PAPER

Extraction of Blood Vessels in Retinal Images Using Resampling High-Order Background Estimation

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SUMMARY In retinal blood vessel extraction through background removal, the vessels in a fundus image which appear in a higher illumination variance area are often missing after the background is removed. This is because the intensity values of the vessel and the background are nearly the same. Thus, the estimated background should be robust to changes of the illumination intensity. This paper proposes retinal blood vessel extraction using background estimation. The estimated background is calculated by using a weight surface fitting method with a high degree polynomial. Bright pixels are defined as unwanted data and are set as zero in a weight matrix. To fit a retinal surface with a higher degree polynomial, fundus images are reduced in size by different scaling parameters in order to reduce the processing time and complexity in calculation. The estimated background is then removed from the original image. The candidate vessel pixels are extracted from the image by using the local threshold values. To identify the true vessel region, the candidate vessel pixels are dilated from the candidate. After that, the active contour without edge method is applied. The experimental results show that the efficiency of the proposed method is higher than the conventional low-pass filter and the conventional surface fitting method. Moreover, rescaling an image down using the scaling parameter at 0.25 before background estimation provides as good a result as a non-rescaled image does. The correlation value between the non-rescaled image and the rescaled image is 0.99. The results of the proposed method in the sensitivity, the specificity, the accuracy, the area under the receiver operating characteristic (ROC) curve (AUC) and the process-
Many methods of retinal blood vessel extraction have been proposed. The previous methods are normally grouped into a pattern recognition method, a matched filtering method, morphological processing, a multi-scale method and a pixel-parallel approach which is designed for the hardware implementation. The pattern recognition method [10]–[13] uses the vessel features such as thickness, color, shape and response signal for classifying or detecting the true vessels from their background. The vessel feature is given by the supervised method or the unsupervised method. The matched filtering method [14]–[18] normally creates a 2-D kernel model and convolves it with a retinal image. The design of a 2-D kernel model is normally based on the vessel properties such as the vessel cross-section which is in Gaussian-shape, vessel’s width which is reducing while the distance between the vessel and the optic disc is increasing. However, the problem of using the matched filtering method is that the matched filter responds to the vessel edges as well as the non-vessel edges. Morphological processing [19], [20] is also used for extracting the vessels from their background. It is done by using a morphological operator such as dilation and erosion to extract vessel in a retinal image. According to the different size of the vessels in a retinal image, the multi-scale method [21], [22] is applied. A pixel-parallel method [23], [24] splits the fundus image into subwindows. The vessels are extracted from each subwindow. The advantage of this method is that it is faster. Moreover, it can be implemented on VLSI chip.

As far as the non-uniform illumination problem in a fundus image is concerned, many background estimation methods in a retinal image have been proposed. The first method is performed by using adaptive estimation based on local neighborhood information [25]. The local contrast normalization [8] is performed in a green channel of RGB color model. The vessels are extracted by growing candidate seeds to fill in the watershed region. The iterative Savitzky-Golay smoothing procedure [26] is used to estimate the retinal background surface. Iterative robust homomorphic surface fitting algorithm, which combines Homomorphic filtering and surface fitting, is also proposed [27], [28]. The retinal image is modeled as an illumination and reflectance component. The weight surface fitting is used to estimate an illumination component while Homomorphic filtering is performed to get a reflectance component. However, this method requires retina-specific information such as vessels, optic disc, maculas and lesions which leads to more complexity and processing time in calculation. Moreover, thin and low contrast vessels and the vessels which appear in high variance of illumination are often removed after the background is removed. Furthermore, the previous methods are not suitable for practical screening systems because they require more processing time, 15 minutes per image on average [12]. The authors have proposed the background estimation method of a fundus image using a high degree polynomial [29] with a global threshold value for extracting the vessels from the background. Although it was assumed that the intensity values along the vessel line were the same, actually they are not. Thus, the previous papers cannot pick up all the vessel regions.

