Automated segmentation of foveal avascular zone in digital colour retinal fundus images

Hanung Adi Nugroho, Dhimas Arief Dharmawan and Litasari

Department of Electrical Engineering and Information Technology, Faculty of Engineering, Universitas Gadjah Mada, Yogyakarta, Indonesia
Email: adinugroho@ugm.ac.id
Email: dhimasariefdharmawan@gmail.com
Email: litasari2011@gmail.com

Latifah Listyalina*
Faculty of Science and Technology – Electrical Engineering, Universitas Respati Yogyakarta, Yogyakarta, Indonesia
Email: listyalina@gmail.com
*Corresponding author

Abstract: One of the diabetes complications, diabetic retinopathy (DR), is characterised by the damage of retinal vessels, especially on the macular region. Located at the centre of retina and appeared as a cloudy dark spot in colour fundus image, macula is a fundamental area for high acumen of colour vision. Foveal avascular zone (FAZ) is located at the centre of macula and encircled by interconnected capillary beds. FAZ has a round or oval shape with an average diameter of 500–600 μm. In DR patients, the FAZ becomes larger due to the loss of perifoveal retinal vessels. In this study, a scheme for automated segmentation of FAZ in colour fundus images is proposed. The scheme consists of four stages: pre-processing, image enhancement, vessels segmentation and FAZ segmentation. Result shows that the average sensitivity, specificity and accuracy obtained are 80.86%, 99.17% and 97.49%. This indicates that the proposed scheme has successfully detected the FAZ.

Keywords: accuracy; diabetes; diabetic retinopathy; foveal avascular zone; fundus images; matched filter; macula; retinal vessels; sensitivity; specificity.


Biographical notes: Hanung Adi Nugroho received BE (Hons) in Electrical Engineering from Universitas Gadjah Mada, Indonesia, in 2001, ME in Biomedical Engineering from the University of Queensland, Australia, in 2005, and PhD in Electrical and Electronics Engineering from Universiti Teknologi PETRONAS, Malaysia, in 2012. He is an Assistant Professor at the Department of Electrical Engineering, Faculty of Engineering, Universitas
Gadjah Mada, Indonesia. His research interests include medical signal and image processing and analysis, computer vision, data mining and statistical pattern recognition.

Dhimas Arief Dharmawan received BE (Hons) in Electrical Engineering from Universitas Gadjah Mada, Indonesia, in 2014. He is a research assistant at the Department of Electrical Engineering and Information Technology, Faculty of Engineering, Universitas Gadjah Mada, Indonesia. His research interests include medical signal and image processing and analysis and neural network.

Litasari received BE in Electrical Engineering from Universitas Gadjah Mada, Indonesia, in 1980 and MSc in Digital System Engineering from the University of Manchester Institute of Science and Technology, UK. She is an Assistant Professor at the Department of Electrical Engineering and Information Technology, Faculty of Engineering, Universitas Gadjah Mada, Indonesia. Her research interests include digital signal and image processing, and pattern recognition.

Latifah Listyalina received BE in Biomedical Engineering from Universitas Airlangga, Indonesia, in 2013. She is a post-graduate student at the Department of Electrical Engineering and Information Technology, Faculty of Engineering, Universitas Gadjah Mada, Indonesia. She is also a lecturer in Universitas Respati Yogyakarta, Indonesia. Her research interests include biomedical signal and image processing, computer vision and pattern recognition.

1 Introduction

International Diabetes Federation (IDF) reported in 2014 that over 387 million people in the world suffered from diabetes, and about 46.3% of them were undiagnosed. Diabetes is a disease caused by the failure of pancreas in secreting enough insulin. As a result, the glucose level in the blood increases which is dangerous to the blood vessels system, particularly in pancreas (Mane and Jadhav, 2014; I. D. Federation, 2014; Alberti and Zimmet, 1998). Over time, diabetes affects many organs, including eyes and retina, which leads to early visual loss or blindness. This complication is commonly associated with diabetic retinopathy (DR) (Kanth et al., 2013). Diabetic retinopathy is characterised by the damage of retinal blood vessels, especially on the macula (Acharya et al., 2009).

