Retinal vessel segmentation using modified symmetrical local threshold

Umar OZGUNALP 1

1 Electrical and Electronics Engineering, Engineering Faculty, Cyprus International University, PB:99258, Nicosia, North Cyprus, Mersin 10 Turkey

Abstract: Retinal vessel segmentation is important for the identification of many diseases including glaucoma, hypertensive retinopathy, diabetes, and hypertension. Also, retinal vessel diameter is associated with cardiovascular mortality. Accurate detection of blood vessels improves the detection of exudates in color fundus images, as well as detection of retinal nerve, optic disc or fovea. A retinal vessel is a darker stripe on a lighter background. Thus, the objective is very similar to the lane detection task for intelligent vehicles. A lane on a road is a light stripe on a darker background (i.e. asphalt). For lane detection, the Symmetrical Local Threshold (SLT) is found to be the most robust feature extractor among the tested algorithms in the Road Marking (ROMA) dataset. Unfortunately, the SLT cannot be applied directly for retinal vessel segmentation. The SLT is a 1D filter and is designed for detecting vertical or close to vertical light stripes with predictable width. In this paper, the SLT is modified to detect dark stripes and four kernels, instead of one, are designed to detect both vertical and horizontal features of a retinal vessel with variable thickness. The proposed algorithm is tested using the High Resolution Fundus (HRF) image database and the accuracy is estimated to be 95.53%. Furthermore, when tested with the Digital Retinal Images for Vessel Segmentation (DRIVE) database, the accuracy is estimated to be 93.69%.

Key words: Retinal vessel segmentation, Feature extraction, Symmetrical Local Threshold, retinopathy

1. Introduction

Ocular fundus images can reveal many pathological diseases related to cardiovascular, endocrine-metabolic, and central-nervous system [1]. Examination of the retinal vessel structure is also an important part of the diagnosis. For instance, tortuosity (non-smooth course of the vessel) is associated with blood pressure, and cardiovascular risks [2]. In [2], an association between the retinal vessel diameter and cardiovascular mortality was found. Furthermore, it is stated in [3] that detection of blood vessels can improve the detection of exudates in a color fundus image. While detecting vascular trees can reveal useful information for the diagnosis of various diseases such as Hypertension, Diabetes, and Glaucoma [4], an accurate detection result can also be used for locating the optic disc [5]. For the stated reasons, automatic detection of blood vessels from ocular fundus images is a vital task.

In the literature, many algorithms have been proposed based on both feature extraction and machine learning. Retinal vessel segmentation algorithms can be categorized into five groups [6]: pattern recognition based, matched filtering based, vessel tracking/tracing based, mathematical morphology based, model based, and machine learning based. In [7], a Gaussian filter has been used to detect retinal vessels. In [8], Match filter

*Correspondence: uozgunalp@ciu.edu.tr
is used as a feature extractor and vessels are detected using a high threshold. Subsequently, additional vein pieces are added to the segmentation based on the initially detected starting points. In [9], the Ridge detector is used to detect retinal vessels. In [4], an improvement on the Matched filter for retinal vessel segmentation has been proposed by measuring numerous perpendicular cross-sectional intensity profiles of retinal vessels and by designing the Match filter accordingly. In [10], a Genetic algorithm has been used to optimize the Match filter to detect retinal vessels. In [11], line tracking has been used to detect retinal vessels. In [12], and [13], CNN-based vessel segmentation is described and in [14], retinal vessels are segmented using an extreme learning machine.

In [15], veins are segmented based on creating vein probability map by filtering images with second derivatives of Gaussians with multiple scales and calculating eigenvalues of the outputs. In [16], the proposed algorithm, first detects and in-paints exudates, and then enhances vessels using multi scale Hessian eigenvalue analysis, and finally detects veins using percentile-based thresholding. In [17], discriminative dictionary learning based retinal vessel segmentation algorithm is proposed, where the proposed algorithm uses fusion of multiple features. [18] utilizes active contours to segment out vessels. [19] extracts multiscale features based on calculated Hessian values and enhances its results by using region growing algorithm. [20] utilizes Match filter to detect retinal vessels. In the algorithm, while retinal vessels are detected using Match filter, the threshold is adjusted based on the first order derivative of Gaussian. The proposed method in [21], first extracts feature maps for vessel pixels, and then employs a neural network to segment out vessel pixels.

