MALIGNANT HYPERTENSIVE RETINOPATHY DIAGNOSING SYSTEMBASEDONRETINA IMAGE

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Abstract- High blood pressure can damage the vessels supplying blood to retina. When the cardiologist finds a hypertension patient who has the symptoms of hypertensive retinopathy, the cardiologist will help him make referrals to ophthalmology for a complete eye diagnosis. However, early recognition of hypertensive retinopathy signs is not always easy to diagnose. Due to a lack of ophthalmic knowledge, the hypertensive retinopathy may be misdiagnosed by the cardiologist. This study provides a malignant hypertensive retinopathy diagnosis system (MHRD system) to promptly and accurately diagnose malignant hypertensive retinopathy based on retina image. The symptoms of malignant hypertensive retinopathy include constricted and tortuous arteries, retinal hemorrhage, hard exudates, cotton wool spots, retinal edema, and papilledema. These symptoms create some bright and dark areas in a gray-level retinal image. When given a retinal image, the MHRD system hence segments the bright areas, dark areas, and vessels from the retinal image. It then diagnoses the malignant hypertensive retinopathy based on the characteristics of the segmented bright areas, dark areas, and vessels. The experiment results show that the MHRD system can give over 85% diagnostic accuracy rate.

IndexTerms- Image Segmentation, Hypertensive Retinopathy, Retinal Image, Keith-Wagener-Barker Grade.

I. INTRODUCTION

In recent years, more and more people in the risk of hypertension because of influence by life style and dietetic culture. There are 6.24 million people facing highly risk of hypertension in Taiwan [1]–[2].Hypertension causes many diseases like stroke and cardiovascular disease. However, because of sometimes the incidence of hypertension with no symptoms, when the body alert, the timing of treatment may be often missed. Since systemic arterial hypertension, retinal vessels will automatically lead to a series of pathological changing cause hypertensive retinopathy [3].

The symptoms of retinal diseases are classified by Keith-Wagener-Barker (KWB) Grades which is usually used for diagnosing malignant hypertensive retinopathy. KWB Grades is a classic study. In 1939 Keith and colleagues described the prognosis of people with differing severity of retinopathy. It was proposed that individuals with signs of hypertensive retinopathy signs, especially retinal hemorrhages, microaneurysms and cotton-wool spots [4].

Fig.1shows malignant hypertensive retinopathy symptoms of different grades according to KWB Grades [5]. In grade 1, retinal vessels gets narrowing, bending and sclerosis. Symptoms of grade 2 are like grade 1 but having light reflex in arteries. For grade 3, there are cotton-wool spots and hemorrhage in retina. In grade 4 there are same symptoms as first three grades plus papilledema [6].

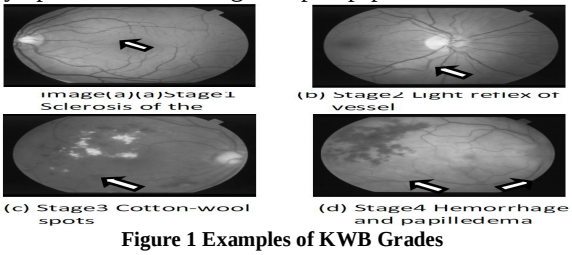


Figure 1 Examples of KWB Grades

Malignant Hypertensive Retinopathy Segmentation (MHRS) is proposed to segment those symptoms of malignant hypertensive retinopathy. Then we proposes Malignant Hypertensive Retinopathy Diagnosing (MHRD) to diagnose by seven features calculated from segmented images.

For knowing state of hypertension patients need to measure blood pressure every day in time. However, measuring blood pressure is not easy thing and early signs of hypertension are not obvious, most patients don't know they already faces the risk of hypertension. Cause delay for treatment until hypertension got more seriously bad.

Moreover, some diseases caused by hypertension like stroke and cardiovascular the doctors may not have sufficient understanding to ophthalmic retinopathy. Due to doctors not familiar with malignant hypertensive retinopathy makes patients forced to run around different departments. Therefore this paper propose an automatically diagnosing system for malignant hypertensive retinopathy, hope to help doctors and patients can know the state of disease faster and also decide treatment quicker. Let patients no more suffer from misunderstanding by different subjects of hypertension treatment.

This section briefly reviews some algorithm which will be applied in this study. At first, to remove background in raw retinal image, Otsu's thresholding method [7] is used for generating a threshold to transform the image into a binary image which will be used as a mask of background. Then, Run Length method [8], [16] is used to enhance vessels region. Before segmenting white area this study enhance those white areas in grayscale image of retina through Positive Cross Filter (PCF) [9]. For de-nosing and segmenting image, the system also use some operations of mathematical morphology. Genetic algorithm is applied to determine those parameters which were used of image segmentation phase and detecting phase. Finally, this

study measure the segmentation accuracy by two different methods, Misclassification error (ME) and Relative foreground area error(RAE)[10]–[11]. Genetic Algorithms (GA) [12]–[13] is an algorithm by mimic biological evolution mechanisms to perform global search within the search spaces and find optimize solution.

II. MHRS METHOD

In this section explains how MHRS segment those symptoms used for diagnosing. The segmentation in MHRS are three phase as follow:

1. Segmenting dark area from grayscale images
2. Separating vessels region and blooding region from dark area
3. Segmenting bright area from grayscale images

At first, MHRS remove background in image to get retinal area image. Then segment lower gray-levels area from retinal image as step 1. Because vessel and blooding in grayscale image have lower gray-levels than other areas, MHRS could segment dark area by an appropriate threshold. In step 2, MHRS need to separate vessel region and blooding region. Because of vessels are elongated shape in retina, MHRS could separate vessels region from dark areas by this feature. After step 1 and 2 MHRS gets vessel region and blooding region images, then segmenting bright area in retinal images. After all these steps MHRS having every symptoms we need for diagnosing statement.