Macula is a fundamental area for high acumen of colour vision and emerges as a cloudy dark spot in the colour retinal image (Punnolil, 2013). It is located in the middle of the retina between the superior and inferior temporal vasculature networks. Foveal avascular zone (FAZ) is located at the very centre of macula devoid of retinal capillaries and encircled by interconnected capillary beds. These retinal capillaries end at the surrounding edge of the FAZ and form a ring-like shape. FAZ has an average diameter of 500 to 600 µm and the physiological shape of the FAZ depends on the vascular pattern (Eladawy et al., 2003). In DR patients, the area of FAZ becomes larger due to the loss of the perifoveal retinal vessels (Ahmad Fadzil et al., 2011).
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Currently, FAZ is analysed based on the fundus fluorescein angiography (FFA) images (Eladawy et al., 2003; Haddouche et al., 2005). However, this method is invasive due to the injection of chemical dye into blood vessels. FAZ enlargement detection at early DR stage is expected to prevent the disease progressing to more severe stages and even leading to visual loss. Although FAZ enlargement detection and measurement in digital colour retinal fundus images are difficult, the retinal vascular information and DR pathologies around the FAZ can be used in the FAZ detection (Fadzil et al., 2011b).

Various studies have been conducted to extract information on retinal capillaries (Chaudhuri et al., 1989). Chaudhuri et al. (1989) introduced a matched filter to detect retinal vessels. This approach used a Gaussian-shaped curve to characterise the gray level contour of retinal vessels in the cross section of the retinal fundus images. Another segmentation using matched filter has been done by Al-Rawi et al. (2007). In this paper, better filter parameters were introduced to increase the matched filter performance in the retinal vessels detection. Result showed that this method achieved the mean accuracy of the segmented retinal vessels of 95.10% and the maximum average accuracy of 95.30% (Al-Rawi et al., 2007).

Osareh and Shadgar (2009) proposed a method to automatically identify retinal vessels in digital colour retinal fundus images based on the Gabor filter and combination of generative Gaussian mixture model and discriminative support vector machine (SVM) for retinal vascular feature extraction and classification, consecutively. The proposed method obtained sensitivity and specificity of 96.50% and 97.10% for the retinal vessels identification. Fraz et al. (2011) used a supervised method to perform retinal vascular segmentation from retinal fundus images based on the Gabor filter, Bayesian classifier and Gaussian mixture model. This proposed method provided the measured area under curve (AUC) of 97.34% and 96.16% for the STARE and DRIVE datasets, respectively (Fraz et al., 2011).

Another approach based on multi-scale line detection has been proposed by Nguyen et al. (2013) to segment the retinal blood vessels and produce comparable accuracy of 94.07% and 93.24% for DRIVE and STARE databases, respectively. Gao (2013) improved the multi-scale line detection technique to detect and segment the retinal blood vessel and obtained higher accuracy of 94.13% and 93.31% for DRIVE and STARE databases, respectively. Retinal blood vessel detection also involved heuristic method. Kavitha and Ramakrishnan (2011) proposed ant colony optimisation (ACO) and edge detection techniques to detect the retinal blood vessels in human retinal images. It achieved the area under curve (AUC) of 0.91 for DRIVE and DIARETDB1 retinal image databases.

The work on the FAZ determination based on the retinal vascular end points and pathologies around or at the perifoveal blood capillary network selection was reported in Ahmad Fadzil et al.’s study (2010). The developed algorithm on the FAZ analysis consisted of median filter, manual CLAHE, morphological operations, seed-based region growing (SRG) and gradient-based region growing (GRG). This algorithm achieved the accuracy from 66.67% to 98.69% with the average accuracy and standard deviation of 89.77% and 7.87%, respectively (Ahmad Fadzil et al., 2010).

The work on the FAZ analysis for DR grading has been conducted by Hani et al. (2009). Hani et al. (2009) used a Gaussian classifier to classify DR. The DR
classification was based on the area of FAZ. This research obtained an average accuracy of 92.2% for DR classification. Another approach of DR grading based on the analysis of FAZ enlargement in digital colour retinal image has been done by Fadzil et al. (2011). This investigation showed that the FAZ area ranges were strongly correlated with the progress of DR stages. The mean accuracy and standard deviation achieved were 92.20% and 3.22, respectively indicating that the proposed method was more accurate, more reliable and faster compared to the pathologies-based DR grading methods (Fadzil et al., 2011).

