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Segmentation of Exudate in Fundus Images Using Graph-Based Algorithm

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Abstract. Diabetes mellitus is a medical term for the designation of the disease known as diabetes. The disease is known to cause a variety of complications in the eyes, and the most common is diabetic retinopathy retinal disorders. One of the early signs of diabetic retinopathy is the emergence microaneurysms. Microaneurysms arise due to weakening of the vessel wall or the smallest blood vessels. Injuries that occur on the vessel causes the formation of exudate that is a point that looks yellowish around the retina. Application of digital retinal image segmentation to aid the detection of exudate is a system that created to segmenting retinal image, so that the resulting of image that can be used as input to the system identification exudate. In this study, include preprocessing operations such as a morphological closing operation to remove the blood vessels, using erosion and dilation operations to eliminate the boundary circumference retina, contrast enhancement, using a logical AND to delete the object instead exudate. While the segmentation method used is graph-based method. Tests conducted with a sample of data taken from Messidor database (http://messidor.crihan.fr) and accuracy was calculated by comparing the result from manually tagging of two people with image segmentation results of the testing program. From the test, the percentage average of accuracy obtains 64.46%.

Keywords: *diabetic retinopathy, exudate, graph-based, segmentation*.

1. Introduction

Diabetes complication causes cataracts, glaucoma, and most importantly, damage to blood vessels inside the eye, a condition known as diabetic retinopathy. Diabetic retinopathy has become a common eye disease in most developed countries. It occurs in 80% of all diabetic cases and is the leading cause of blindness [1].

Diabetic retinopathy is the most feared complication from diabetes mellitus because of its high incidence. One of the early signs of diabetic retinopathy is the emergence of microaneursysms. Microaneursysms arise due to weakening of the vessel wall or the smallest blood vessels. Injuries that happen on the vessel causes the formation of exudate that looks yellowish dots around the retina. The result of microvascular damage causes pathological changes and cellular dysfunction which can be seen in non-vascular tissue. Early microvascular damage is difficult to explain by circulatory changes [2].

This study focused on the detection of exudate at fundus diabetic retinopathy images using image processing technology, which is the process of image segmentation using graph-based methods.

2. Material and Methode

2.1 Data Input

The input image is a digital fundus images of diabetic retinopathy with 2240 x 1488 pixel resolution, which is derived from the database Messidor at http://messidor.crihan.fr. Messidor a research program concentrating on the study of diabetic retinopathy.

2.2 Diabetic Retinopathy

According to the Early Treatment Diabetic Retinopathy Study Research Group (EDTRS) [3] Diabetic retinopathy is divided into two classes, namely Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy(PDR). NPDR is a reflection of clinical hiperpermeabilitas and incompetent blood vessels caused by the blockage and capillary leak. Characteristics of non-proliferative diabetic retinopathy begins with bleeding resulting in microaneurysm, hard exudate, cotton wools, inter retinal microvasculer and venous disorders. Some patients with pathology of diabetic retinopathy need to be diagnosed with diabetes [4,].

In simple words, Diabetic retinopathy is the damage of the blood vessels in the retina of the eye. Diabetic retinopathy is a symptom of diabetes that the most common and a major cause of blindness in American adults that caused by the blood vessels in the retina. In some people with diabetic retinopathy, blood vessels may swell and leak fluid. In other cases, new abnormal blood vessels grow on the surface of the retina.

2.3 Exudate

Signs of diabetic retinopathy aberration such as the emergence of microaneurysm, a tiny red dot in the retinal blood vessels. This happens because the walls of the smallest blood vessels (capillaries) are damaged. In some cases microaneurysm burst, causing bleeding. Along with the leakage of blood, fat and protein as well drop out of the blood vessels which eventually forms a small bright spot called exudates.

From visual, exudates appear in different forms with white or yellowish with varying sizes.