In this paper, a novel and accurate retinal vessel segmentation algorithm is proposed. The proposed algorithm is inspired by the Symmetrical Local Thresholding (SLT), which was originally proposed for lane detection (for intelligent vehicles). The detection of a lane from a road image and the detection of a vein from a retinal fundus image has certain similarities. For instance, detecting a lane marking requires the detection of a light stripe on a darker background and in the case of veins, it is necessary to detect a darker stripe on a lighter background. In the literature, it can be seen that some of the generic computer vision algorithms are already common for both lane marking segmentation, and retinal vessel segmentation. For instance, in [22], edge detection has been used to extract lane features and in [23], edge detection has been used for vein segmentation. In [24], a matched filter has been used to segment out lane markings and in [4], a matched filter has been used to segment out veins in retinal images. In [25], and [26], Gaussian filter-based lane feature extraction has been used and in [7], a Gaussian filter has been used for vein segmentation. In [27], Ridges have been used to extract lane features and in [9], Ridges have been used for vein segmentation. Although, there are many lane feature extractors in the literature, in [28], the authors tested the most common lane feature extractors and concluded that, although its simplicity, the SLT is the most accurate algorithm among those tested. However, there are differences between veins and lanes. The thickness of a vein can change considerably compared to a lane marking. Also, while lane markings are vertical or close to vertical, a vein can be in any orientation. the SLT is specifically designed for lane marking extraction and thus, several modifications are necessary on the SLT for vein detection. Hence, in this paper, a modified version of the SLT is proposed for vein segmentation on retinal images. The rest of the paper is organized as follows: in section 2.1, the features of a vein on a digital fundus image are described. In section 2.2, the standard SLT algorithm has been described. In section 2.3, proposed modifications on the SLT are described. In section 2.4, the applied post processing is described. In section 3, experimental results are given and a comparison is made in terms of sensitivity (SE), specificity (SP), and accuracy (ACC). Finally, in section 4, the paper is concluded. The block diagram of the proposed algorithm is shown in Figure 1.
2. Materials and methods

2.1. Features of a vein on a digital fundus image

Conventionally, to segment retinal vessels, only the green channel of the image is used for vessel segmentation [4]. Thus, in this paper, only the green channel of the RGB image is extracted (only the green pixel values are used and red, and blue pixel values are ignored) and treated as a grey scale image. An example input fundus image and its single channel output is provided in Figure 2.

It is observed that a retinal vessel has a Light-Dark-Light (LDL) property. This means that each pixel on a vein should have a lower intensity value compared to the two sides of the vessel. For instance, if the vein is vertical or close to vertical, the pixels on the left-hand side and the pixels on the right-hand side should both have higher intensity values. On the other hand, if the vein is horizontal, the pixels on the top and the pixels on the bottom should both have higher intensity values. This is demonstrated in the Figure 3. In Figure 3 (a), an example of a vertical vein extracted from an ocular fundus image is demonstrated. In Figure 3 (b), an example of a horizontal vein extracted from an ocular fundus image is demonstrated. Another important property of a vein captured by ocular fundus image is its thickness. The thickness of a vein can change considerably. This is demonstrated in Figure 4. In Figure 4 (a), example image with thin veins are shown, while in figure 4 (b), example image with thick veins are shown. Both of the images are extracted from the same ocular fundus image. The algorithm proposed in this paper is inspired by the SLT, which is useful for extracting lane markings from a road image. In the next section, the SLT and its use for lane marking extraction will be described. Then, properties of a lane and a vein will be compared and modifications on the SLT algorithm will be proposed for vein detection.