Better results of the retinal image-based classification of DR have been obtained by Ahmad Fadzil et al. (2011) and Hani et al. (2010) with the independent component analysis (ICA) and Gaussian classifier as the classification methods. Both methods used ICA to separate retinal pigment as the aid of the retinal blood vessel segmentation process. These methods achieved a sensitivity of 90.81%, specificity of 98.29% and accuracy of 97.46% (Ahmad Fadzil et al., 2011). Meanwhile, Hani et al. (2010) gained sensitivity, specificity, and accuracy of 100%, > 98% and 99%, consecutively.

Moreover, since a user interruption in the selection of the retinal blood vessel endpoints to determine the FAZ is required, another research work by Hani et al. (2011) was proposed to improve the FAZ determination in a computerised DR grading system. Result showed that the proposed system consistently maintained moderate sensitivity, specificity, and accuracy of >73%, >77% and >77% consecutively DR stages detection. Although the proposed method obtained moderate performance, it showed a possibility to be used for both early DR detection and effective treatment of severe DR cases.

In this work, a scheme for segmentation of foveal avascular zone in digital colour retinal fundus images is proposed. The proposed scheme consists of four image processing stages, which are pre-processing, image enhancement, retinal blood vessels segmentation and FAZ segmentation. With these four steps, the results are evaluated in term of sensitivity, specificity and accuracy of the FAZ area.

2 Scheme

Automated segmentation scheme of foveal avascular zone in digital colour retinal fundus images steps is described as follows. The first step is pre-processing. Pre-processing step consists of two stages, i.e. green channel acquisition and cropping of each digital colour retinal fundus image. Then, image enhancement technique is performed using multiscale top-hat transformation and histogram fitting stretching operation. In the next step, blood vessel segmentation is performed using matched filter and length filter. Finally, the FAZ area is found by performing the FAZ segmentation. A flowchart showing an automated segmentation of FAZ steps is presented in Figure 1.

2.1 Pre-processing

The proposed method begins with the pre-processing step which consists of two operations. These steps are green channel acquisition and cropping of each digital colour retinal fundus image. Green channel acquisition is performed by taking the green channel matrix on each given digital colour retinal fundus image. The second stage of the pre-processing step is image cropping. In the cropping stage, digital colour retinal fundus
images with resolution of $565 \times 584$ pixels are automatically cropped into $200 \times 200$ pixels. The cropping methods are as follows.

1. A point $(x, y)$ in the image indicating the FAZ pixel is determined interactively.
2. From that point, the region of interest (ROI) with resolution of $200 \times 200$ is determined.
3. Based on the ROI, cropping is done using MATLAB®.

Cropping is done not only to make all images the same size but also to minimise the working area. This technique is chosen because FAZ is commonly located in the centre of the retinal image. Thus, cropping can make the computation time shorter.

**Figure 1** Flowchart of automated segmentation of FAZ
2.2 Multiscale top-hat transformation

Top-hat transformation is a combination of opening and closing techniques. Top-hat transformation can be divided into two operations, i.e. white top-hat transformation ($WTH(x, y)$), and black top-hat transformation ($BTH(x, y)$). Those transformations can be written as equations (1) and (2) (Liao et al., 2014).

\[ \text{WTH}(x, y) = f - f \circ b \]  
\[ \text{BTH}(x, y) = f \cdot b - f \]  

Multiscale top-hat transformation is performed to avoid the poor quality of the top-hat transformation image result due to the improper use of the structure element. $B$ is a structure element sequence with $B = \{B_0, ..., B_i, ..., B_n\}$, and $B_0$ is the basic structure element, so $B_i$ to $B_n$ elements can be expressed as equation (3).

\[ B_i = B_0 \oplus B_1 \oplus ... \oplus B_n \]  

Using equation (3), equations (1) and (2) can be re-expressed as equations (4) and (5) as follows.

\[ \text{WTH}_i(x, y) = f - f \circ B_i \]  
\[ \text{BTH}_i(x, y) = f \cdot B_i - f \]  

