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EXUDATE DETECTION AND FEATURE EXTRACTION USING ACTIVE CONTOUR MODEL AND SIFT IN COLOR FUNDUS IMAGES

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ABSTRACT

In the world, Diabetic Retinopathy is the leading cause of vision loss. Early symptoms of this disease are exudates, so early diagnosis and treatment at right time is very important to prevent blindness. In this paper the Active contour model (ACM) is implemented to detect exudates and it is used to obtain accurate borders of lesions, and then the local features of detected exudates are extracted using Scale invariant feature transform(SIFT). The publicly available DiaretDB1 database of color fundus image set is used for testing the implemented method.

Keywords: color fundus images, diabetic retinopathy (DR), level set, segmentation, mathematical morphology, SIFT.

1. INTRODUCTION

Diabetes mellitus will lead to vision loss that is the retina gets damaged. Often diabetic retinopathy has no early warning signs. For early detection and treatment the screening programme will help a lot. International diabetes federation estimated that in the world the number of diabetic patients in 2011 is about 366 million and it will be increased to 552 million by 2030. By forming three variety of symptoms, It will be identified and those are first one is microaneurysms, second haemorrahages [1]. Third, the retinal edema and hard exudates [2].

In this paper, we concentrated on hard exudates detection in color retinal images. In the macula region the exudates are located and will give extremely useful information for the ophthalmologist [3-4]. Various types of exudates detection algorithms are proposed already. Some of them used gray scale morphology [1, 5, 6]. We adopted first the morphology based to extract the region of exudates. To raise sensitivity, an active contour method (ACM) applied to get correct boundary of the exudates. After the detection of exudates, the variational level set method will be implemented [7-8]. After having the correct boundaries of exudates, the several features of lesions are extracted using SIFT algorithm. SIFT [9] algorithm is tested by having the scale, rotation and illumination changes in the ACM applied exudates image.
The remaining paper is organized as follows: section 2 is having description of preprocessing. In section 3 ACM is used to get precise boundaries. Section 4 will give the explanation of feature extraction using SIFT. Experimental results are presented in section 5. Some conclusions will be given in section 6.

2. PREPROCESSING AND REGION OF EXUDATES SELECTION

In color fundus images exudates appear as bright, Yellowish pattern with irregular shapes. The leakage of proteins and lipids from the blood into the retina via damaged blood vessel [10-11] will form the exudates. The exudates size and shape varies in a wide range, so it is difficult to get automatic exudates detection.

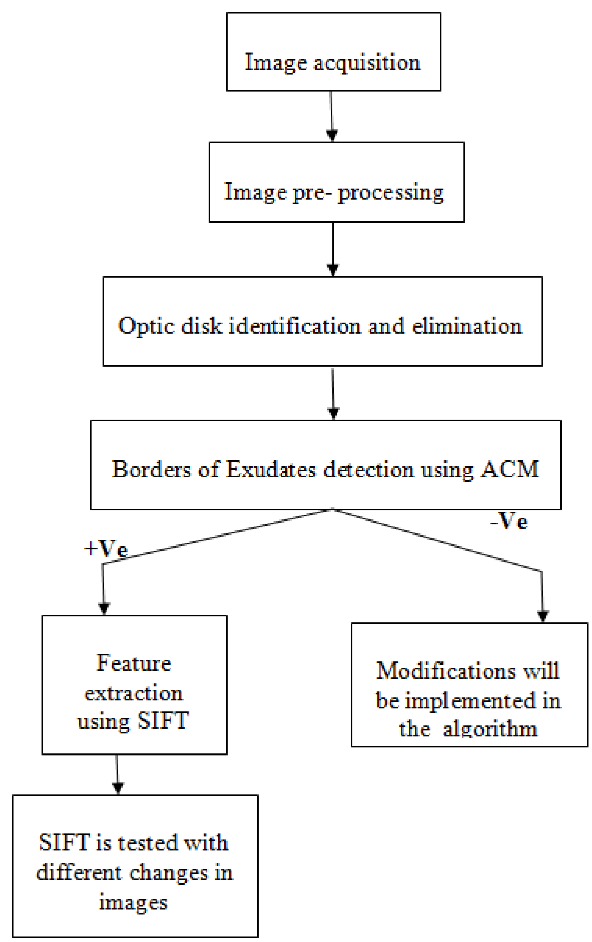

Figure-1. Work flow of implemented method.

2.1 Image preprocessing

The color retinal images having Red (R), Green (G), Blue (B), intensity channels. In green channel, we are having most of the information about lesions compared to other two channels. So we implement our method on this channel. To raise the contrast of exudates Contrast Limited

ARPN Journal of Engineering and Applied Sciences

Adaptive Histogram Equalization (CLAHE) is applied to the green channel, it is shown in Figure-2. So that the edges of lesions are increased.

