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Fundus Retina Blood Vessel Segmentation with H-Minima Transformation

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***Abstract* – In this paper we used the H-minima transform for blood vessel segmentation. The aim of this paper is to get the high accuracy of blood vessel segmentation in retinal images. In this paper the good result and good performance is get. We compared our result with other methods. Also for simulation result we will implement on DRIVE and STARE database.**

***Keywords* – Blood Vessel Segmentation, H-Minima, DRIVE Database, STARE Database.**

I. INTRODUCTION

With today's advancing technology, support of developing hardware and software systems, the developments in the field of medicine have increased considerably. In particular, medical image analysis and processing systems have taken a considerable lead. Along with the advances in technology, significant progress has been made in the number and effectiveness of the computerized techniques used in medical studies. Automatic image processing and analysis is the most promising computer comprehension and visualization techniques used in the field of medical diagnosis and treatment. In this context, high resolution retinal images at most clinical locations provide many features that can be used in diagnosis and treatment. Developments over the last 15 years in the field of medical image processing allow different features, changes, diseases and degenerations in retinal images to be automatically perceived. The retina is a capillary semi-transparent and slightly pink-red color that covers the inside of the eyeball. The retina is an eye layer located behind the eye that contains light sensitive cells and nerve fibers that carry information about the image to the brain and perform visual function. The retina is basically composed of two main layers, the inner sensory layer (neurosensory) and the outer pigmented layer. The inner sensory layer is composed of 10 separate cellular layers. The point where the picture falls is in the 9th floor. The diameter of this point is about 1 millimeter. In addition, the retina, the so-called reticular layer, completely covers the inner rear wall of the eye sphere and is composed of millions of sight cells and nerve cells to which they are attached. The extensions of these nerve cells come together to form the visual nerve. The veins feeding these cells are also located in the retina layer. In fact, if the eye looks like a digital camera, the retina can be thought of as a sensor that senses the image and transforms it into electricity. The electrochemical reactions necessary to perceive light are basically a sensory catheter. The sensory layer consists of photoreceptor cells that perceive the outermost layer of light. The photoreceptor turns the cells into electrical energy in accordance with the apparent light wavelength, that is, the color. These stimuli are made by the ganglion cells located in the innermost layer of the retina. There are two types of photo receptor cells. These are cone and rod cells. Rod cells are responsible for seeing at twilight, and they allow us to see objects in varying shades of black and white. Rod cells are 110-125 million cubic meters. The cone cells can even respond to light, and provide fine details and bright colors in bright light. The number of cone cells is 6.3-6.8 million. In different regions of retinas, rod and cone cells have different densities. There is no rod cell in the retina center where the light focuses, a specialized region called macula, a fovea (yellow dot), and a sharp-looking rod cell, where cone cells are found. As you move away from the center of the retina, the density of cone cells decreases, while that of rod cells increases. Looking at a spot of dust on a dot size or a vast view of a high hill, the image falls on the macula (macula lutea), a yellowish area about 1.5 millimeters wide on the retina. The diameter of this area is less than half a millimeter (0.4 mm). In the central region, the retina is thinned and shows a thin depression. This is called the yellow spot (fovea centralis). This is the center where the view is clearest. This area consists entirely of cone cells. When we focus on an area or a spot, the eyes move in such a way that the sparkle coming from this area falls on the fovea. It is also helpful if the eye is moving. Cells in the fovea can often suffer from disease called age-related macular degeneration. As can be seen from Figure 1.1, the optic disc is composed of 3 segments of blood vessels, yellow dot (macula, fovea) and optic nerves that constitute retinas.

II. SENSITIVITY, SPECIFICITY AND ACCURACY

There are several terms that are commonly used along with the description of sensitivity, specificity and accuracy. They are true positive (TP), true negative (TN), false negative (FN), and false positive (FP).

If a disease is proven present in a patient, the given diagnostic test also indicates the presence of disease, the result of the diagnostic test is considered true positive (TP).

If a disease is proven absent in a patient, the diagnostic test suggests the disease is absent as well, the test result is true negative (TN).

Both (TP) and (TN) suggest a consistent result between the diagnostic test and the proven condition (also called standard of truth).