This paper proposes a retinal blood vessel extraction using the resampling high-order background estimation in order to estimate the background which is the non-uniform data while preserving the thin and low contrast vessels in the retinal image. The unwanted data which is defined as bright pixels is set as zero in the weight matrix. After that, the estimated background is given by using a polynomial weighted surface fitting method. However, some vessels such as thin and low contrast vessels are sensitive to the changed illumination, so they must fit data with a higher degree polynomial. But surface fitting with a high degree polynomial provides complexity in calculation and requires more processing time. To solve these problems, rescaling an image down using different rescaling parameters is tested. The correlation value between the non-rescaled image and the rescaled image by different scaling parameters shows the performance of the background estimation. The candidate vessel seeds are given by applying the local thresholding method. To identify the true vessel area, the candidate vessel seeds are grown in order to occupy the space inside the vessel wall and after that, the vessel is eroded by an active contour without edge in order to preserve the true vessel size. In the vessel extraction, this paper compares the results of the manual segmentation made by 2 observers, who were instructed and trained by an ophthalmologist, in order to provide the manual segmentation from the DRIVE database [12], [30] with the results of other methods in the sensitivity, specificity, accuracy, area under the receiver operating characteristic curve (AUC) and processing time.

## 2. Problem Analysis of Retinal Blood Vessel Extraction

In this paper, the method of extracting vessels by removing the estimated background from the original grayscale image is evaluated. The vessels are extracted by applying the adaptive local threshold. However, to estimate the background by using the linear method such as a large mean and median filter is not suitable because of the non-uniform illumination problem in the retinal image. This problem is that many vessels are removed from the original grayscale image before the vessel extraction process. Moreover, the vessels, which are extracted by applying the adaptive local threshold from the removed background, are incomplete vessels because the values of the vessel intensity along the vessels are not the same. In this section, the problems of retinal blood vessel extraction which are the background estimation problem and the vessel area identification problem are discussed.

### 2.1 Background Estimation Problem

In a fundus image, the vessels are presented as reddish or dark pixels and many of these pixels are connected along a linear line. They normally start from an optic disc and go all over the retina forming the vascular tree. The vessels become thinner and smaller when the distance from the op-
tic disc is increasing. In the same image, the contrast and color of the vessels are different because of the vessel types (veins or arteries), their diameter and where the vessels are situated. The contrasts and colors of the vessel in each area are also different because of the non-uniform illumination as shown in Fig. 1. For example, comparing between area A which is close to the optic disc and area B and C which are far from the optic disc, the contrast of the vessel manually segmented from the area A in Fig. 1 (a) as shown in area MA in Fig. 1 (b) is obviously higher than the ones manually segmented from the area B and C in Fig. 1 (a) as shown in area MB and MC which are far from the optic disc in Fig. 1 (b). Even though there is the vessel information in area B and C as shown in area MB and MC in the manual segmentation image (Fig. 1 (b)), they are difficult to be extracted from their background because of their low contrast problem. The thin and low contrast vessel (such as the vessel in area B and C in Fig. 1 (a)) is very important information in the screening system. This is because the early state of the disease can be observed by examining the changes in the vessels which normally occur at capillaries, and are represented as thin and low contrast vessels. One problem of vessel extraction in a retinal image is the non-uniform illumination problem. The retinal image is normally suffered by non-uniform illumination caused by image obtainment, retina response and limitation of the medical device. The non-uniform illumination problem causes low efficiency in the vessel extraction. To solve the non-uniform illumination problem, shade correction [31] is recommended to be employed in order to enhance the vessel contrast. The shade correction tries to estimate the background of an image and removes it from the original image. However, many vessels are simultaneously removed from the image when the estimated background is removed. To solve this problem, based on the fact that the background intensity of a fundus image is nonlinear data, this paper proposes the polynomial weight surface fitting method for background estimation in retinal surface fitting process. However, the vessels which are located in high variation intensity areas require higher degree polynomial fitting because they are quite sensitive to the background which is changed by non-uniform illumination in fundus images. Unfortunately, higher degree polynomial fitting is suitable for fitting the background of a fundus image which suffers from non-uniform illumination, it requires more processing time and parameters. To solve this problem, rescaling an image down by using different scaling parameters is proposed for reducing the calculation parameter in the background estimation process.