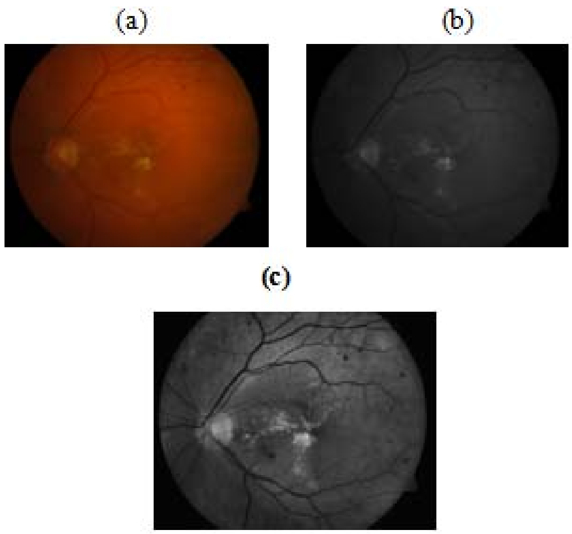

Figure-2. (a) Color fundus image (b) Green channel image (c) CLAHE image.

2.1.1 Optic disk elimination

Optic disk and exudates appear in a similar manner. So optic disk elimination is important for precise segmentation of exudates. The optic disk resides maximum area in the retinal image and for this reason, by using connected component analysis, it is eliminated.

2.1.2 Exudates region extraction

The exudates regions are extracted using Walter *et al*. proposed a morphology based technique [5]. There is high contrast between vessels and background so it is necessary to eliminate the vascular system by having adjusted structuring element in grayscale morphological closing operation. By applying thresholding bright objects are obtained. But the boundaries of the lesions are not precise by having this method, and it is the drawback so to get more precise boundaries of lesions will move to further steps.

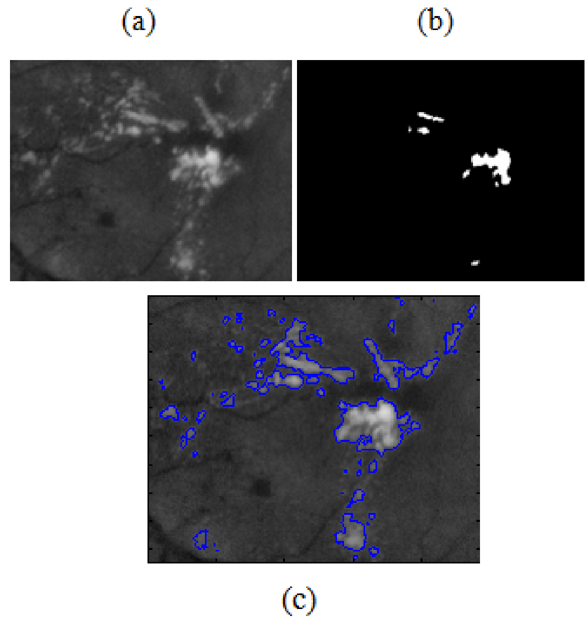

Figure-3. (a) Part of Green channel exudated image (b) Image of exudates region for initialization of Active contour (c) Active contour method applied image.

3. ACTIVE CONTOUR MODEL

Our goal is to recognize the exudates region on the retinal image with proper description of their exact shape. By having ACM the mostly likely boundary of extracted exudates region will be obtained. The exudated binary image is used for initial position for active contour model in Figure-3.

The accurate boundary of exudates are obtained by using variational level set model [7-8], which is efficient in computation wise, and also the movement of contour towards the object boundary is more compared to other segmentation models such as snakes [12], Geometric active contours (GAC) [13], Gradient vector flow (GVF) [14], and traditional level sets [15].

The initial level set contour φ is defined around the detected exudates.

For successive iteration, to minimize the total energy function of contour steepest descent gradient flow is computed. By changing the δ value the computation time will be reduced for 200 iterations.

$$\frac{\partial\varphi}{\partial t} = \mu\left[\nabla\varphi - div\left(\frac{\nabla\varphi}{|\nabla\varphi|}\right)\right] + \lambda\delta(\varphi)div\left(g\frac{\nabla\varphi}{|\nabla\varphi|}\right) + u g\delta(\varphi)$$

Where ∇ is lapalcian operator and δ is dirac delta function.