Figure 1: Block diagram of the proposed retinal vessel segmentation algorithm.
Figure 2: An example RGB image captured by a fundus camera and its green channel.

Figure 3: Example cross sectional areas for vertical and horizontal veins. (a) an example vertical vein extracted from an ocular fundus image. (b) an example horizontal vein extracted from an ocular fundus image.

Figure 4: Example cross sectional areas for thin and thick veins. (a) An example thin vein. (b) An example thick vein. Where there is a considerable thickness difference between two different veins in an ocular fundus image.
Algorithm 1 Symmetrical local threshold

\[ F \leftarrow \emptyset \]

\[ \text{while } I_p \in \text{ImageSize do} \]

\[ \text{if } I_p - T_h > \text{Average}_R \text{ and } I_p - T_h > \text{Average}_L \text{ then} \]

\[ F_{I_p} \leftarrow 1 \]

\[ \text{end if} \]

\[ \text{end while} \]

2.2. Symmetrical local threshold

A lane departure warning system (LDWS) is one of the crucial components of the intelligent vehicles. These systems are designed to warn the driver when the ego vehicle is departing from the road. The key component of a LDWS is the lane detection. Lane detection algorithms can be divided into two categories: feature-based and model-based [29]. While feature-based lane detection algorithms segment lane markings or road area, model-based algorithms, firstly extract the feature map, and then based on certain assumptions such as fixed road curvature, fixed road width or flat road, lanes are modelled (defined) by mathematical equations. In both of the cases, the first step is to segment the lane features. For lane feature extraction, many algorithms have been proposed including edge detectors [22], Otsu algorithm [30], Gabor filters [31], Local threshold [28], Matched filters [24], and the SLT [32]. Although feature extraction is the first and vital component of a lane detection system, there is no benchmark available for lane marking feature extraction. However, in [28], the authors implemented the most common lane feature extractors and compared them quantitatively using ground truths supplied in Road Marking (ROMA) datasets. ROMA dataset consists of 116 road images from diverse road scenes including variable lighting conditions, variable scene content, and variable road types. For these images, pixels from lane markings are manually labelled as ground truth lane pixels. Although, the SLT offers simplicity, the authors in [28], concluded that the SLT is the most robust feature extractor among those tested.

The SLT is designed to extract light stripes with vertical or near vertical slope. The SLT processes images row by row independently. In each row of the image, for each pixel, it calculates the average of the pixels on the left-hand side within the range, and then calculates the average of the pixels on the right-hand side within the range. If the intensity value of the pixel (Ip) minus a threshold (Th) value is larger than both left average (Average_L) and right average (Average_R), that pixel is estimated to be a feature point. As mentioned before, a lane marking has a dark-light-dark (DLD) property. DLD means that compared to the pixel intensity, the pixels on the left and pixels on the right need to be darker. The used threshold (the threshold is set to be 4 for the experiments) is necessary to remove noise from homogeneous areas. The pseudo-code of the algorithm is shown in Algorithm 1. The algorithm is illustrated in Figure 5, where the test pixel is shown with a blue dot and the area that is used to calculate the left average and the right average is shown with a yellow horizontal line.