A. Preprocessing Phase

There are retina and background in a raw image from data which were MHRS used. MHRS have to remove background first before enhancement or segmentation because background's gray-levels are way different with other parts of image. If MHRS calculate with background will cause lower of accuracy of segmentation. Therefore in this subsection introduce how MHRS remove background.

In order to remove background from image $\boldsymbol{I}$ MHRS use Otsu's method to calculate a threshold which produces a mask of background. At first MHRS transforms the color image into a grayscale image $\boldsymbol{I_{Gray}}$ as follow:

$$I_{Gray}(i,j)=0.299\times I_R(i,j)+0.587\times I_G(i,j)+0.114\times I_B(i,j) \quad (1)$$

$I_R(i,j)$, $I_G(i,j)$, and $I_B(i,j)$represent R, G and B values in $I(i,j)$. MHRS separate background and retina area through the different in gray-levels. Because background's gray-levels near to 0, MHRS use Otsu's method to calculate a threshold value $\boldsymbol{T_o}$ for generating a binary image $I_{Bi}(i,j)$as follow:

$$I_{Bi}(i,j) = \begin{cases} 0, if\, I_G(i,j) < T_o, \\ 1, \quad otherwise. \end{cases} \quad (2)$$

0 and 1 means the gray-level of black and white. The mask of background was shown in Fig.2.

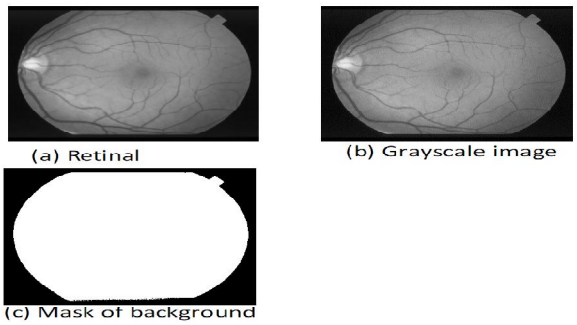


Figure 2 Examples of preprocessing

B. Vessel & Blooding Region Segmentation

This subsection is to segment vessel region and blooding region for diagnosing. Because dark areas contain vessel region and blooding region, MHRS segmenting in two stages. MHRS firstsegment vessel region. Due to vessels often too thin or gray-levels are too close to surrounding area. MHRS needs to enhance vessels by Run Length and Gamma Equalization. Then calculate threshold value and transform images to binary. Next, MHRS use mode filter and opening to remove noises. In final, MHRS segmenting vessels by features of shape. After vessel region, MHRS segment blooding region by the same way but removing vessels region by images which was segmented in last stage.

C. Vessel Region Segmentation

For segmenting vessels MHRS use Run Length method to enhance vessel region, result shown as Fig. 3. In Fig. 3 it shows that those vessels got darker and some micro vascular also became clearer.

After Run Length method, MHRS increase different of vessels region and other areas by Gamma Equalization. Calculate Maximum gray-levels $\boldsymbol{Max_i}$ and minimum value $\boldsymbol{Min_i}$, then calculate every pixels for enhanced pixel $\boldsymbol{H_i}$by following formula:

$$H_i = \left(\frac{P_i - Min_i}{Max_i - Min_i}\right)^{gamma} \times 255 \quad (3)$$

After enhancement MHRS calculate threshold value $\boldsymbol{T_{(i,j)}}$by Local Cross Thresholding for creating binary image. In each pixel $\boldsymbol{P_{(i,j)}}$as center corresponds to a cross $\boldsymbol{C}$, whichcontains surrounding pixels $\boldsymbol{C_k}$ as following formula. Then calculate average gray-levels of $\boldsymbol{C}$as$\boldsymbol{T_{(i,j)}}$ to generate binary results $\boldsymbol{I_{BW}(i,j)}$.

$$C = \begin{cases} P_{(i-C_k,j)}, P_{(i-(C_k-1),j)}, \dots, P_{(i,j)}, \dots, P_{(i+(C_k-1),j)}, P_{(i+C_k,j)} \\ P_{(i,j-C_k)}, P_{(i,j-(C_k-1))}, \dots, P_{(i,j)}, \dots, P_{(i,j+(C_k-1))}, P_{(i,j+C_k)} \end{cases} \quad (4)$$

$$I_{BW}(i,j) = \begin{cases} 255, & if\ P_{(i,j)} > T_{(i,j)}, \\ 0, & otherwise. \end{cases} \quad (5)$$

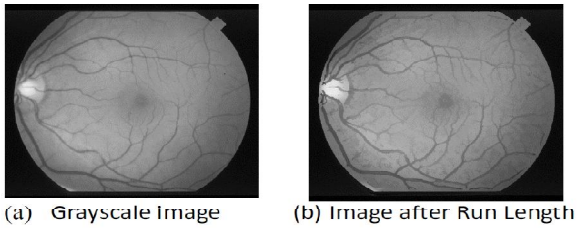


Figure 3 Image after Run Length

Next step we going to remove those pixels, which are too small or not vessels pixels in $\boldsymbol{I_{BW}}$. Each pixel corresponds to a $S \times S$ window $\boldsymbol{Maj}$, thenreplacecentral pixel with mode value of $\boldsymbol{Maj}$. For an example we using 3×3 window as Fig. 4:

$$P_{(i,j)} = Mode(P_{1,2\ldots,8}) \quad (6)$$

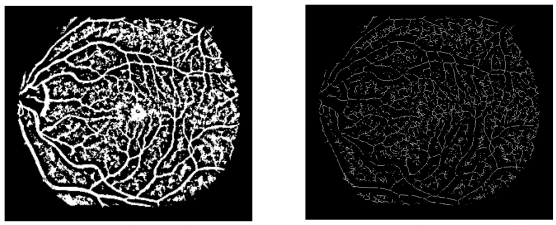
After Mode filter there are still some noises in images so MHRS remove them by Opening. Opening operates twice on binary image $\boldsymbol{I_{BW}}$ with circular structuring element whose radius is 1 pixel. Finally, after these two methods MHRS removed almost all noises and going to detect vessels region from image.