Maximal responses of the light and dark areas of the grayscale image denoted by $f'_w$ and $f'_b$ are then formulated as follows.

\[ f'_w = \text{argmax} \left\{ \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \text{WTH}_i(x, y), 1 \leq i \leq n \right\} \]  
\[ f'_b = \text{argmax} \left\{ \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \text{BTH}_i(x, y), 1 \leq i \leq n \right\} \]  

Obtaining the details of the image using equations (6) and (7) is no less important. Each image detail denoted by $\text{DWH}_i$ and $\text{DBTH}_i$ can be written as equations (8) and (9).

\[ \text{DWH}_i(x, y) = \text{WTH}_{i+1} - \text{WTH}_i \]  
\[ \text{DBTH}_i(x, y) = \text{BTH}_{i+1} - \text{BTH}_i \]  

Likewise, maximal responses of the light and dark areas of the grayscale image detail denoted by $f''_w$ and $f''_b$ may be expressed using equations (10) and (11) below.

\[ f''_w = \text{argmax} \left\{ \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \text{DWH}_i(x, y), 1 \leq i \leq n \right\} \]  
\[ f''_b = \text{argmax} \left\{ \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \text{DBTH}_i(x, y), 1 \leq i \leq n \right\} \]
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Having obtained the maximal responses of the light and dark areas of the grayscale image detail, the maximum light and dark image features denoted by $f_u$ and $f_d$ can be written as equations (12) and (13) below (Liao et al., 2014).

$$f_u = f_u^c + f_u^d$$

(12)

$$f_d = f_d^c + f_d^d$$

(13)

Finally, the multiscale top-hat transformation image ($f_{mh}$) can be found as follow.

$$f_{mh} = f_u - f_d = (f_u^c + f_u^d) - (f_d^c + f_d^d)$$

(14)

2.3 Histogram fitting stretching

Contrast stretching is an important technique to enhance the low contrast image. Contrast stretching works by transforming the gray level of the input image to the wider range using certain function. If the transformation function has a linear shape, this technique is named gray linear stretching which can be expressed as equation (15) below (Liao et al., 2014).

$$I' = I_{max}' - I_{min}' (I - I_{min}) + I_{min}$$

(15)

$I$ and $I'$ are the gray levels of the unenhanced and enhanced images. Furthermore, $[I_{max}, I_{min}]$ and $[I_{max}', I_{min}']$ denote the maximum and minimum gray level values of the original and enhanced images, consecutively. $I_{max}$ and $I_{min}$ value are determined by taking care of the image histogram resulted from the multiscale top-hat transformation. Assuming that the image histogram resulted from the multiscale top-hat transformation has a Gaussian shape, this histogram can be formulated as follows.

$$P(x) = ce^{-(x-a)^2/b^2}$$

(16)

$I_{max}$ is equal to $a+3b$ while $I_{min}$ is equal to $a-3b$. The values of $a$, $b$, and $c$ can be determined using a curve fitting technique on the image histogram resulted from the multiscale top-hat transformation.

2.4 Matched filter

Matched filter is a common technique used to detect one-dimensional (1D) signal such as in radar and digital communication applications. Moreover, matched filter is also feasible to be used in two-dimensional signal detection applications such as objects within images detection. To perform objects detection within images, the matched filter is upgraded into two-dimensional filter or a spatial filter that produces an output as the spatial correlation between an input and a reference image (Pratt, 2007). Commonly, digital colour retinal fundus images have low contrasts that increase the complexity of the retinal blood vessels segmentation. Thus, in this study, the matched filter is used to perform the blood vessel detection. The main idea of using a matched filter is to take a number of samples in the retinal blood vessel cross-section. Then, the gray level of those samples is approximated using a Gaussian curve (Chanwimaluang and Fan, 2003).
The use of a matched filter on the digital colour retinal fundus image is done by convolving twelve matched filter kernels with the digital colour retinal fundus images. Matched filter kernel \( K(x,y) \) can be written as equation (17) (Chaudhuri et al., 1989).

\[
K(x,y) = -\exp\left(\frac{-u^2}{2\sigma^2}\right) \quad \forall \vec{p}_i \in N
\]  