2.2 Vessel Region Identification Problem

The retinal blood vessels which are extracted from the removed background image are given by the local thresholding method. These extracted vessels are not complete vessels because of their various sizes and different intensities. This paper defines the pixels given by applying the local thresholding method as the candidate vessel seeds. These candidate vessel seeds need to be extended in order to occupy the space inside the vessel wall which is not represented after applying the local thresholding method. Then, the grown seeds or extended pixels are eroded in order to get the true vessel area. The basic concept of true vessel region identification is shown in Fig. 2.

According to Fig. 2 (a), the candidate vessel seeds which are given by applying the local thresholding method are represented by the black pixels while the dashed lines
represent the true vessel wall. To get the true vessel region, the candidate vessel seeds need to be grown to completely occupy the region inside the true vessel wall as represented by the gray pixel in Fig. 2 (b). However, the grown vessel seeds need to be eroded in order to get the true vessel area which is defined as the area inside the vessel wall as shown in Fig. 2 (c).

3. Proposed Method

The proposed method of vessel extraction is shown as a block diagram in Fig. 3. First the background of the fundus image is estimated by applying the polynomial weight surface fitting method. The estimated background is subtracted from the original grayscale image in order to reduce the non-uniform illumination problem in the fundus image. The candidate vessel seeds are extracted from the removed background image by applying the local thresholding method. Since the candidate vessel seeds are not the complete vessels, the true vessel area identification method is needed. This section explains the background estimation and the true vessel area identification method.

3.1 Background Estimation

An original image, which is represented as the RGB color model as shown in Fig. 4 (a), is converted to a grayscale image as shown in Fig. 4 (b) and is used as an input image. In the vessel extraction, the green channel of RGB color image is normally chosen as an input image because the green channel provides better contrast than other channels. However, some vessel information does not occur only in the green channel but also in other channels. This paper applies the vessel extraction in a grayscale image which is given by weighing each channel based on the human perception [32], [33] as shown in Eq. (1).

\[
I_g(x, y) = 0.2989R(x, y) + 0.5870G(x, y) + 0.1140B(x, y)
\]  

(1)

where \(I_g\) is grayscale value. The R, G and B are the red, green and blue components respectively.

In the vessel extraction, since the over and under-estimation generally occur when the darker and the brighter pixels are used in the estimation process, the weight matrix, Fig. 4 (c), is applied in order to discard the unwanted data before the estimation process. After that, the fundus background is estimated by using the polynomial weighted surface fitting method. However, the background that requires a higher degree polynomial fitting leads to calculation complexity and longer processing time, so rescaling the image down before the background estimation process in order to reduce calculation complexity and processing time is needed.

3.1.1 Data Weighing

To estimate the background of a fundus image, the bright pixels (such as Optic disc and Exudate), and the dark pixels (such as microaneurysm, hemorrhage and vessels) are generally defined as unwanted data in order to discard over and under-estimation problems respectively. However, in practicality, some vessels are removed from the image after the background is removed because the intensity of the vessels is nearly the same as their background. For the proposed method, under-estimation is acceptable while over-estimation is not acceptable. This is because the vessel will be removed when the estimated background value is higher than the original image. Thus, only the bright pixels are defined as unwanted data as shown in Fig. 4 (c). In this paper, the global threshold value is calculated by using mean and standard deviation of intensity of each image in order to get the weight matrix.