2.3. Multi-scale multi-directional SLT

There are several differences between lane markings and retinal vessels. First, retinal veins have LDL property instead of DLD. Thus, pixel intensity plus a threshold needs to be lower than both the left average (Average_L) and right average (Average_R). For vein segmentation, the SLT is modified accordingly. Second, the SLT is a one-dimensional approach. Since, a lane marking on a road image is assumed to be horizontal or nearly horizontal, DLD feature is checked from left to right. Veins can be both horizontal and vertical. Thus, the SLT
algorithm is applied both vertically and horizontally. Third, veins have more variable thickness compared to lane
markings. It is common practice to use multiple kernels with variable thicknesses in vein segmentation. In the
proposed algorithm, similar logic is applied. The SLT uses a range to calculate $Average_L$ and $Average_R$ (i.e.
the number of pixels used to calculate the average). To consider both thick and thin veins, the SLT is applied
twice with a low range value (12 pixels) and a high range value (25 pixels) for both vertically and horizontally
(please note that these values are selected for the HRF database and when testing with the DRIVE dataset,
thickness values are changed directly according to the ratio between the image width of the HRF images and
the image width of the DRIVE images). Thus, the input image is filtered with the SLT four times in total:
two times in the vertical direction with different range values, and two times in the horizontal direction with
different range values. Each feature map is then passed through image erosion and image dilation respectively to
remove disconnected noises before applying logical "OR" operator. Input and output feature maps can be seen
from Figure 6. Subsequently, these four feature maps are combined together using a logical "OR" operator.
The pseudo-code of the algorithm is shown in Algorithm 2.

2.4. Post processing using major axis length

Connected component analysis and filters like median filter are the most commonly applied techniques to
eliminate disconnected noises such as salt and paper noise. It is already known that the veins are stripes. So,
even if there is a discontinuity, in the extracted vein one axis needs to be much larger than the other axis.
Thus, such a connected component has much larger perimeter, compared to a connected component with the
same size (total number of connected pixels). This can be observed from Figure 7. In Figure 7, two examples
of connected components are shown. When the properties of connected components in the figure are measured,
the connected component on the left is consist of 40449 pixels and its major axis length is measured as 140
(major axis length is the distance between two farthest pixels in a connected component). On the other hand,
the connected component on the right is consist of only 2028 pixels and its major axis length is measured as
156. It is a common approach to use connected component analysis to remove small sized noises by filtering
based on the number of connected pixels. However, since veins have stripe like shape and resemble the shape
Algorithm 2 Multi-Scale Multi-Directional SLT

\begin{algorithmic}
\State $F \leftarrow \emptyset$
\State $Fh1 \leftarrow \emptyset$
\State $Fh2 \leftarrow \emptyset$
\State $Fv1 \leftarrow \emptyset$
\State $Fv2 \leftarrow \emptyset$
\While{$I_p \in \text{ImageSize}$}
\If{$I_p + T_h < \text{Average}_{R1} \&\& I_p + T_h < \text{Average}_{L1}$}
\State $Fh1_{I_p} \leftarrow 1$
\EndIf
\If{$I_p + T_h < \text{Average}_{R2} \&\& I_p + T_h < \text{Average}_{L2}$}
\State $Fh2_{I_p} \leftarrow 1$
\EndIf
\If{$I_p + T_h < \text{Average}_{Up1} \&\& I_p + T_h < \text{Average}_{Down1}$}
\State $Fv1_{I_p} \leftarrow 1$
\EndIf
\If{$I_p + T_h < \text{Average}_{Up2} \&\& I_p + T_h < \text{Average}_{Down2}$}
\State $Fv2_{I_p} \leftarrow 1$
\EndIf
\EndWhile
\State \textbf{Erode} $Fh1$ then \textbf{Dilate} $Fh1$
\State \textbf{Erode} $Fh2$ then \textbf{Dilate} $Fh2$
\State \textbf{Erode} $Fv1$ then \textbf{Dilate} $Fv1$
\State \textbf{Erode} $Fv2$ then \textbf{Dilate} $Fv2$
\State $F = Fh1 \mid Fh2 \mid Fv1 \mid Fv2$
\end{algorithmic}

shown on the right, it makes sense to use major axis length to eliminate small objects for vein segmentation. Accordingly, major axis length of each connected component is measured and disconnected components are eliminated based on this metric. Example of an input feature map and its output feature map can be seen from the Figure 8.

