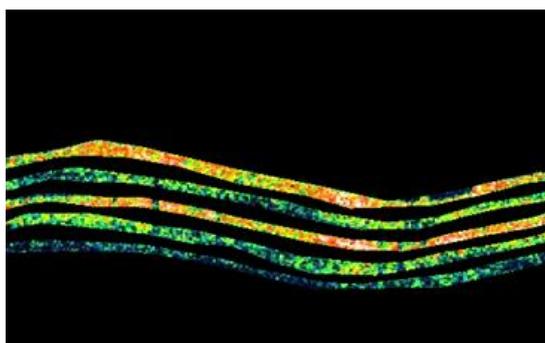


Fig 3.1 Normalised Graph Cut Segmentation

Its simplicity and speed enables it to run on large datasets. Pixels are represented as nodes in graph and edges are formed between the nodes with weights corresponding to two similar pixels. The pixels within a smaller and pre-determined neighbourhood N are considered for reducing the number of edges in the graph. The two terminal nodes are represented as object and background where the source the sink are not related to any pixel in the image. Object and background models are used to determine the corresponding weights. Edges are formed between the source and sink and all other non-terminal nodes. This segmentation should have a partition such that the similar pixels are which are close to each other belong to the same partition depicting the image pixel resemblance.

4.1. CLUSTERING

A clustering method such as k-means clustering is used to form clusters as shown in the fig 4.1. The distances are calculated using Mahalanobis and Euclidean distance. K means algorithm is an iterative technique which is used to segment the image into k clusters. By using the grayscale intensity of each pixel, the K-Means implementation can be made to partition the image. 0 to 255 equally spaced values were chosen for the starting

partitions. In order to increase the number of results available and to study the effects due to variation of the parameter the number of partitions used are varied as that of in colour image segmenting setup.

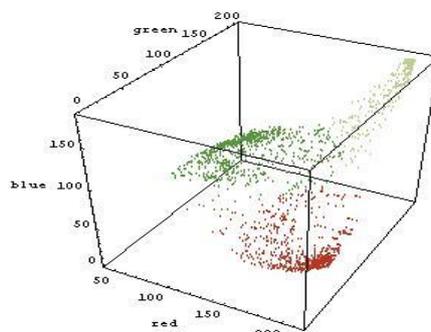


Fig 3.2 Colour Based Clustering

For this case, the same initial partitions as used in the colour segmentation along with K-Means were used in order to make the comparison of results more meaningful. The initial random assignment is an important factor since the resulting cluster depends on it and so the result is not the same for each run which is a drawback. It minimizes the intra-cluster variance but does not ensure that the result has a global minimum of variance. The k-means clustering algorithm is commonly used in computer vision as a form of image segmentation. The results of the segmentation are used to aid border detection and object recognition. In this context, the standard Euclidean distance is usually insufficient in forming the clusters. Instead, a weighted distance measure utilizing pixel coordinates, RGB pixel color and/or intensity, and image texture is commonly used. To access the diameter and tortuosity of blood vessels manual planimetry methods were used. To segment blood vessels and optic disc curvelet transforms, contourlet transforms, watershed segmentation, were used. Efficient pixel segmentation is not possible. Vessel tracking is not implemented in the existing system. Thin vessel pixels cannot be segmented properly due to the low illumination and brightness. They are not fit for noisy medical image edge detection because noise and edge belong to the scope of high frequency.

4.2. Modified Fuzzy C Means Clustering

In case of retinal disorders the characteristics of the blood vessels in the retina have some variation. Segmentation of blood vessels is a tedious task in oct image. This paper presents an improvised algorithm for such segmentation. Fuzzy c means algorithm [7] has robust characteristics for ambiguity. Hence it can retain more information. Different textures are separated by edges which acts as boundaries. The separation in image intensity from one pixel to another are also known as edges. Edges are important characteristics of an image since it denotes a higher frequency. By highlighting the edges of the image, process such as image segmentation, data compression and reconstruction can be done easily. This algorithm uses texture for edge detection and provides the first and second order derivatives of the image. Thereby providing even small details of the image.

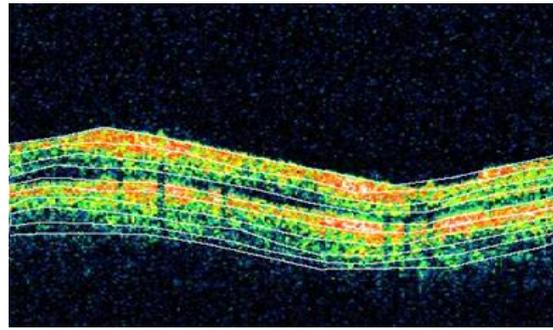


Fig 3.3 FCM Based Normalised Graph Cut Segmented Image

V. CONCLUSION

We reported a fluid-associated abnormality detection and segmentation method in this manuscript. Detection and segmentation of fluid-associated abnormalities in clinical data is a challenging problem in several aspects. Patients might have different severity of disease, which makes the size, location, and shape of fluid regions unpredictable. Moreover, simultaneously improving true positives and controlling false positives is clinically important. We have introduced a layer-dependent stratified sampling strategy [14] to solve the problem. This method reduces the smoothing effect and preserves the property of the edges of the image. The accuracy is relatively higher when compared to other algorithms.

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