$P_{i-1,j-1}$	$P_{i-1,j}$	$P_{i-1,j+1}$
$P_{i,j-1}$	$P_{i,j}$	$P_{i,j+1}$
$P_{i+1,j-1}$	$P_{i+1,j}$	$P_{i+1,j+1}$

Figure 4 Example of Mode filter

For detecting MHRS judged by vessel itself must be slender shape so operate Thinning [14] to vessel region image. Then get vessels before Thinning operation$\boldsymbol{L_i}$ and vessels after Thinning operation $\boldsymbol{Thin_i}$as Fig.5.

After Thinning MHRS calculate pixel numbers of each vessel in $\boldsymbol{L_i}$and $\boldsymbol{Thin_i}$ get $\boldsymbol{Count_{L_i}}$ and $\boldsymbol{Count_{Thin_i}}$. Because the width of vessel after Thinning became only one pixel, $\boldsymbol{Count_{Thin_i}}$equals to this vessel's length and $\boldsymbol{Count_{L_i}}$means are a numbers of vessel. When MHRS got vessel's length and area we can calculate vessel's width $\boldsymbol{Wid_i}$.



(a) Image before Thinning (b) Image after Thinning

Figure 5 Example of Thinning

At final, because the feature of vessel in retina appears as a main vessel which is the longest and widest vessel disperse other smaller vessels. Since MHRS have the main vessel's width $\boldsymbol{Wid_{long}}$, we can set this as first requirement. Also for same reason the length of main vessel $\boldsymbol{Thin_{long}}$ can be second requirement to judge object in image is vessel or not. MHRS use these two requirements to create image $\boldsymbol{V_i}$ with only vessels as following formula:

$$V_i = \begin{cases} 1, if\ \ Wid_i \le Wid_{long}, and\ Thin_i > V_l \times Thin_{long}, \\ 0,\ otherwise. \end{cases} \quad (7)$$

V_l is a parameter between 0and 1 which used to adjust $\boldsymbol{Thin_{long}}$for detecting vessel. Results of vessel regions segmentation shown as Fig.6.

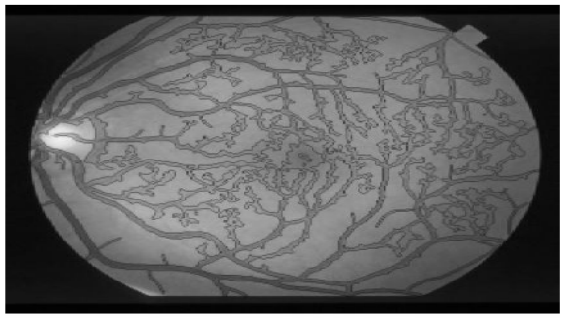


Figure 6 Example of vessel regions segmentation

B. Blooding Region Segmentation

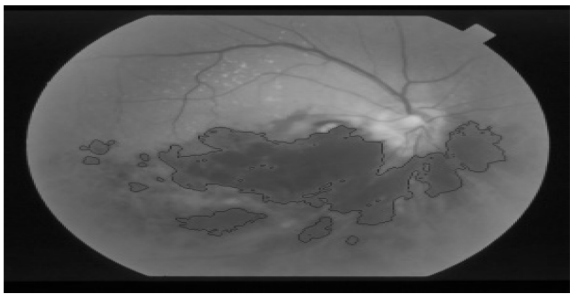


Figure 7 Example of blooding regions segmentation

In this subsection MHRS going to segment blooding region in retina. Because blooding region appears as lower gray-levels in grayscale image just like vessel region. For segmenting blooding region MHRS use similar method to segment vessel region. First MHRS need to enhance blooding region by Gamma Equalization only. Here MHRS don't use Run Length method because blooding region is larger area than vessel region in retina. Using Run Length method may cause more noise in image. After enhancement, MHRS use the same way to create binary image but different parameters. Then to get blooding region only, MHRS need to remove vessel region from image so we use following formula to get image $\boldsymbol{Blood_{(I,j)}}$and example of segmentation shown in Fig.7.

$$Blood_{(i,j)} = \begin{cases} 1, & if\ V_i = 0, \\ 0, & otherwise. \end{cases} \quad (8)$$

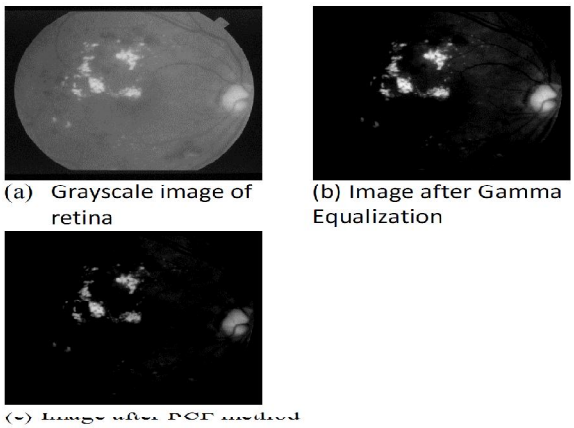
C. Bright Area Segmentation

In this subsection MHRS segment whit area in retina which contains optic disc and cotton-wool spots. For segmenting MHRS have to enhance white area first but white area in grayscale image has far higher gray-levels. Therefore MHRS enhance by different Equalization method. Calculate average gray-levels $\boldsymbol{Avg_i}$ of whole image, then for each pixel $\boldsymbol{P_i}$ if its gray-levels lower than $\boldsymbol{Avg_i}$replace to 0, others pixels operate by same Gamma Equalization. As a result, those pixels whose gray-levels higher will increase disparity to other pixels and dark area pixel can't influence result of enhancement.