Figure 1. Retinal affected exudate (source: *http://messidor.crihan.fr*)

2.4 Graph Theory in Image Processing

Graph-based segmentation techniques generally represent problems graph $G = (V, E)$ where $VI \in V$, considered pixel of the image and the E are pairs of neighboring pixels. Each E has a weight (w) of the grayscale value of the image itself [5].

$$W((p,q)) = |\ f(p)-f(q)\ | \tag{1}$$

Where:

$f(p)$ and $f(q)$: value of gray pixels p and q

2.5 Pairwise Area Comparison Predicate

D is defined as a predicate for evaluating whether or not there is evidence for a boundary between the two components. This predicate is based on the size of the dissimilarity between elements along the boundary of the two components relative to a measure of dissimilarity between any two elements in the neighborhood component. The resulting predicate compares inter-component differences to the within component differences and are thereby adaptive with respect the local characteristics of the data [5].

Defined internal difference (int) of the component C (V is the greatest weight in the components of the *Minimum Spanning Tree (MST (C, E))*, defined by:

$$Int(C) = \max_{e \in MST(C,E)} w(e) \tag{2}$$

One intuition underlying this measure is a component of C is given only remains connected when at least the weight of the $Int(C)$ are considered.

The defining difference *between (Dif)* of two components $C_1, C_2 \subseteq V$ is the minimum weight of the two components are related,

$$Dif(C_1,C_2) = \min w((v_i,v_j)).vi \in C1,\ vj \in C_2,\ (vi,vj) \in E \tag{3}$$

If no edge connected between C_1 and C_2, then consider Dif $(C1,C2)=\infty$. In principle, the difference in size will be a problem, because it only reflects the smallest edge weight between the two components. In practice it was found that this measure works quite well although there limitations.

Area comparison of local predicates evaluates if there is evidence for a boundary between couples or components by checking if the difference between the components of $Dif(C_1, C_2)$, is large relative to the internal differences in at least one of the components of $Int(C_1)$ and $Int(C_2)$.

A threshold function is used to control the degree where the difference between the components must be greater than the minimum internal difference.

The pairwise area comparison predicate is defined as follows :

$$D(C_1,C_2) = \begin{cases} true & if\ Dif(C_1,C_2) > M\ Int(C_1,C_2) \\ false & other \end{cases} \tag{4}$$

Where the minimum internal difference (*M Int*) is defined as follows :

$$M\ int(C_1,C_2) = min\ (int(C_1) + \tau\ (C_1),\ int(C_2) + \tau(C_2)) \tag{5}$$

Threshold function allows you to control the degree to which the difference between two components must be greater than their internal difference in order for there to be evidence of the boundary between the two components. For small components, *Int (C)* is not a good measure to the local characteristics of the data. Therefore, threshold functions based on the size of its components, defined by :

$$\tau\ (C) = k/\ |C| \tag{6}$$

Where | C | is denoted the size of C and k is a constant parameter. It is clear that for small components be required large evidence as a limitation. In practice k sets the scale of observation. However k is not a minimum size of the component. Smaller components are allowed when the component has significant differences between the neighboring components[5].

3. Segmentation Process

The process of image segmentation consists of several processes, such as image preprocessing and segmentation process. The process is as follows :

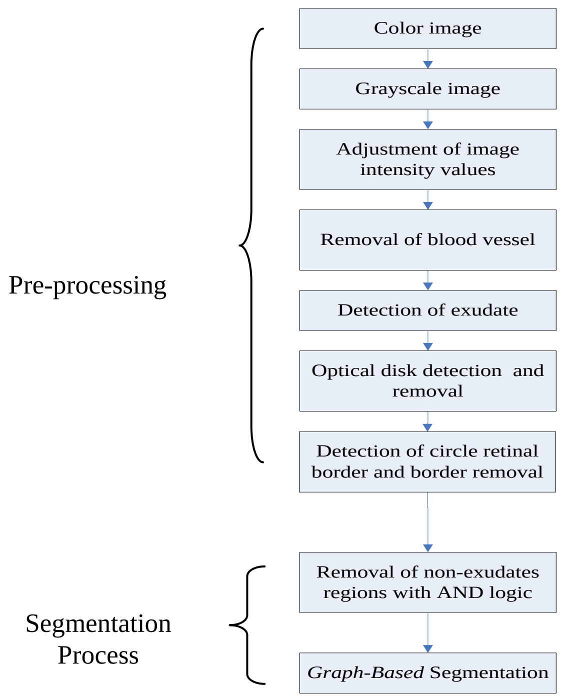

Figure 2. The entire segmentation process.