3. Results and discussion

To quantify the performance of the algorithm, publicly available the High-Resolution Fundus (HRF) image database [4] is used. In this database, both healthy retinas, and pathological retinas with their hand labelled ground-truths are provided. The database includes images from healthy eyes, eyes with signs of diabetic retinopathy, and eyes with signs of glaucoma. The dataset provides 15 images for each group. Examples of input images and their segmented outputs are provided in Figure 9. To quantify the performance of the proposed algorithm, three different metrics are used: sensitivity, specificity, and accuracy. Equations for these metrics can be found below.

\begin{align}
\text{Sensitivity (SE)} &= \frac{TP}{P} \tag{1} \\
\text{Specificity (SP)} &= \frac{TN}{(TN + FP)} \tag{2}
\end{align}
Figure 6: Combined feature maps. (a) Thin vertical vein segmentation. (b) Its output after morphological operations. (c) Thin horizontal vein segmentation. (d) Its output after morphological operations. (e) Thick vertical vein segmentation. (f) Its output after morphological operations. (g) Thick horizontal vein segmentation. (h) Its output after morphological operations.

Figure 7: Example connected components, where on the left a connected component with a total number of 40449 pixels and with a major axis length of 140 is shown. On the other hand, on the right, a connected component with a total number of 2028 pixels and with a major axis length of 156 is shown.

\[ \text{Accuracy (ACC)} = \frac{TP + TN}{TP + TN + FP + FN} \]  

where \( TP \) stands for the total number of true positives, \( P \) stands for the total number of positives, \( TN \) stands for the total number of true negatives, \( FN \) stands for the total number of false negatives, and \( FP \) stands for the total number of false positives. It should be noted that only one metric, such as accuracy, is not enough to truly quantify the algorithm. Vein pixels are only a small portion of the total number of pixels in the image. Thus, the algorithms favouring true negatives to true positives can give higher accuracy but might not segment out vein pixels as effectively as desired. Thus, sensitivity and specificity are also important metrics.

The proposed algorithm is tested for each set (three sets in total) separately and sensitivity, specificity, and accuracy are measured for each image and their calculated mean values are shown in Table 1.

In Table 1, the sensitivity, specificity, and accuracy of the proposed algorithm and the algorithms in [4, 15], and [16] are shown. It is seen that the proposed algorithm outperformed the algorithm described in [4]
in terms of sensitivity, specificity, and accuracy in all sets of images. The algorithm described in [16], while
achieving good accuracy, has relatively low sensitivity compared to all other described algorithms. Compared
to the algorithm described in [15], while in some cases [15] performs better in terms of sensitivity and specificity,
in other cases, the proposed algorithm achieves better results. On the other hand, in all cases, the proposed
algorithm performs better in terms of accuracy. In Table 2 average sensitivity, specificity, and accuracy of the
algorithms are shown. In addition to the previous algorithms, in this table, results of the [17] is also shown
(no available data for this algorithm for the individual sets). From the table, it can be seen that in terms of
accuracy only [16] performs better then the proposed algorithm. On the other hand, [16] has relatively low
sensitivity compared to all other algorithms in the table.

Although, the HRF database [4], supplies high resolution fundus images, in the literature DRIVE [9]
database is more widely used for evaluation of retinal vessel segmentation algorithms. Thus, the proposed
algorithm is also tested in the DRIVE database. The images for the DRIVE database were obtained from a
diabetic retinopathy screening program in the Netherlands. The screening population consisted from subjects
between 25-90 years of age and 40 images are randomly selected for creating the database. Among these images,
33 do not show any sign of diabetic retinopathy and 7 show signs of mild early diabetic retinopathy. Among
these 40 images, 20 of the images are selected as training and other 20 of the images are selected as test set.
The test set is manually labelled twice. One set is then used as gold standard and the other set is used for
evaluating the proposed algorithm with respect to a human observer. The sensitivity, specificity, and accuracy
for the second human observer is measured and the obtained values can be seen from the first row of Table. 3.

It should be noted that the estimated sensitivity, specificity, and accuracy of the algorithms on the HRF
database considers all the input image pixels. However, in the DRIVE database, a mask image is provided
that delineates the FOV along with each input image (this was not available for the HRF database). Thus,
while calculating sensitivity, specificity, and accuracy only the pixels within this mask are considered.