$$H_i = \begin{cases} \left(\frac{P_i - Min_i}{Max_i - Min_i}\right)^{gamma} \times 255, & if P_i > Avg_i, \\ 0 & otherwise. \end{cases} \quad (9)$$

Furthermore, MHRS use PCF method to remove those pixel whose gray-levels higher than $\boldsymbol{Avg_i}$ but not symptoms objects. As Fig.8, PCF method can make white

area in retina image obvious and there no pixels we don't need. After these two steps enhancement MHRS create binary image by Local Cross Thresholding method and remove noise by the same way as these two method used before. In these different phase of segmenting all those parameters were decide by Genetic Algorithm. Now, MHRS segment all symptoms which were need for diagnosing. Next subsection will explain how to calculate these parameters basic on Genetic Algorithm



(a) Grayscale image of retina

(b) Image after Gamma Equalization

(c) Image after PCF method

Figure 8Image of PCF method

D. GBSPD

MHRS method used many parameters in calculating of segmentation and these parameters decide results of segmentation. For deciding Parameters MHRS use Genetic-Based Segmentation Parameter Detector (GBSPD) which is a method based on Genetic Algorithm. In process of GBSPD, the standard image is ground truth which is manually delineated. GBSPD uses ground truth to evaluate whether results of segmentation good or not. Therefore in GBSPD, the fitness of Genetic Algorithm is calculating by the differentness between results of segmentation and ground truth. The differentness is the ***F***-value which was calculated through two measuring methods ME and RAE.

In MHRS method, there are many parameters decided by GBSPD as follow. In vessel segmenting phase there are $\boldsymbol{m_{vessel}}$ means size of window in Run Length, $\boldsymbol{gamma_{vessel}}$ for Gamma Equalization, cross size $\boldsymbol{C_{vessel}}$ of Local Cross Thresholding, Mode filter size $\boldsymbol{S_{vessel}}$ and $\boldsymbol{V_l}$ for adjusting terms of vessel detection. In blooding segmenting phase there are $\boldsymbol{gamma_{blood}}$, $\boldsymbol{C_{blood}}$ and $\boldsymbol{S_{blood}}$. Finally in white area segmentation phase are $\boldsymbol{gamma_{bright}}$, cross size of PCF method $\boldsymbol{S_{PCF}}$, $\boldsymbol{C_{bright}}$ and $\boldsymbol{S_{bright}}$.

All those parameters compose chromosomes which were encoded as a binary string in GBSPD. For each chromosome $\boldsymbol{ch}$ consists of several concatenated substrings of eight bits as follow: $\boldsymbol{Str_{m_{vessel}}}$, $\boldsymbol{Str_{gamma_{vessel}}}$, $\boldsymbol{Str_{C_{vessel}}}$, $\boldsymbol{Str_{S_{vessel}}}$, $\boldsymbol{Str_{V_l}}$, $\boldsymbol{Str_{gamma_{blood}}}$, $\boldsymbol{Str_{C_{blood}}}$, $\boldsymbol{Str_{S_{blood}}}$, $\boldsymbol{Str_{gamma_{bright}}}$, $\boldsymbol{Str_{S_{PCF}}}$, $\boldsymbol{Str_{C_{bright}}}$ and $\boldsymbol{Str_{S_{bright}}}$. Each substring represents a parameter in decimal as: $\boldsymbol{N_{m_{vessel}}}$, $\boldsymbol{N_{gamma_{vessel}}}$, $\boldsymbol{N_{C_{vessel}}}$, $\boldsymbol{N_{S_{vessel}}}$, $\boldsymbol{N_{V_l}}$, $\boldsymbol{N_{gamma_{blood}}}$, $\boldsymbol{N_{C_{blood}}}$, $\boldsymbol{N_{S_{blood}}}$, $\boldsymbol{N_{gamma_{bright}}}$, $\boldsymbol{N_{S_{PCF}}}$, $\boldsymbol{N_{C_{bright}}}$, $\boldsymbol{N_{S_{bright}}}$. Although substrings with more bits could make these parameters more randomly, GBSPD need to consider efficiency of algorithm. For increasing efficiency and not losing randomness GBSPD adjust each substring as follow:

$m_{vessel} = 1 + N_{m_{vessel}} \times 0.1$; $gamma_{vessel} = 0.5 + N_{gamma_{vessel}} \times 0.001$; $C_{vessel} = 1 + N_{C_{vessel}} \times 0.1$; $S_{vessel} = 1 + N_{S_{vessel}} \times 0.01$; $V_l = 0.1 + N_{V_l} \times 0.001$; $gamma_{blood} = 0.5 + N_{gamma_{blood}} \times 0.001$; $C_{blood} = 1 + N_{C_{blood}} \times 0.5$; $S_{blood} = 1 + N_{S_{blood}} \times 0.01$; $gamma_{bright} = 0.5 + N_{gamma_{bright}} \times 0.001$; $S_{PCF} = 1 + N_{S_{PCF}} \times 0.5$; $C_{bright} = 1 + N_{C_{bright}} \times 0.5$; $S_{bright} = 1 + N_{S_{bright}} \times 0.01$.

GBSPD applies segmented images compared with ground truth to train the most appropriate values for parameters by genetic algorithm. GBSPD uses the measurement as the fitness function of a chromosome $\boldsymbol{ch}$ based on all thoseparameters with ground truth. Then we explain how GBSPD train parameters in three phases as Selection, Crossover and Mutation.