However, no medical test is perfect. If the diagnostic test indicates the presence of disease in a patient who actually has no such disease, the test result is false positive (FP). Crossing and branching in the veneer can complicate the image model. Most medical images pose significant problems in removing blood vessels, such as signal noise, image intensity shift, and image contrast mishandling.

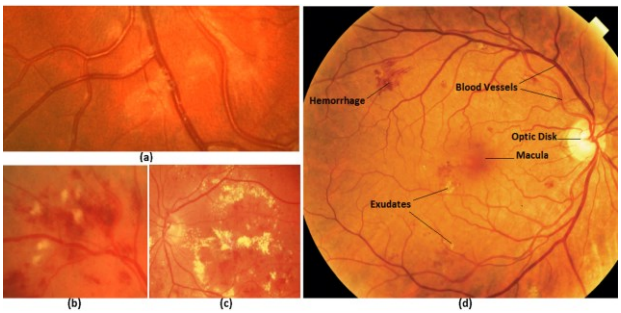

Fig. 1. Morphology of retinal images: a) Central vascular reflex and background Irregularity b) Cotton wool spots, c) Stiff axes, d) Retinas anatomic structures.

III. Database

3.1. DRIVE Database

20 Retinal images taken from the DRIVE retina database were used, and 20 retinal images were used for the test [9]. The DRIVE retina database was derived from a DR imaging program in the Netherlands. The imaging program included 400 diabetic patients aged 25-90 years, with 40 images randomly selected. Each image was in JPEG format and was shot using a Canon CR5 non-myDriatic 3CCD camera with a 45 degree image area (FOV). The resolution of the first images was 768 x 584, and each image area was cropped to obtain images with a resolution of 565 x 584 including a circle with a diameter of about 540 pixels. Figure. 2 Is an example of a normal and pathological image.

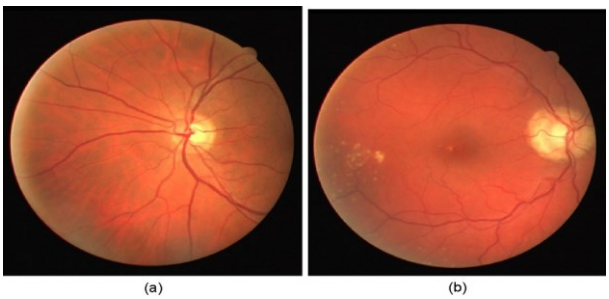

Fig. 2. Retina images from DRIVE: a) healthy retina b) retinal pathology showing.

3.2. STARE Database

The STARE database [10] contains 20 images for segmentation of blood vessels, 10 of which are pathological images. Figure. 2.5 shows retina images from the STARE database. The field of view was drawn using a Canon TRV-50 fundus camera with 35 degrees (FOV). The resolution of the captured images is 605 × 700, and each image area is cropped to obtain images at a resolution of 650 × 500 including a diameter circle. Two observers are manually segmenting all images. The first observer divides by 10.4% pixel vein, and the second observer divides by 14.9% vein. The second observer had much more segmentation of the thinner veins than the first observer, indicating that the segmentation difference between the two observers was the reason. Performance the marking as a definite reference is calculated by the segmentation of the first observer.

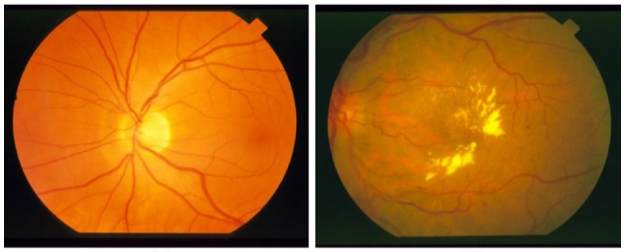

Fig. 3. Retina Images from STARE: (a) healthy retina, (b) pathological retina.

IV. Result

Result

The result for DRIVE database is shown in table 1.