3.1.2 Retinal Surface Fitting

The non-uniform illumination problem in a retinal image is focused in this paper. Since the distribution of the illumination in a fundus image is not in a linear distribution form, fitting the curve by using the linear fitting method is not suitable for estimating the background data. Thus, this paper uses the polynomial weighted surface fitting [27], [28] which is formulated as Eq. (2) and Eq. (3) to estimate the background of a fundus image.

\[
\vec{E} = S \vec{P}
\]  

(2)

where \(\vec{E}\) is estimated background vector, \(S\) is surface matrix, and \(\vec{P}\) is parametric surface vector.
where \((m \times n)\) is the number of image pixels and \((x, y)\) is the pixel coordinate.

To estimate the fundus image size \((m \times n)\), the estimated background vector \(\vec{E}\) is given by rearranging the estimated background image in every pixel of every position \((x, y)\). The surface matrix is defined as \(A^th\) order polynomial which has \(n\) parameters. The number of elements \((N)\) of the surface matrix \(S\) depends on the selected degree polynomial. The higher the degree of the polynomial that is selected, the greater the calculating parameters are needed. The parameter vector based on the weight least-squares estimation can be calculated by Eq. (4).

\[
\vec{P} = (S^T W_{gh} S)^{-1} (S^T W_{gh} \vec{I}_g)
\]

where \(W_{gh}\) is a diagonal weight matrix \((m \times n) \times (m \times n)\) and \(\vec{I}_g\) is defined as the intensity vector of the grayscale image.

3.1.3 Reduction of Calculation Parameter

Even though the higher degree polynomial leads to the better suitability of background estimation in extracting the vessels, it also produces greater parameters. Moreover, it requires complexity in calculation and it is time consuming. Practically, in the calculation process, the calculation parameters are reduced by ignoring the pixel that is weighed as ‘0’ in the weight matrix. However, many of these pixels need to be calculated, for example, the normal and the diseased case which do not have any bright lesions such as hard exudate. To solve this problem, the method of rescaling an image down using different scaling parameters before the background estimation process is proposed. Twelve scaling parameters \((sf)\) which are 1, 0.9, ..., 0.3, 0.25, 0.2, 0.125 and 0.1, are tested on each image. The estimated background of each different scaling parameter is rescaled up in order to be the same size as the original grayscale image before the background removal process. In this paper, the bicubic interpolation technique is used to rescale an image down before the background estimation and to rescale an image up before the background subtraction process. This is because it is a fast and easy method while it provides good results as using an input image.

3.2 Vessel Region Identification

The estimated background done in 3.1 is removed from the original grayscale image in order to eliminate non-uniform illumination. This background-removed image is then utilized as input data of the next process of vessel region identification. In the vessel region identification, candidate vessel seeds are extracted from the image using the local thresholding method and local window. In determining the threshold, Otsu’s thresholding method [34] which is assumed as a simple one is applied in this process, and the local window size basically depends on average width of vessels which is defined as 8 pixels [35]. In this paper, we therefore apply weighted averaging in local area of 9 × 9 (which covers average width of 8 pixels) using Gaussian low-pass filter to smooth the image before automatic computation of the fixed thresholding value from each area. However, the extracted candidate vessel seeds in this step are not completed in term of shape due to fixed threshold value so that we propose to recover them by dilating and then eroding them as described in the following sections.

3.2.1 Dilation

In order to recover vessel shape, dilation using mathematical morphology with a square structuring element is performed on the extracted candidate vessel seeds. Due to the average width of the vessel (8 pixels), the square structuring element is set at 4 × 4 according to half of the average size of the vessel [35]. Since the grown vessel seeds by dilation are assumed to include some noises due to fixed threshold value, these noises should be eliminated before operating the dilation process. In this paper, we assume that a vessel consists of a group of pixels connecting along a line so that vessel pixel group can be differentiated from non-vessel-pixel group by an appropriate number of pixels in the group as threshold value.