3.1 Converting RGB to grayscale

Digital image of the retina is a color image. so it must be converted into a grayscale image. To convert it, used the equation :

$$I\,(x, y) = (R + G + B)\,/\,3 \tag{7}$$

3.2 Adjustment of image intensity values

To adjust image intensity values is used imadjust function. Adjustment of image intensity value used to clarify the existing objects in the image.

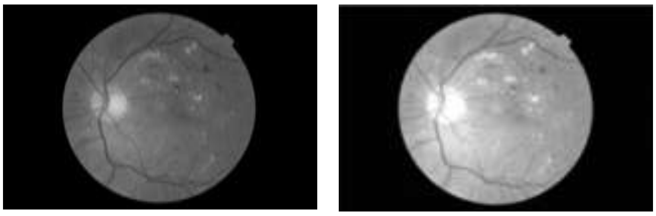

Figure.3. Image grayscale (left) results intensity adjustment (right)

3.3 Early Detection of Exudate

Column filter is used to detect exudate. Colfilt filter works by rearranging each m x n of a block into a column of temporary matrix then apply "sliding" block type. Then let the response at any point in the center of the Block equal to the maximum value within the block. Colfilt then returned to its original size.

But at this stage, exudate detection is not perfect because it was mixed with other objects such as haemorraghes.

3.4 Blood Vessels Removal

Segmentation method of blood vessels in retinal images using Max-Tree Branches filtering approach achieved 91.04% in comparison with the results of manual segmentation by an expert observer first. Accuracy will achieve an average result of 92.19% in comparison to the results of manual segmentation by a second expert observer [6].

In this study used morphology operation to segment blood vessel. Morphology operation are used is closing operations, a combination of erosion and dilation operations.

Various operator developed based on two basic operators. One of them is morphological filter. This filter can reduce needn't object [7,8].

Dilation process is done first, and then followed by erosion process.

$$A \bullet B = (\,A \oplus B\,)\ \P\ B \tag{8}$$

The dilation function serves to expand the area of exudate while erosion function is useful to eliminate blood vessels.

Figure 4. Fundus images with blood vessels that have been removed

3.5 Optical Disk Detection and Optical Disk Removal

Generally, optical disk has a maximum value. The location of the optical disc will only refer to one place. The system will search for the maximum value of each column. After the optical disk is found then made a mask. The mask is made like the shape of the optical disk that like a circle shape to decrease the detection errors. The areas that covered by the cover will removed.

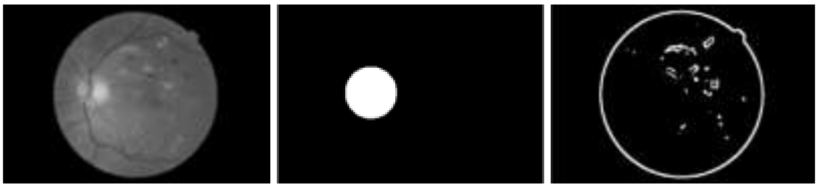

Figure 5. Removal of optical disk

3.6 Detection of Circle Retinal Border and Border Removal

Border detection is to clean up the noise at the edge of the retina so that the circumference of the circle then generated images without the circle line. Generated from the gray image. Then, do edge detection using "edge" function. The approach used is "canny" method.

After that, the process of morphological dilation and erosion operations performed. Dilation operation is defined by the equation :

$$A \oplus B = \{z \mid [\,()_z \cap A\,] \subseteq A\} \tag{9}$$

While the equation for the erosion operation A ¶ B, is defined as :

$$A \text{ ¶ } B = \{\, z \mid (B)_z \subseteq A\} \tag{10}$$

Dilation is used to enlarge the circle object. And then made another smaller circle by performing morphological operations of erosion. Circular border will be obtained from the reduction of the area of a large circle with a smaller circle area. The formula of reduction operation :

$$g\,(\,x,y\,) = f\,(\,x,y\,) - h\,(\,x,y\,) \tag{11}$$

Subtraction between two images produces a new image where the pixel at coordinates (x, y) resulting from the reduction of the pixel at the same location on 2 pieces of the image.