Table 1. Result for DRIVE database

Image number	Specificity	Sensitivity	Accuracy
1	0.97	0.76	0.95
2	0.98	0.70	0.95
3	0.97	0.68	0.94
4	0.98	0.61	0.95
5	0.98	0.65	0.95
6	0.97	0.65	0.94
7	0.98	0.60	0.95
8	0.98	0.61	0.95
9	0.98	0.64	0.95
10	0.98	0.68	0.95
11	0.98	0.61	0.95
12	0.97	0.70	0.95
13	0.98	0.64	0.94
14	0.97	0.72	0.95
15	0.98	0.70	0.96
16	0.98	0.68	0.95
17	0.97	0.70	0.95
18	0.97	0.73	0.95
19	0.97	0.81	0.96
20	0.97	0.77	0.95

The result for STARE database is shown in table 2.

Table 2. Result for STARE database

Image number	Specificity	Sensitivity	Accuracy
1	0.95	0.72	0.93
2	0.96	0.64	0.94
3	0.94	0.81	0.93
4	0.96	0.70	0.94
5	0.96	0.70	0.94
6	0.97	0.73	0.95
7	0.97	0.83	0.96
8	0.96	0.82	0.95
9	0.97	0.81	0.96
10	0.96	0.77	0.94
11	0.97	0.80	0.96

Image number	Specificity	Sensitivity	Accuracy
12	0.97	0.86	0.96
13	0.97	0.77	0.95
14	0.97	0.76	0.95
15	0.97	0.73	0.95
16	0.98	0.59	0.94
17	0.98	0.76	0.96
18	0.98	0.68	0.97
19	0.97	0.76	0.96
20	0.96	0.66	0.94

The comparison between results of accuracy, specificity and sensitivity for DRIVE database is shown in figure 4.

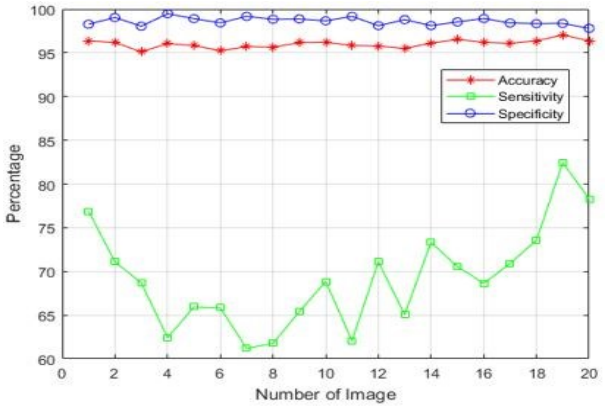

Fig. 4. Comparison of the result for DRIVE

The comparison between results of accuracy, specificity and sensitivity for STARE is shown in figure 5.

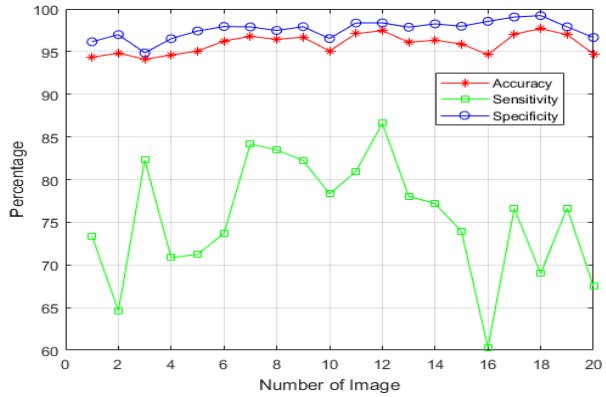

Fig. 5. Comparison of the result of STARE Database

V. Conclusion

In this study, we used unsupervised method to subtract the vessels in the retina, based on H-minima transformation algorithm is proposed to accurately extract the vessels from the retinal images, taking into consideration the features of retinal images. First, some preprocessing has been applied to the images. To do this, the best sub-bands of color images were initially chosen. We then corrected the brightness changes in the retinal images by applying the local processing function described. The resulting image in this section was an image of uniformity and flatness. We then improved the contrast by enhancing the contrast of the image, improving the edges of the image (playing a role in determining the image better and determining the contrast of the image). This method is based on a multilayered neural network scheme for classifying pixels as veins and non-veins, a gray-level co-ordinate matrix, and a feature vector representing each pixel of 12 features. The proposed method has been successfully developed; as evidenced in the simulation results, better results were obtained in the removal of vessels than in other methods.

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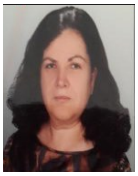

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