The sensitivity, specificity, and accuracy for the proposed algorithm on the DRIVE database can also
be seen from Table. 3. From Table. 3, it could be noticed that while the accuracy of the automated algorithms
are relatively closer to the human observer, the sensitivity of the human observer is by far better. Table. 3,
shows that in terms of accuracy the proposed algorithm outperforms [4, 18], and [19]. On the other hand, the
proposed algorithm outperforms [4, 20, 21], and [19] in terms of specificity.
Figure 9: Example vein segmentation results, where in the first column, input images are shown, in the second column calculated veins for the input images are shown, and in the last column, manually labelled ground truth veins are shown.
Table 1: Performance evaluation on the HRF database.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Mean SE%</th>
<th>Mean SP%</th>
<th>Mean ACC%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed Healthy</td>
<td>80.18</td>
<td>97.60</td>
<td>95.97</td>
</tr>
<tr>
<td>Odstrcilik et al. [4] Healthy</td>
<td>78.61</td>
<td>97.50</td>
<td>95.39</td>
</tr>
<tr>
<td>Yu et al. [15] Healthy</td>
<td>79.38</td>
<td>97.67</td>
<td>95.66</td>
</tr>
<tr>
<td>Annunziata et al. [16] Healthy</td>
<td>68.20</td>
<td>99.35</td>
<td>95.87</td>
</tr>
<tr>
<td>Proposed diabetic retinopathy</td>
<td>75.02</td>
<td>96.58</td>
<td>95.08</td>
</tr>
<tr>
<td>Odstrcilik et al. [4] diabetic retinopathy</td>
<td>74.63</td>
<td>96.19</td>
<td>94.45</td>
</tr>
<tr>
<td>Yu et al. [15] diabetic retinopathy</td>
<td>76.04</td>
<td>96.25</td>
<td>94.60</td>
</tr>
<tr>
<td>Annunziata et al. [16] diabetic retinopathy</td>
<td>69.97</td>
<td>97.87</td>
<td>95.54</td>
</tr>
<tr>
<td>Proposed glaucomatous</td>
<td>79.56</td>
<td>96.72</td>
<td>95.54</td>
</tr>
<tr>
<td>Odstrcilik et al. [4] glaucomatous</td>
<td>79.00</td>
<td>96.38</td>
<td>94.97</td>
</tr>
<tr>
<td>Yu et al. [15] glaucomatous</td>
<td>78.90</td>
<td>96.62</td>
<td>95.18</td>
</tr>
<tr>
<td>Annunziata et al. [16] glaucomatous</td>
<td>75.66</td>
<td>97.85</td>
<td>96.03</td>
</tr>
</tbody>
</table>

Table 2: Average performance evaluation on the HRF database.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Mean SE%</th>
<th>Mean SP%</th>
<th>Mean ACC%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed algorithm</td>
<td>78.25</td>
<td>96.97</td>
<td>95.53</td>
</tr>
<tr>
<td>Odstrcilik et al. [4]</td>
<td>77.60</td>
<td>96.69</td>
<td>94.94</td>
</tr>
<tr>
<td>Yu et al. [15]</td>
<td>78.10</td>
<td>96.85</td>
<td>95.15</td>
</tr>
<tr>
<td>Annunziata et al. [16]</td>
<td>71.28</td>
<td>98.36</td>
<td>95.81</td>
</tr>
<tr>
<td>Yang et al. [17]</td>
<td>79.15</td>
<td>96.72</td>
<td>95.17</td>
</tr>
</tbody>
</table>

The proposed algorithm has an algorithmic complexity of O(N), where N is the number of pixels in the input image. The algorithm is implemented on MATLAB and the run time is measured as 2.94 seconds on average for the HRF database and 174 ms for the DRIVE database using i7 – 8750H CPU on the HRF database. The implemented algorithm currently uses a single thread and it is also possible to improve the run time significantly by using multiple threads on multiple cores or by utilizing GPU.