(17)

\( N \) is the neighbourhood which is defined for \( N = \{(u,v) | |u| \leq T, |v| \leq L/2\} \), where \( T \) is a positive real number. Furthermore, the value of \( \vec{p}_i \) is defined in the following equations.

\[
\vec{p}_i = [uv] = \vec{p}r^*_i
\]

\[
r^*_i = \begin{bmatrix}
\cos \theta & -\sin \theta \\
\sin \theta & \cos \theta
\end{bmatrix}
\]

(18)

(19)

where \( r^*_i \) is the rotation matrix. Matched filter kernel that has been designed using equation (17) are normalised so that they have zero mean values. The normalised kernel functions \( K'_i(x,y) \) can be expressed as equations (20) and (21) below.

\[
K'_i(x,y) = K_i(x,y) - m_i
\]

(20)

\[
m_i = \frac{1}{a} \sum_{r \in k} K'_i(x,y)
\]

(21)

\( a \) is the number of \( N \) member while \( m_i \) is the mean value of the matched filter kernel \( K(x,y) \) (Al-Rawi et al., 2007).

2.5 Length filter

Length filter has similar function to other filters. Length filter works by applying certain threshold value on the labelled image. If the object on the labelled image has a smaller number member than the threshold value, then this object is minimalised. Length filter is commonly applied to reduce undesirable noise in the binary image (Ardizzone et al., 2008).

2.6 Foveal avascular zone segmentation

The last step of digital colour retinal fundus image processing is the segmentation of foveal avascular zone (FAZ). The FAZ segmentation is performed in five steps as follows.

1. The centre pixel of the vessel image is chosen as the reference point.
2. The vessel image is divided into eight rights triangle objects, each sized 100 × 100 pixels, and then object labelling operation is performed on each object.
Then, the distance between the reference point and all vessel pixels on that object is measured.

The retinal blood vessel endpoints are the pixels on each triangle that have the closest distance to the reference point.

Finally, all the points in the previous stage are connected to obtained the FAZ area.

2.7 Testing parameters

To analyse the segmentation results, a number of parameters are used, such as True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN), sensitivity, specificity and accuracy. These parameters are obtained by comparing the results of the proposed method to the ground truth. TP is the number of right data identified as right, while TN is the number of false data identified as false. On the other hand, FP is the number of false data identified as right, while FN is the number of right data identified as false. The three remaining parameters values can be defined based on the TP, TN, FP, and FN values. All of them can be defined using equations (22), (23) and (24) below.

\[
\text{Sensitivity} = \frac{TP}{TP + FN} \times 100\% \quad (22)
\]

\[
\text{Specificity} = \frac{TN}{TN + FP} \times 100\% \quad (23)
\]

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \quad (24)
\]

Sensitivity is equal to the True Positive Ratio (TPR), while False Positive Ratio (FPR) is equal to 100% – specificity.

3 Results and discussions

3.1 Digital colour retinal fundus image database

In this work, DRIVE database is used to test our scheme. DRIVE consists of 40 digital colour retinal fundus images, but only thirty five images are used in this study, due to the appearance of FAZ in the digital colour retinal fundus images. Examples of the used and unused images are shown in Figure 2.

There is a fundamental difference between the two images in Figure 2. In the left image, the FAZ can be observed, which is located at the centre of the image. In contrast, in the right image, the FAZ is located at the edge of the image that makes it difficult to identify. The left image shows the criteria used in this study where the FAZ should be observed.
Figure 2  Examples of (a) used digital colour retinal fundus image and (b) unused digital colour retinal fundus image

![Figure 2](image)

Figure 3  Examples of (a) red, (b) green, and (c) blue channel image

![Figure 3](image)
3.2 Pre-processing

Pre-processing step consists of two operations, namely green channel acquisition and cropping of each digital colour retinal fundus image. The colour retinal image has an RGB format which each channel is represented by a certain matrix. Therefore, the green channel acquisition is performed by taking the matrix representing the green channel. The red and blue channels are obtained using similar way. The red, green, and blue channel images are depicted in Figure 3.