3.2.2 Erosion

The dilated candidate vessel seeds are eroded in order to recover the vessel shape. In erosion of dilated candidate vessel seeds, especially thin vessels with low contrast, we apply the active contour without edge method based on the Chan-Vese Algorithm [36]. In this method, the global statistic is used to extract the objects from background-removed image. Although this method is generally sensitive to the initial contour and requires manual setting as its disadvantage, the dilated candidate vessel seeds whose shape is close to the expected results need less processing time without manual setting as the advantage of the proposed method. The eroded candidate vessel seeds are then grouped by using the 8-connected-component labelling method. Among those groups, vessel groups are differentiated from non-vessel groups by using appropriate number of vessel pixels in the group as threshold value. A sample of vessel region identification following the block diagram in Fig. 5 is shown in Fig. 6.
4. Experimental Results

Vessel extraction is one of the most important processes in medical applications such as automatic DR scanning system, and so on. In this paper, we focus on the problem of vessel extraction, especially very thin and low-contrast ones, since the extracted retinal blood vessels would be correctly removed from the retinal images in the next process. In the experiments, we therefore aim to mainly evaluate the performance of our proposed blood vessel extraction which would reflect to the blood vessel removal process.

4.1 Database

To evaluate the efficiency of the proposed method, the well known public dataset, which is the DRIVE database [12], is tested. The DRIVE database consists of 40 images which are made up of a test and training set and a ground-truth set made by 2 experts. In the ground-truth set, the manual observation set made by the 1st observer is used as the gold standard while the other made by the 2nd observer is used as the manual segmentation. The images of the DRIVE database are acquired by using a Canon CR5 non-mydriatic 3CCD camera with a 45° field of view (FOV). Each image was captured using 8 bits per color plane at 768 × 584 pixels. The field of view of each test image is a circular area within the image of 540 × 540 pixels. The DRIVE database is widely used as the test set because it is an open database. Moreover, this database provides the ground-truth which are two manual segmentations. Thus, this database is widely used as the test set and it was also used to test the performance of the previous methods. In addition, the performance of the previous methods when it comes to accuracy, sensitivity, specificity is widely compared by calculating the experimental results with this database. This is because the experimental results of the previous methods are tested and compared to the experimental results using the same database and conditions. This paper tested 40 images from both test and training set of the DRIVE database. In the performance evaluation, the experimental results are compared with the previous methods in sensitivity, specificity, accuracy, area under the ROC curve (AUC) and processing time per image. Since the previous methods and the proposed method used all 20 sample images from the test sets of the DRIVE database to test the performances, it means we use the same database and the same condition. All of the tests were performed on a computer with an Intel® Core™ i7-2640M CPU @ 2.8GHz.

4.2 Vessel Extraction by Removing Background

The retinal blood vessels are extracted by removing the estimated background from the original grayscale image. The estimated background is calculated using the polynomial weight surface fitting. The six different degree polynomials which are the 4th to the 9th are used to estimate the background of the image. The experimental results of using each degree polynomial are shown in 2 types which consist of the estimated background and the extracted vessel by subtracting the estimated background from the image respectively as shown in Fig. 7. In the true vessel region identification process, this paper sets the appropriate pixels for non-candidate vessel seeds and non-vessel regions as 20 pixels and 100 pixels respectively. The vessels which are extracted by removing the estimated background using the 6th degree polynomial provide the better result when it is compared with the 4th and the 5th degree polynomial. This is because it does not only extract the main vessels which are veins and arteries, but also preserves thin and low contrast vessels as shown in the red circle in Fig. 7. Furthermore, it provides nearly the same result as a fitting curve with the 7th degree polynomial. However, the fitting curve using the 7th degree polynomial requires more parameters than the 6th degree polynomial, so that 6th degree polynomial is chosen.
To compare the proposed method performance with the conventional fitting method using the 4th degree polynomial, 1-D signal is scanned and plotted. This paper chooses the 260th line (row) as shown in Fig. 8 to plot because this line passes through many structures of the retina which are the optic disc, macula, fovea, vessels and so on. The result gained from using the 260th (row) of estimated background with the 4th to the 9th degree polynomial fitting is plotted as a 1-D signal and compared with the original signal and the smooth signal which is acquired by using a mean filter. The area inside the dashed circle in Fig. 8, shows the error in vessel extraction caused by fitting the background using the 4th and the 5th degree polynomial. Hence, background estimation using the 4th and the 5th degree polynomial fitting is not good enough to estimate the background of an image. However, higher degree polynomial fitting requires more pa-
4.3 Rescaling Image Down for Retinal Background Fitting in Higher Degree Polynomial