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4. FEATURE EXTRACTION USING SIFT

Midlevel features are more attracted in recent years, and among them SIFT [16] features are invariant to rotation, scaling, translation and small distortions with respect to geometrical changes [17]. SIFT is more robust among local invariant feature descriptors. The main idea is to look for the extreme points in the scale space, to find the extreme points in the scale space, to find stable feature points known as key points the extreme points are filtered. It is having major stages (a) Scale space detection, (b) Key point localization (c) Orientation assignment (d) Key point descriptor. The first stage used difference of Gaussian (DOG) function to identify potential interest points [16], which were invariant to scale and orientation.

Instead of Gaussian DOG was used to raise the computation speed [16, 18, 19].

$$D(s, t, \sigma) = (G(s, t, k, \sigma) - G(s, t, \sigma)) * I(s, t)$$
$$= L(s, t, k, \sigma) - L(s, t, \sigma)$$

Where * is convolution operator. $G(s, t, \sigma)$ a variable scale Gaussian, $I(s, t)$ is the input image, $D(s, t, \sigma)$ is difference of Gaussian with scale k times. In the key point localization they are rejected the low contrast points and edge responses are eliminated. Hessian matrix is used to compute principal curvatures and key points are eliminated. From the gradient orientations of sample points within a region around the key point in order to get an orientation assignment, an orientation histogram was formed [16]. SIFT applied for exudated image is shown in Figure-4.

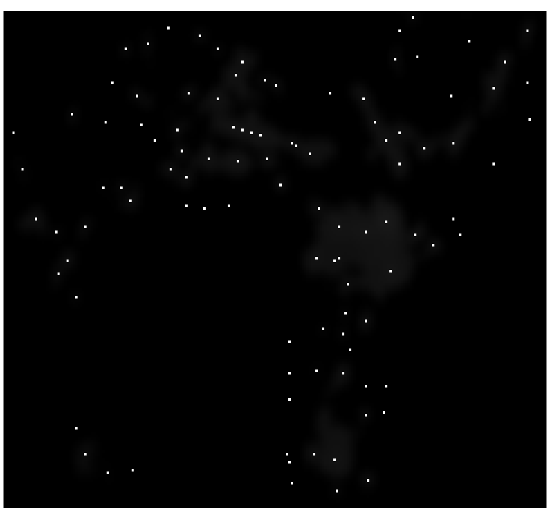
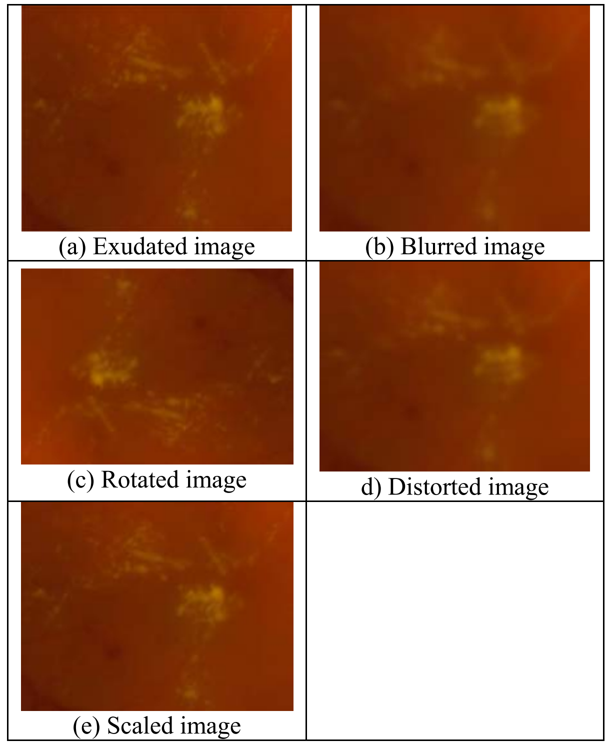


Figure-4. SIFT applied exudated image.

5. EXPERIMENTAL RESULTS



(a) Exudated image
(b) Blurred image
(c) Rotated image
d) Distorted image
(e) Scaled image

Figure-5. Exudated images for testing.

Table-1. Comparison between SIFT and SURF finding number of matches on time.

	SIFT	SURF
Total matches	165	258
Total time (ms)	51.5	49.02

The SIFT algorithm is compared with Speeded up robust feature algorithm (SURF). SIFT detects the most feature points compared to SURF with less time with different changes in images like rotation, scaling, blurring, distortions.

6. CONCLUSION AND FUTURE WORK

In this paper variational level set active contour method was used to detect accurate boundaries of exudates with less time. Morphological operations are taken as initialization for ACM method to raise the sensitivity. But the detected regions of exudates are all not real exudates. So we used SIFT to locate key points on exudates. With these feature points we can match images in large databases. It is more robust with different changes in images with exudates compared to SURF. SIFT locates more key points so it is necessary to reduce its dimension and further classification must be done to differentiate normal and abnormal images.

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