In Figure 3, the green channel image has the best contrast and illumination compared to the other two channels. Therefore, the green channel is selected in the subsequent process. The second process of the pre-processing step is image cropping. The cropping process is done automatically on the green channel image from the initial resolution of $565 \times 584$ pixels to $200 \times 200$ pixels. Figure 4 shows an example of the cropping process result. In Figure 4, the black frame shown in the left image is omitted, and the estimated macular region is obtained as shown in the right image.

Figure 4  Retinal fundus images (a) before and (b) after cropping operation

3.3 Image enhancement

Image enhancement step is divided into two operations, which are multiscale top-hat transformation and histogram fitting stretching. Multiscale top-hat transformation operation is performed according to equations (1) to (14). Figure 5 shows the multiscale top-hat transformation image result. In Figure 5, the multiscale top-hat transformation image has a higher contrast than the input image. Thus, the contrast of the retinal blood vessels to the background has been successfully enhanced.

The output image of the multiscale top-hat transformation process becomes the input of the fitting histogram stretching process. This step is performed with a linear contrast stretching operation according to equation (15) with the consideration of the upper ($I_{\text{max}}$) and bottom ($I_{\text{min}}$) limits. Both values can be determined using equation (16) by taking into account the results of multiscale top-hat transformation and histogram approaches. Figure 6 shows the input and output images of this operation. As shown in Figure 6, histogram fitting stretching operation increases the image contrast. This is proven by the
clear distinction between the retinal vessels and the background. Along with the increase of the image contrast, the process of retinal blood vessels segmentation can be run optimally in the subsequent process.

**Figure 5** Retinal fundus images (a) before and (b) after Multi-scale Top-Hat Transformation operation

![Retinal fundus images](image)

**Figure 6** Retinal fundus images for (a) input and (b) output of histogram fitting stretching

![Retinal fundus images](image)

### 3.4 Retinal blood vessel segmentation

Retinal blood vessels segmentation is implemented using matched filter and length filter. The matched filter is performed by convolving 12 matched filter kernels with images taken from the earlier step. Each kernel is calculated according to equations (17), (18), (19), (20) and (21). The kernel is rotated 12 from $\theta = 0^\circ$ to $165^\circ$, with the change value of $\theta$ is equal to $15^\circ$. Each pixel of the obtained images is only taken for the maximum value.

There are several matched filter parameters other than $\theta$ which are important to be determined, namely $\sigma$, $L$ and $T$. For this reason, the segmentation tests have already been
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done to get the optimum values of these parameters. Testing is conducted by comparing the retina vessel segmentation results to the ground truth. The test is performed on image 26 until 30, with \( \sigma \) equals to 1, \( L \) equals to 6–8.5 and \( T \) equals to 5–6 for \( \theta \) rotation from 0° until 165°.

From the test, the values of TPR and FPR are obtained. Based on the TPR and FPR values, the values of the quality factor (QLT) can be determined using equations (25) and (26) below.

\[
TPR = FPR \times Q_{LT}
\]

\[
Q_{LT} = \frac{TPR}{FPR}
\]

According to the above equations, the best values of \( L \) and \( T \) are obtained as shown in the Table 1. It appears that the tests on the five images yield the same pair values of \( L \) and \( T \), which are 8.5 and 5.1. These pairs give the \( Q_{LT} \) values of 3.98, 3.81, 4.70, 4.53, and 4.15 respectively. Figure 7 shows an example image of the retinal blood vessels segmentation with a matched filter using \( L \) and \( T \) values in Table 1.

<table>
<thead>
<tr>
<th>Image number</th>
<th>( L )</th>
<th>( T )</th>
<th>( Q_{LT} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>26</td>
<td>8.5</td>
<td>5.1</td>
<td>3.98</td>
</tr>
<tr>
<td>27</td>
<td>8.5</td>
<td>5.1</td>
<td>3.81</td>
</tr>
<tr>
<td>28</td>
<td>8.5</td>
<td>5.1</td>
<td>4.70</td>
</tr>
<tr>
<td>29</td>
<td>8.5</td>
<td>5.1</td>
<td>4.53</td>
</tr>
<tr>
<td>30</td>
<td>8.5</td>
<td>5.1</td>
<td>4.15</td>
</tr>
</tbody>
</table>