Considering the fact that the background estimation using higher degree polynomial fitting provides more processing time and parameters, this paper solves these problems by rescaling an image down before fitting the background. Twelve different scaling parameters which are 0.1, 0.125, 0.2, 0.25, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 and 1 are examined. The performance evaluation of a background estimation using different scaling parameters is measured by using a correlation value. The correlation value of each image is calculated by comparing the estimated background of the non-rescaled image and the rescaled images. The correlation value of an estimated background using different scaling parameters is compared with a non-rescaled image as shown in Fig. 9.

The correlation result shows that using 0.25 as a scaling parameter provides a better result than the others. It is because its result is nearly the same compared with using higher scaling parameters, 0.3 to non-rescaled image. Moreover, it is in an accepted value which is set at 0.99. Figure 10 shows the extracted vessel results of 12 different scaling parameters.

Figure 11 shows the extracted vessel and the estimated background using 4 different scaling parameters. The results show that to rescale an image down before background estimation by setting scaling parameter at 0.25 provides the best results compared with the others. This is because it not only reduces the processing time and the parameters in calculation, but also provides the results which are nearly the same as the results of setting the scaling parameter at 1 and 0.5 respectively. Moreover, the result is better than setting scaling parameter at 0.125 and 0.1.

Figure 12 shows the experimental results of 5 different images which fit the data by the same degree polynomial, the 6th degree polynomial, while each image is rescaled down by using four different scaling parameters which are 1 (non-rescaled image), 0.5, 0.25 and 0.125 respectively. The experimental results are compared with the manual segmentation done by the 1st observer [12], [30] pixel by pixel at the same position (x, y) of a retinal image. According to the resolution of the retinal image, the smallest vessel is equal to one pixel so that the segmented pixel from the experimental results which is represented in both experimental and the manual segmentation result made by the 1st observer is decided as the true vessel. The results show that rescaling an image down using the scaling parameter at 0.25 is better than the others. It is because it not only provides the same results as using a non-rescaled image (sf = 1) or rescaling an image using the scaling parameter at 0.5, but it also re-
quires fewer calculation parameters. Moreover, it provides a better result compared with using the scaling parameter at 0.125. Considering the thin and low contrast vessel extraction, the experimental result is compared with the manual segmentation made by 2 observers as shown in Fig. 13.

This paper uses 4 widely known performance measures to evaluate the performance of the proposed method which are the sensitivity, the specificity, the accuracy and the area under the receiver operating characteristic (ROC) curve (AUC). The sensitivity, specificity and the accuracy of the performance are calculated by Eq. (5), Eq. (6) and Eq. (7) respectively.

\[
sensitivity = \frac{TP}{TP + FN} \tag{5}
\]
\[
specificity = \frac{TN}{TN + FP} \tag{6}
\]
\[
accuracy = \frac{TP + TN}{TP + FN + TN + FP} \tag{7}
\]

where TP is true positive, TN is true negative, FP is false positive and FN is false negative.

The receiver operating characteristic (ROC) curve is a plot of the sensitivity versus the \( 1 - specificity \) by using a varying threshold on the probability map. The area under the ROC curve (AUC) which the maximum value is equal to 1 is used for measuring the performance. The larger the AUC value, the better performance it is. In this paper, DRIVE database is selected for performance evaluation of the proposed method. In evaluation, we follow the process as shown in the block diagram in Fig. 5. The key factor in the first block of Candidate Vessel Seeds Grouping is threshold value for vessel seed grouping. If the threshold value is small, noises would be picked up and errors occur. In case of large threshold value, very small vessels would not be extracted and grouped. In this paper, we have performed the pre-test for threshold value determination in advance. In the pre-test, number of connected pixels in a retinal image are varied from 5 to 40 pixels for grouping in pixel groups of vessel candidates (8 groups; step up by 5 pixels), and the experiments are performed in each pixel-number group in
Table 1  Performance evaluation using appropriate threshold value.