Initially, GBSPD randomly generates N chromosomes $\boldsymbol{ch}$, each $\boldsymbol{ch}$ consists of $\boldsymbol{Str_{m_{vessel}}}$, $\boldsymbol{Str_{gamma_{vessel}}}$, $\boldsymbol{Str_{C_{vessel}}}$, $\boldsymbol{Str_{S_{vessel}}}$, $\boldsymbol{Str_{V_l}}$, $\boldsymbol{Str_{gamma_{blood}}}$, $\boldsymbol{Str_{C_{blood}}}$, $\boldsymbol{Str_{S_{blood}}}$, $\boldsymbol{Str_{gamma_{bright}}}$, $\boldsymbol{Str_{S_{PCF}}}$, $\boldsymbol{Str_{C_{bright}}}$ and $\boldsymbol{Str_{S_{bright}}}$. In order to train the most fitness parameters, GBSPD repeatedly performs mutation, crossover and selection until reach the numbers of operating we set.

In mutation operation, GBSPD randomly decide one bit $\boldsymbol{b}$ in every substrings as $\boldsymbol{Str_{m_{vessel}}}$, $\boldsymbol{Str_{gamma_{vessel}}}$, $\boldsymbol{Str_{C_{vessel}}}$, $\boldsymbol{Str_{S_{vessel}}}$, $\boldsymbol{Str_{V_l}}$, $\boldsymbol{Str_{gamma_{blood}}}$, $\boldsymbol{Str_{C_{blood}}}$, $\boldsymbol{Str_{S_{blood}}}$, $\boldsymbol{Str_{gamma_{bright}}}$, $\boldsymbol{Str_{S_{PCF}}}$, $\boldsymbol{Str_{C_{bright}}}$ and $\boldsymbol{Str_{S_{bright}}}$ for each $\boldsymbol{ch}$. Then replace $\boldsymbol{b}$ with $\boldsymbol{\sim b}$ to generate a new chromosome, where the operator "NOT" symbolizes by "~".

In crossover operation, a random number generator is used to designate $\boldsymbol{N'}$ pairs of chromosomes from $\boldsymbol{N}$ reserved chromosomes. Each pair contains two chromosomes $\boldsymbol{ch_1}$ and $\boldsymbol{ch_2}$. Then, for those child chromosomes $\boldsymbol{ch_{child}}$ having $\boldsymbol{P}$ bits from $\boldsymbol{ch_1}$ and $\boldsymbol{P'}$ bits from $\boldsymbol{ch_2}$.

In the selection operation, GBSPD choose optimal chromosomes are selected from the $\boldsymbol{N}$ chromosomes reserved in the previous iteration. For each iteration create $2 \times \boldsymbol{N}$ chromosomes in the mutation and crossover operations according to their fitness function. The GBPD performs mutation, crossover, and selection continuously until reach operate times which was set in experiment. Consequently, the MHRS methods use GBSPD to obtain the optimal values of parameters.

III. MHRD METHOD

In this section explains how MHRD method diagnosing Malignant Hypertensive Retinopathy. MHRD diagnose by seven features which are calculated from those

segmented images from MHRS. These features were decided by symptoms from KWB Grades. For diagnosing, features have to be unique in its levels of KWB Grades. So when features were selected MHRD calculating as follow. In vessel region image MHRD calculate degree of curve in peripheral vessels and brightness of reflecting in vessels. In white areas images, because of cotton-wool spots appeared when grade 3 of Malignant Hypertensive Retinopathy and in healthy retina there is only optic disc in white area. MHRD calculate degree of pixels dispersion in white areas to judge whether there are cotton-wool spots or not. Finally, in blooding regions images as the same reason of white areas, MHRD calculate degree of pixels dispersion in blooding regions images as a feature.

After MHRD got all those features still need to normalize before diagnosing because size of images may not be the same. Differences of images could make value of features and result of diagnosing different. Then after normalization, MHRD compare features to diagnose which grade the input image is.

A. Features Selection

In order to select features which are unique and able to distinguish different grades of Malignant Hypertensive Retinopathy. MHRD select these symptoms basic from KWB Grades and calculate features value from segmented images of these symptoms. These symptoms are observed in vessel regions, white areas and blooding regions in retina. As shown in table 1, these symptoms represent each grade.

Table 1 Symptoms of each grade

Grades	Curve of vessel	Reflect of arterioles	Cotton-wool spots	Hemorrhage	Papilledema
I	+	+	−	−	−
II	+	+	−	−	−
III	+	+	+	+	−
IV	+	+	+	+	+

Features of Vessel Region

In vessel regions MHRD select features of first two grades. Images of first two grades vessel appear curved and having bright reflection in middle of vessels. Bright reflection in grayscale image appears as higher gray-levels. In this subsection explain how MHRD calculate these two features.

For calculate degree of curving, MHRD uses smoothing method [17] to get smoother vessels. Then calculate distances between pixels before smoothing and after as first feature. For each endpoints $\boldsymbol{V_{endpoint}}$ of vessel regions images $\boldsymbol{V}$ backtracking $\boldsymbol{N}$ pixels. Then for each pixel $\boldsymbol{V_{(i,j)}}$ of vessels calculate the coordinate two pixels before and after. New pixel $\boldsymbol{V_{smooth(avg(i),avg(j))}}$ created by average of these five coordinates. Finally calculate distance between $\boldsymbol{V_{(i,j)}}$ and $\boldsymbol{V_{smoth(avg(i),avg(j))}}$ as follow:

$$Distance_{smooth} = \sqrt{\left(i - avg(i)\right)^2 + \left(j - avg(j)\right)^2} \quad (10)$$

Endpoints are detected by scanning whole image to find pixels which having only one vessel pixel in surrounding area. Example as Fig. 9:

After we get the distance MHRD need to normalize the distance avoiding size of different images influence value of distance. So MHRD normalizing as follow:

$$Normalized_{Distance_{smooth}} = \frac{Distance_{smooth}}{Height+Width} \quad (11)$$

Where $\boldsymbol{I}$ means input images $\boldsymbol{Height}$ and $\boldsymbol{Width}$ represent length and width of $\boldsymbol{I}$. After normalizing distance become value between 0 and 1, then calculate average and standard deviation as first feature $\boldsymbol{F_1}$ and second feature $\boldsymbol{F_2}$.