The next stage is to perform the segmentation of the entire images, with a pair of values of \( L \) and \( T \). Using this segmentation, the average levels of sensitivity, specificity, accuracy and \( Q_{LT} \) obtained are 81.95%, 80.85%, 80.95% and 4.37. Referring to Figure 7, it shows that there are non-blood vessels objects which can be categorised as noise. To overcome this, a length filter is used. The length filter operates by applying a threshold value (N). The number of noise pixels in a neighbourhood which is less than the value of \( N \) will be omitted. In this study, the value of \( N \) is selected from the sets of \{50, 100, 150 and 200\}. The results of the filter length for the four values of \( N \) can be seen in Figure 8.

The next stage is the segmentation of the entire images, with the four \( N \) values. From this segmentation, with \( N = 50 \), the average levels of sensitivity, specificity, and accuracy obtained are 80.36%, 85.07% and 84.62% respectively. The values of \( Q_{LT} \) and \( Q_N \) can also be defined by taking the ratios of TPR and FPR. This experiment results in the \( Q_N \) value of 5.56. Meanwhile, for \( N = 100 \), the average levels of sensitivity, specificity, accuracy and \( Q_N \) obtained are 79.23%, 85.87%, 85.24% and 5.82 respectively.

Furthermore, for \( N = 150 \), the average levels of sensitivity, specificity, accuracy, and \( Q_N \), obtained are 78.57%, 86.20%, 85.47% and 5.92 respectively. Finally, for \( N = 200 \), the average levels of sensitivity, specificity, accuracy and \( Q_N \) obtained are 77.99%, 86.43%, 85.24% and 5.99. By comparing the available data, it can be said that the result of the length filter segmentation with \( N = 200 \) gives the best result, compared to \( N = 50, 100 \) and 150 because it has the highest \( Q_N \) value.
Figure 7  An example image of the retinal blood vessels segmentation with a matched filter for $\sigma = 1, L = 8,5, \text{and } T = 5,1$

Figure 8  Length filter image result with (a) $N = 50$, (b) $N = 100$, (c) $N = 150$, and (d) $N = 200$
3.5 Foveal avascular zone (FAZ) segmentation

According to the steps described earlier, the process of the FAZ segmentation is presented in Figure 9. As shown in Figure 9, the FAZ segmentation process consists of (a) determination of the image centre point, (b) detection of the blood vessels end points, (c) establishment of the polygon and (d) detection of the FAZ. The image centre point is marked with a green plus sign (+), while the endpoints of blood vessels are marked with red plus signs (+). Furthermore, the polygon is formed by white lines, and the FAZ is characterised by the white region. Figure 10 shows the comparison between the detected FAZ of the proposed method and the ground truth.

**Figure 9** FAZ segmentation process: (a) determination of the image centre point, (b) detection of the blood vessels end points, (c) establishment of the polygon, and (d) detection of the FAZ.
The next stage is the FAZ segmentation on all digital colour retinal fundus images. At this stage, the high mean of sensitivity, specificity and accuracy are obtained (80.86%, 99.17% and 97.49%, respectively). In addition, the obtained average radius difference of the detected FAZ of the proposed method and the ground truth is quite small, which is 5.49 pixels. The results indicate that our scheme has successfully detected the FAZ area automatically. However, this method is not fully automatic due to the user interruption needed to select the initial point of the FAZ centre point. We suggest other researcher to develop an automated method for the centre of macula or fovea detection that can be used to substitute the user point. Fully automated FAZ area detection can be used to assist ophthalmologists to diagnose or detect DR.

4 Conclusion

A scheme for automated segmentation of foveal avascular zone (FAZ) in digital colour retinal fundus images has been successfully developed. The proposed scheme consists of four image processing stages, which are pre-processing, image enhancement, retinal vessels segmentation and FAZ segmentation. Result shows that the average levels of sensitivity, specificity and accuracy obtained are 80.86%, 99.17% and 97.49%, respectively. This finding shows that the proposed scheme has successfully detected the FAZ area automatically. Further research work can be conducted on the use of this proposed method for DR grading.

References

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