<table>
<thead>
<tr>
<th>Dataset/Performance</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Accuracy</th>
<th>AUC</th>
<th>Processing time (sec)</th>
</tr>
</thead>
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<tr>
<td>Test set</td>
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<td>0.9676</td>
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<tr>
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<td>0.9614</td>
<td>1.7514</td>
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Table 2  Comparison between the conventional methods and the proposed method in DRIVE database.

<table>
<thead>
<tr>
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<th>DRIVE database</th>
<th>AUC</th>
<th>Processing time (sec)</th>
</tr>
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<td>All background</td>
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<td>-</td>
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<td>Proposed Method</td>
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<td>0.9717</td>
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</table>

Figure 14  Receiver operating characteristic (ROC) curve for the DRIVE database.

order to find the most appropriate threshold value which obtains the best average accuracy. In this paper, the best threshold for removing the candidate vessel seeds is 20 pixels as describe in Sect. 4.2. The ROC curve which is the results of relation between sensitivity and specificity is plotted varying the 8 threshold values in Fig. 14. The performances of the most accurate threshold in terms of sensitivity, specificity, accuracy, AUC, and processing time are shown in Table 1.

Figure 14 shows the ROC curve of the test set of the DRIVE database. Table 2 shows the vessel extraction performance of the proposed method and the previous methods. All methods are tested on the same database which is the test set of DRIVE database [12]. The results show that the sensitivity, specificity, accuracy, area under the receiver operating characteristic curve (AUC) and processing time of the proposed method is as good as other methods while it requires less processing time.

5. Discussions

The vessel extraction plays an important role in many applications. However, it is difficult to extract all vessel structures especially the thin and low contrast vessels because of the non-uniform illumination problem in the retinal image. To preserve most of vessel structures in a retinal image, the background estimation method is proposed in this paper. To evaluate the performance of the proposed method, we utilize DRIVE database [12] to test with the proposed method. The experimental results in Table 2 show that the proposed method provides the best result in sensitivity. That means the proposed method is sensitive to the extraction of thin and low contrast vessels in a retinal image. Basically, the sensitivity would be traded off with specificity so that the specificity of the proposed method is a bit decreased. Considering in accuracy, the proposed method actually provides lower accuracy than the results of the previous methods ([10] and [11]). This is acceptable because the objective of the proposed method is to preserve thin and low contrast vessels after the background removal process so that it is necessary to design the method with high sensitivity. There are some false positive errors given by the proposed method. These errors should be accepted because in this case sensitivity is more preferable than accuracy, and the proposed method is designed for a mass screening system in which the final decision is made by a specialist doctor. Table 2 shows that the proposed method provides the best result in the area under the receiver operating characteristic curve (AUC) compared with the previous methods. Moreover, the proposed method requires less processing time to extract the vessel from the
image than the previous methods ([12], [13] and [20]) except the one made by Alonso-Monteset et al. [23]. Although, the proposed method requires more processing time, the experimental results which are the accuracy and the AUC are better.

6. Conclusion

The background estimation using resampling high-order background estimation for retinal blood vessel extraction is proposed in this paper. This background estimation method is estimated by using the higher order degree polynomial fitting method in order to preserve thin and low contrast vessels after the background removing process. Resampling the image before background estimation is performed in order to reduce complexity in calculation caused by using the higher degree polynomial fitting. The candidate vessel seeds are extracted from the removed background by the local thresholding method. These candidate vessel seeds are grown up in order to cover the vessel region. Then the grown vessel seeds are eroded by using the active contour without edge in order to get the vessel region. The result shows that the proposed method can preserve not only main vessels but also thin and low contrast vessels after the background removal process.

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