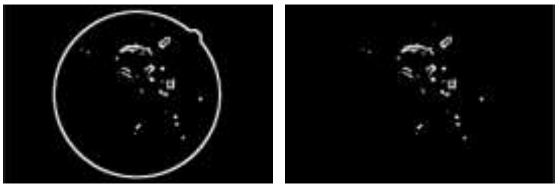

Figure 6. Removal of border retinal

3.7 Removal of non-exudates regions

AND logic is used to eliminate noise in the detection process of exudate. Image segmentation is applied to a grayscale image to extract the bright spots in comparison. This area (bright features) represented by a binary 0 (black) while non-exudate (dark feature) is represented as a binary 1 (white).

Illustration of the application of the concept of AND logic can be seen in the following table 1:

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Table 1. Illustrations of AND logic

p	*q*	*p AND q*
black	black	black
black	white	white
white	black	white
white	white	white

The process of dark feature removal , also shown in the figure below :

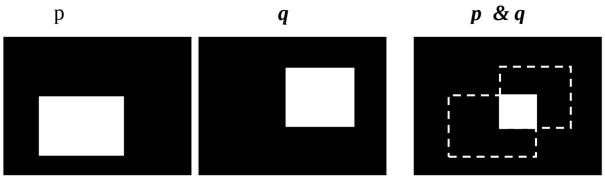

Figure 7. The process of applying the logical *AND*

From the figure it can be seen as the process of applying the logical *AND* in the exudate segmentation. The *p* image obtained from the previous process (removal of the retinal circle limit), the image is processed with the closing process. Then the result of the closing process is done the removal of objects not exudate through a process of logical *AND* with the image of *q*.

The *q* image is dark features resulting from the initial grayscale image which is processed by adaptive histogram equalization, then the image is converted to binary image, then performed negation, and produced dark features.

After the non exudate removed then do segmentation with graph-based methods.

3.8 Graph-Based Segmentation

As previously described, the graph is weighted graph. To determine the weights of the graph, we used the measure of absolute intensity difference between the two pixels are connected in the edge. The weight of the graph is determined from :

$$W((v_i, v_j)) = |I(p_i) - I(p_j)| \tag{12}$$

Where : $I(p_i)$ = intensity of p_i pixel
$I(p_j)$ = intensity of p_j pixel

The graph can not be separated from the concept of the tree which is the most important concept in the process of segmentation. If *G* is a weighted graph, the weight spanning tree of *G* is the sum of the weights on all sides of the tree spanning them. Spanning tree that has the minimum weight is a minimum spanning tree (MST). The main processing step is building a minimum spanning tree, MST. Here the algorithms that used to construct the MST is Kruskal algorithm. Kruskal algorithm is one of the basic algorithms that can be used to determine the minimum spanning tree by means indulge first graph edges from small to large. Then, repeatedly sided with the smallest weight and not form a cycle in T inserted into the set T.

The input is a graph $G = (V, E)$ with *n* vertices and *m* edge. Output is a segmentation of *V* into components $S = (C_1, C_2, ..., Cr)$. The sequence of Segmentation using the graph-based [5].