Next step MHRD finds feature in bright reflection of vessels. Due to reflection appears in middle of vessels MHRD use Thinning method to get image of vessels after Thinning as Fig.10. For calculating degree of reflection, MHRD take $\boldsymbol{N}$ pixels as a period calculate average of brightness $\boldsymbol{Avg_{vesselbright}}$ and maximal brightness $\boldsymbol{Max_{vesselbright}}$ of whole vessel. Then the third feature $\boldsymbol{F_3}$ calculated as follow:

$$Feature_{bright} = \frac{Avg_{vesselbright}}{Max_{vesselbright}} \quad (12)$$

For normalizing, MHRD take $\boldsymbol{Max_{vesselbright}}$ as denominator to make $\boldsymbol{F_3}$between 0 and 1.

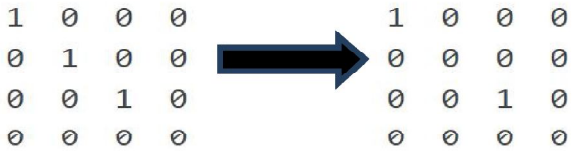


Figure 9 Example of endpoint calculating

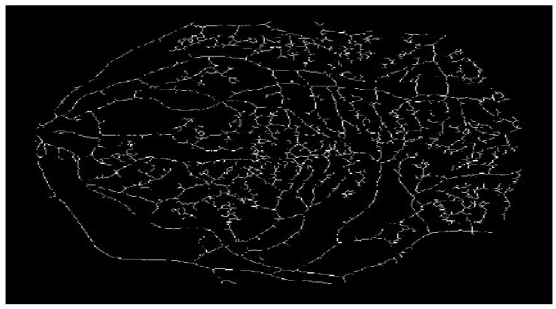


Figure 10 Image of vessel after Thinning

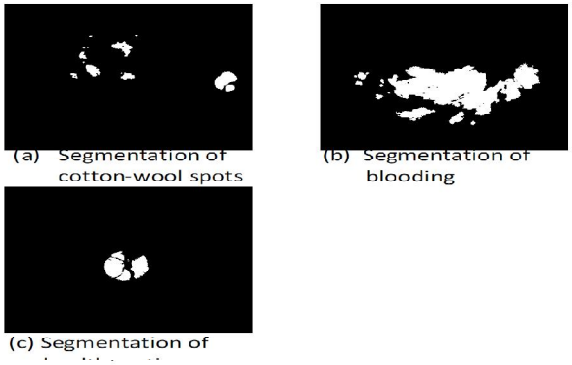


Figure 11 Segmentation of symptoms images

Features of Blooding Region & Bright Area

MDRD diagnoses grades 3 and 4 of Malignant Hypertensive Retinopathy by white areas and blooding regions images. In grade 3 there are cotton-wool spots in retina. In healthy retina images there is only the optic disc (a white area), if appearing cotton-wool spots will cause more objects in white areas. For blooding regions images there are many irregular large objects. But blooding regions will not having objects when retina is healthy as Fig.11.

Therefore, MHRD calculate the dispersion of pixels as feature of these symptoms. In case of white areas, for all pixels $\boldsymbol{P_{bright(i,j)}}$ which were segmented before, MHRD calculate a central point $\boldsymbol{Center_{bright(Avg(i),Avg(j))}}$ by average of coordinate. Then find distance between every pixel and $\boldsymbol{Center_{bright(Avg(i),Avg(j))}}$ asdispersion. Alsodispersion needs to be normalized as follow:

$$Normalized_{Distance_{brightdistribute}} = \frac{Distance_{distribute}}{Height+Width} \quad (13)$$

After normalizing MHRD calculate average and standard deviation as two features $\boldsymbol{F_4}$ and $\boldsymbol{F_5}$of white areas. Then use the same way to calculate $\boldsymbol{F_6}$, $\boldsymbol{F_7}$ of blooding areas. Ultimately, MHRD gets all seven features for diagnosing

B. Features Comparing

After feature selection MHRD use those seven features to compare and diagnose Malignant Hypertensive Retinopathy. In this subsection explain how MHRD comparing features. At first classify all images according to KWB Grades and ophthalmology expert's opinions. Four grades in KWB Grades and one grade for healthy retina. There are seven features $\boldsymbol{F_{1\sim7}}$ of each image. MHRD calculate the average value of $F_{1\sim7}$ in a grade as $\boldsymbol{ClusterCenter_{F1\sim7}}$.

For an input image create three segmented image vessel regions, blooding regions and white areas by MHRS first. Then MHRD calculate seven features by these three images as $\boldsymbol{Input_{F_{1\sim7}}}$ and comparing to $\boldsymbol{ClusterCenter_{F1\sim7}}$ of each grade. MHRD calculate comparing distance as follow:

$$D = \sum_{i=1}^{7} w_i \times \left|F_i - ClusterCenter_{F_i}\right|^{r_i} \quad (14)$$

$\boldsymbol{ClusterCenter_{F1\sim7}}$ has the closest comparing distance is the result of diagnosing. $\boldsymbol{F_i}$means$\boldsymbol{i_{th}}$feature for comparing. Here the $\boldsymbol{w_i}$ and $\boldsymbol{r_i}$is a weights value which were decided by Genetic Algorithm to adjust feature for diagnosing. Because of each feature represents different symptoms, every feature influence results of diagnosing differently. Therefore, MHRD uses $\boldsymbol{w_i}$ and $\boldsymbol{r_i}$to adjust each feature in order to increase accuracy of diagnosing.