4. Conclusion
In this paper, a retinal vessel segmentation algorithm has been proposed. The proposed algorithm is based on the symmetrical local threshold, which is originally designed as a feature extraction algorithm for the lane detection. The lane markings and retinal vessels are similar structures in a sense that both of them represent a stripe on a digital image. In the literature, it is seen that many feature extraction algorithms for lane feature extraction and retinal vessel extraction are common such as ridge detectors, steerable filters, and Match filtering. However, SLT is designed and only used for lane detection. Furthermore, although there is no benchmarking for lane feature extractors, researchers who created ROMA dataset, tested most common lane feature extractors and concluded that the SLT is the most robust lane feature extractor among tested. Accordingly, in this paper symmetrical local threshold, for the first time, used for retinal vessel segmentation. Also, to be able to detect retinal vessels with variety of thickness’s and orientation, the SLT is modified and made suitable for vessel segmentation. A lane marking has a higher intensity compared to both its left-hand side and its right-hand side.
Table 3: Performance evaluation on the DRIVE database.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Mean SE%</th>
<th>Mean SP%</th>
<th>Mean ACC%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Second human observer</td>
<td>78.07</td>
<td>97.12</td>
<td>94.73</td>
</tr>
<tr>
<td>Proposed algorithm</td>
<td>72.46</td>
<td>96.82</td>
<td>93.69</td>
</tr>
<tr>
<td>Odstrcilik et al. [4]</td>
<td>70.60</td>
<td>96.93</td>
<td>93.40</td>
</tr>
<tr>
<td>Marin et al. [21]</td>
<td>70.67</td>
<td>98.01</td>
<td>94.52</td>
</tr>
<tr>
<td>Zang et al. [20]</td>
<td>71.20</td>
<td>97.24</td>
<td>93.82</td>
</tr>
<tr>
<td>Al-diri et al. [18]</td>
<td>72.82</td>
<td>95.51</td>
<td>92.58</td>
</tr>
<tr>
<td>Palomera-perez et al. [19]</td>
<td>64.40</td>
<td>96.70</td>
<td>92.50</td>
</tr>
</tbody>
</table>

On the other hand, a retinal vessel has a darker intensity compared to both its left-hand side and its right-hand side (if the vein is vertical) or has a darker intensity compared to both its upper-hand and its lower-hand (if the vein is Horizontal). Thus, instead of applying the SLT row by row horizontally as in the case of lane feature extraction, for retinal vessel segmentation, two different kernels are applied; one for the horizontal vein segmentation, and one for the vertical segmentation. Then, considering the variation of the retinal vessels, the SLT is applied twice for each case: once for thick veins with the thick SLT, and once for thin veins with the thin SLT. It should also be noted that applying kernels with variable thickness and orientation is a common practice for filters such as Match filters of steerable filters. By combining these outputs with logical "OR" operator, the output gave high response to both vessels with different thickness and orientation. While, filters like Match filter, gives high response to the stripe like pattern, it is not necessary for a structure to have LDL pattern. On the other hand, symmetrical local threshold check both sides (i.e. left and right) and ensures that both sides of the anchor pixel satisfy this property. On the other hand, vessel light reflexes (a bright strip in the middle of vessel) are not considered in this paper and can cause disruption at the middle of the thick vessels. The algorithm is tested on high resolution retinal fundus images for both healthy eyes, diabetic eyes, and eyes with glaucoma supplied by the HRF image database. In all categories, the proposed algorithm achieved to segment retinal vessels with an accuracy of 95.53% and a sensitivity of 78.25% with a run time of 2.94 seconds on average using a single thread implementation. When tested with the DRIVE database, the proposed algorithm achieved to segment retinal vessels with an accuracy of 93.69% and a sensitivity of 72.46% with a run time of 174 milliseconds on average using a single thread implementation.

References