0. Sort *E* into $(e_1, e_2, ... e_m)$.
1. Perform segmentation start from S^0, where each node v_i is in the component itself.
2. Repeat step 3 for each e_q of $(e_1, e_2, ... e_m)$.
3. If the weight of *eq* relatively small difference of the internal components is connected, merge the components, otherwise do nothing. Or more formally, if $C_i \neq C_j$ and $w(eq) \leq Mint(C_i, C_j)$ where $C_i C_J \in S$ is the component that clearly connected with *eq*, update *S* by combining C_i and C_j.
4. Return $S = S^m$

A complete process of forming MST up segmentation process is as follows, Sequence segmentation process using graph-based method is more clearly seen in the following flow chart :

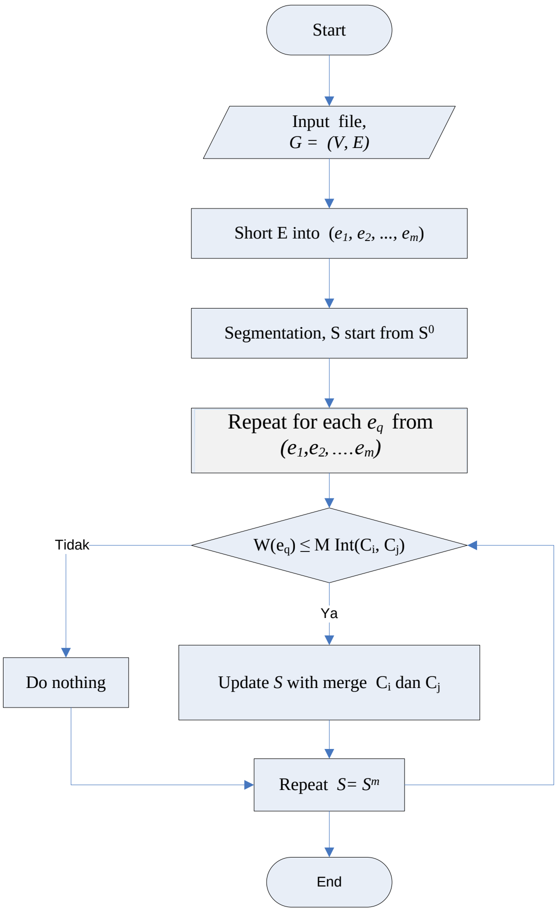

Figure 8. Flowchart of graph-based segmentation process

Here is the result of the segmentation exudate on the program :

(a) (b) (c)

Picture 9. Segmentation Results. (a) Original image, (b) graph-based segmentation, (c) merged image

4. Results

Tests conducted using 100 samples diabetic retinopathy fundus images by comparing results from manual segmentation exudate with the results of the segmentation program. Than 100 samples, 97 of which the data successfully detected the presence or absence of exudate in the test images.

Then also calculated the number of patches of exudate on each image that has been segmented by application. Then compare with the results of manual segmentation.

Table 2. Results of the comparison two observer

The image number	The amount of exudate by manual segmentation			The amount of exudate by segmentation Program	Accuracy (%)
	Observer 1	Observer 2			
18	6	7	0	4	61,54
19	18	14	16	13	81,25
20	10	12	11	6	54,55
23	12	15	13,5	8	59,26
24	10	12	11	8	72,73
25	9	12	10,5	3	28,57
26	32	32	32	25	78,13
28	45	51	48	40	83,33
29	36	40	38	18	47,37
30	8	14	11	1	9,09
31	48	44	46	41	89,13
32	28	29	28,5	18	63,16
37	17	15	16	13	81,25
38	19	18	18,5	11	59,46
39	2	1	1,5	1	66,67
43	5	6	5,5	3	54,55
51	15	14	14,5	7	48,28
52	15	15	15	5	33,33
57	3	3	3	3	100,00
66	10	11	10,5	10	95,24
67	13	14	13,5	7	51,85
71	6	5	5,5	5	90,91
84	38	42	40	35	87,50
85	10	10	10	6	60,00
88	4	4	4	2	50,00
89	6	6	6	4	66,67
96	3	3	3	2	66,67
				Percentage average =	64,46

5. Conclussion

Based on the discussion and description of the applications that have been created and the trials that have been implemented, applications can detect the presence of exudate from a fundus image that have been tested with correct answer 97% of all images population samples. While the average percentage of segmentation accuracy by program on each sample image is 64.46%.

Although the average percentage of segmentation accuracy is not so good, but this application can be categorized as an application that can help the work of someone who works in an ophthalmologist to detect exudate automatically.

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