C. GBDPD

In this section we explain how GBDPD decide two parameters to increase accuracy of diagnosing. The method of GBDPD is similar to GBSPD in three phases of Genetic Algorithm. The main difference is the way setting chromosome and possible range for parameters.

GBDPD decide $\boldsymbol{w_i}$and$\boldsymbol{r_i}$ which are corresponding to those seven features, so there are fourteen parameters to decide. Each parameter represented by a 10 bits binary string and all these strings compose a chromosome. Therefore each parameter could be a number between 0 and 1023. With lager range GBDPD could try more possible parameters but in MHRD $\boldsymbol{w_i}$ and $\boldsymbol{r_i}$ hugelyeffectresults in calculation. For increasing efficiency GBDPD limits $\boldsymbol{w_i}$ and $\boldsymbol{r_i}$to a reasonable range as follow:

$$w_i = \frac{w_i}{sum(w_i)} \quad (15)$$

$$r_i = r_i \times 0.005 \quad (16)$$

After adjusting operation GBDPD makes parameters in a better performing range. Then GBSPD also trains parameters in three phases: selection, crossover and mutation as GBSPD method.

IV. EXPERIMENTAL RESULTS

This section is to present experimental results of our proposed method. Retina images used are downloaded from two public open databases, STARE [18] and HRF [18] databases. Images on both databases are classified and organized by experts. We also manually depict the ground truth of vessel regions, blooding regions and white areas for comparing to segmented images.

We used total 70 images of Malignant Hypertensive Retinopathy, and all these images from STARE database. These images with resolution of 605× 700 pixels and 8 bits for each RGB channel. For healthy retina we have total 15 images also with 8 bits for each RGB channel and 466 × 700 pixels, all from HRF database. All these images of retina were captured and collected by ophthalmologist.

Then we present experimental results of MHRS first, which are segmenting images of vessel regions, blooding regions and white areas. Then show those parameters decided by GBSPD. After MHRS, we show the accuracy of diagnosing from MHRD and parameters calculated by GBDPD.

A. MHRS's Experimental Results

In this section represent segmenting results of MHRS by white areas, blooding regions and vessel regions. Also using other segmenting methods of retinopathy symptoms compare to MHRS. For three parts of MHRS GBSPD operated 1,000 times to trains parameters which made results optimized.

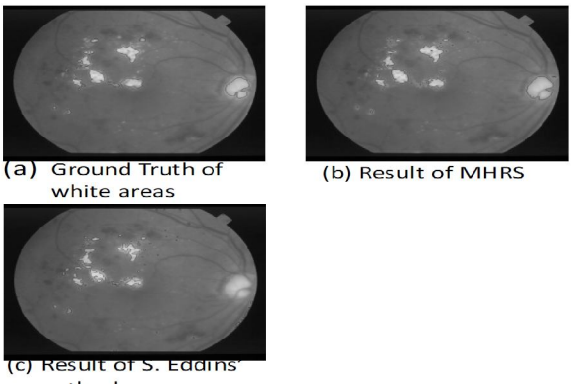


Figure 12Comparison of results images of white areas

In white areas, our experiment used 25 images contain cotton-wool spots from STARE database and ground truth of these images. To measure results we use ME and RAE two methods and comparing MHRS to S. Eddins' watershed method [14]. As Fig.12 shows that S. Eddins' method segment more pixel which are not symptoms objects caused lower accuracy. Also in S. Eddins' method didn't segment optic disc out. Error rate are in table 2 which shoes MHRS method segmenting better than S. Eddins' method. After GBSPD training, parameters we used in experiment of white areas segmentation are as follow $gamma_{bright}$ = 0.74, S_{PCF} = 180, C_{bright} = 60, S_{bright} =2.

In blooding regions, our experiment used 10 images contain hemorrhage in retina and all these images come from STARE database. To evaluate performance of MHRS, we compare with Diabetic Retinopathy Image Segmentation (DRIS) method [9]. Also using ME and RAE to calculate error rate in table 3. Fig 13 shows that DRIS method did not remove vessel in blooding segmentation and cause more small pieces objects of blooding regions. MHRS can segment blooding regions without vessel and have lower error rate. After GBSPD training, parameters we used in experiment of blooding regions segmentation are as follow $gamma_{blood}$ = 0.68, C_{blood} = 180, S_{blood} = 2.

Table 2Error rate of white areas segmentation

Method	ME	RAE
MHRS	0.009	0.335
S. Eddins'	0.02	0.538

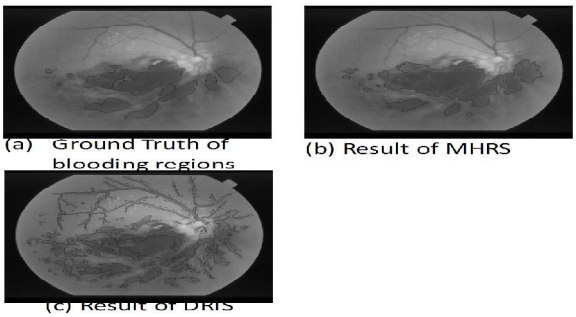


Figure 13 Comparison of results images of blooding regions

Table 3 Error rate of blooding regions segmentation

Method	ME	RAE
MHRS	0.05	0.385
DRIS	0.16	0.711

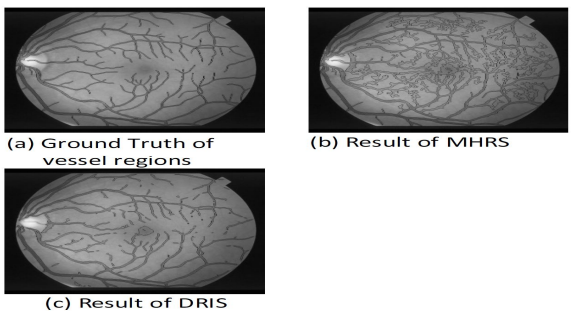


Figure 14 Comparison of results images of vessel regions

Finally in vessel regions, we test 70 images from STARE database. Also using ME and RAE to evaluate and compare with DRIS method. Result of segmentation in Fig. 14 which shows MHRS is able to segment more microvascular which is tiny branch of vessel and MHRS will not cause broken vessel segmenting. DRIS method segmentation with less noise but cause lots of vessels were break into pieces. Although DRIS segmentation with lower error rate but in order to diagnosing we need consequent vessel to calculate feature value. Therefore MHRS still the better way to segment minutiae vessels for diagnosing. After GBSPD training, parameters we used in experiment of vessel regions segmentation are as follows: m_{vessel} = 13 , $gamma_{vessel}$ = 0.7 , C_{vessel} = 20 , S_{vessel} = 1, V_l = 0.25.

Table 4 Error rate of vessel regions segmentation

Method	ME	RAE
MHRS	0.23	0.574
DRIS	0.21	0.568

B. MHRD's Experimental Results

Table 5 Images amount of each grade

	healthy	grade 1	grade 2	grade 3	grade 4
No. of images	15	19	16	25	10

In this subsection represent performance of MHRD method to diagnose disease. It will explain data we used for experiment first. Then shows how GBDPD trains parameters and data used for training and testing in experiment. Finally, is the results of diagnosing in MHRD.

Table 6Parameters trained by GBDPD

	Test 1	Test 2	Test 3	Test 4	Test 5	ave. of acc.
health	4	4	4	4	4	
grade 1	2	3	2	3	4	
grade 2	3	4	2	1	0	
grade 3	1	1	2	1	1	
grade 4	4	4	4	4	4	70/100
acc.	0.7	0.8	0.7	0.65	0.65	0.7

Table 7 Accuracy of MHRD diagnosing (Five grades)

	w	r
F1	**3.38**	**0.25**
F2	1.98	0.2
F3	2.62	0.05
F4	2.67	0.04
F5	1.77	0.18
F6	1.75	0.16
F7	2.19	0.08

MHRD use 70 images from STARE database and 15 images from HRF database for experiment. Numbers of images in each grade are in table 5. Although these images from two databases are having different size, but not influence results of diagnosing because of normalization in MHRD. All these 85 images are classified by experts according to KWB Grades for calculating cluster centers.

In this experiment we design two different testing for MHRD because the grade 1 of KWB Grades describe as mild changes of arteries. But these mild sclerosis and devious of arteries are too difficult to observe even experts usually need diagnose by instrument. Diagnosing just

depend on image is unrealistic so we test diagnosing for combine first two grades and separate two grades as table 2 and table 8.

Table 8 Accuracy of MHRD diagnosing (Four grades)

	test 1	test 2	test 3	test 4	test 5	ave. of acc.
normal	4	4	4	4	4	
grades 1 & 2	5	6	8	7	6	
grade 3	3	2	3	3	3	
grade 4	4	4	4	4	4	86/100
acc.	0.8	0.8	0.95	0.9	0.85	0.86

The experiment is random repeatedly test for five times. For each time randomly use 60 images as training data and rest 20 images as testing data. GBDPD operating 2,000 times for training parameters in once test. After all we use the average value of five times diagnosing accuracy as the final accuracy of MHRD.

After GBDPD training parameters which MHRD used are shown in table 6. As table 7 and 8 show that accuracy of MHRD are quite effective. In MHRD diagnosing for five grades have 70% and for four grades can reach 86%.

CONCLUSION

In this study we proposed an automatically diagnosing system of Malignant Hypertensive Retinopathy. This system is operating by two stages MHRS and MHRD. At first MHRS remove background in original image at preprocess phase then segment white areas, vessel regions and blooding regions. For segmenting vessel regions MHRS enhance vessels in images by Run Length and Gamma Equalization method then calculate threshold value by Local Cross Thresholding to create binary image. Removing noise pixels and detect vessel regions at last. In blooding regions MHRS use similar way to enhance and segment blooding regions with removing vessel regions in dark areas of grayscale retina images. After blooding regions, MHRS segment white areas through PCF method and enhancement method. Finally use GBSPD to train parameters used in segmenting base on Genetic Algorithm.

In order to evaluate results of MHRS we use two measurements ME and RAE. MHRS also compared results to other segmenting method as S. Eddins' watershed method with white areas and DRIS with vessel regions and blooding regions. In experimental results shows that MHRS has better performance on white areas and blooding regions segmentation. For vessel regions segmenting, although DRIS has lower error rate but DRIS segment fewer details of vessel regions than MHRS.

In MHRD method we select seven features of Malignant Hypertensive Retinopathy base on KWB Grades. MHRD diagnose by comparing these features and using weight of each feature to increase accuracy. Because these features represent different symptoms, MHRD give different feature a weight to adjust them in diagnosing. Those weights were train by GBDPD method which is also base on Genetic Algorithm to optimize parameters. In experimental results shows that MHRD has 86% accuracy of diagnosing.

Our proposed diagnosing system is proved to support doctors diagnosing patients. Doctors could increase diagnosing speed by refer to the results of our system. MHRS and MHRD also are valuable to related researcher to consult. Moreover our method could be also applied to other related eye disease by changing features. Our proposed method could be a good chance to promote related research.

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