Abstract—In this paper, a multiscale line filter is proposed which is integrated with phase congruency to detect the network of vessels in retinal images. The proposed line filter can reduce the influence of step edges compared with Gaussian matched filter, and the post process use the phase congruency demonstrated a substantial improvement in detecting vessels which have low contrast or minor width. The performance of the proposed method is evaluated on the publicly available databases DRIVE and STARE. The experimental results show that an effective and robust detection can be achieved.

Keywords: retinal image, blood vessel, multiscale line filter, phase congruency

1. Introduction

Diabetic retinopathy (DR) is the commonest cause of blindness in the worldwide working-age population. The blood vessels is the most stable object in retinal fundus image which can reflect the state of the disease, and is also a landmark for localizing the optic nerve, fovea and lesions of DR [1]. Therefore, a reliable vessel detection is a prerequisite for subsequent retinal image analysis.

Blood vessels have some notable characteristics such as a Gaussian shape of cross-sectional grey-level profile, the vessels is piecewise linear and connected which formed a treelike structure, and the vasculature originates from the same location [2]. Many researchers have proposed a variety of techniques to detect vessels that generally fall into four categories. **Matched filter based**: The Gaussian matched filter first presented by Chaudhuri et al. employs a two-dimensional linear kernel that has a Gaussian cross-profile section and rotated into 12 different direction [3], and Zhang et al. propose a multiscale production of Gaussian matched filter to satisfy a wide range of vessel widths [4]. In [5] and [6] a multiscale Gabor filter is applied to vessel detection; **Vessel model based**: Wang et al. proposed a vascular representation and segmentation algorithm based on a multiresolution Hermite mode [7]. A “Ribon of Twiins” model presented by Al-Diri et al. uses a pair of contour to capture each vessel edge [8], while maintaining width consistency. Tsai et al. proposed a model based algorithm for locations of vascular structures branch and cross over in retinal images [9]; **Machine learning based**: Many method such as Fuzzy clustering [10], ANN [11], SVM [12] and other supervised or unsupervised techniques are frequently integrated with previous mentioned approaches for the final classification of positive vessel pixels; **Morphological processing based**: Morphological operators which is suitable for extracting linear shapes from background which can be very useful for vessel detection. Based on morphology method Zana et al. proposed an approach for the detection of vessel-like patterns in a noisy environment [13], and morphological reconstruction can be used to integrate segmentation fragment into a final vessel in [14]. Many published literature also use the morphological processing [15], [16] to roughly extract the vessel before lesions detection due to its simplicity and effectivity.

However, several challenges have emerged in the procedure of vessels detection from retinal images [1]. Blood vessels have a wide range of width, and there are many non vessels such as step edge will be introduced during the detection. Many proposed detection techniques are based on the grey-level and gradient information of retinal images, in case of the unideal or unsuitable lightness and low contrast condition, the difficulty of vessels extraction will be increased especially for the minor vessels. In addition, the border of optic disc and bright lesions in fundus image will also terribly influence the detection results of matched filters.

In this paper, a multiscale line filter extended from [17] and [18] is proposed for the enhancement of blood vessels in retinal image which focus on degrading the adverse impact caused by step edge, such as borders of optic disk, lesions and the field of view, and improve the ability of
detecting the vessel has a high curvature. The proposed filter which composed of a dual first-order derivative of unscaled Gaussian with different standard deviation will also match real vessels in a better way. We then applied the measurement of phase congruency [19] to detect low contrast and minor vessels in the enhancement result of multiscale line filter. The flowchart of our vessel detection method is shown in Fig. 1. In the rest of the paper, the proposed methods are detailed in Section 2. The experimental results and performance evaluation are presented in Section 3, and followed by the conclusions in Section 4.

2. Methodology

2.1 Preprocessing

The motivations for applying some preprocessing are to normalize the intensity distribution of retinal image and remove the background noises. The green channel $I_g$ of retinal color image is used as the input cause which has the best contrast and saturation.

We first use the shade correction [20] to normalize the illumination of $I_g$. A median filter of size $40 \times 40$ is adopted to smooth $I_g$, and a estimate of background image $I_{bg}$ is obtained. The illumination normalized image $I_{sc}$ can be computed by

$$I_{sc} = I_g - I_{bg}$$

with

$$I_{bg} = I_g \ast f_m$$

where “∗” is convolution operator and $f_m$ is the median filter.

Next we employ a edge-preserving smoothing to remove background noises while preserving vessel edges. We expect to find a new image $I_{eps}$ which is as close as possible to $I_{sc}$, meanwhile, is as smooth as possible everywhere except across the edge in $I_{sc}$. Hereby we use a weighted least squares optimization framework proposed in [21] to achieve the edge-preserving smoothing, the new image $I_{eps}$ can be obtained by minimizing the following quadratic functional

$$F = \sum_q ((I_{eps})_q - (I_{sc})_q)^2 + \lambda \left( \alpha_x \left( \frac{\partial I_{eps}}{\partial x} \right)_q + \alpha_y \left( \frac{\partial I_{eps}}{\partial y} \right)_q \right)^2$$

where $q$ denotes the coordinate of a pixel. The goal of the first term is to minimize the distance between $I_{eps}$ and $I_{sc}$, while the second term is to smooth $I_{eps}$. The parameters $\alpha_x$ and $\alpha_y$ are smoothness weights which depend on $I_{sc}$, while $\lambda$ is used to balance the effects achieve by the two terms. An preprocessing example is shown in Fig. 2.

2.2 Multiscale line Filter

The Gaussian matched filter is a well-known method of vessel detection which estimate the gray-level profile of the cross section of the vessel by a Gaussian function [3], and the matched template can be rotated into different directions to detect the whole vessel network. However, the Gaussian matched filter responds not only to vessels but also to non-vessel edges [22], such as the border of optic disk, light lesions and the field of view as illustrated in the first row of Fig. 3. To overcome the sensitivity to non-vessel edges and improve the detection for the vessel has a high curvature, we extend the line filters proposed in [17] and [18] which are based on a nonlinear combination of linear filters.

Let $G_\sigma(x, y)$ denotes the unscaled Gaussian function $G_\sigma(x, y) = e^{-(x^2+y^2)/2\sigma^2}$, its first derivative $G'_\sigma(x, y)$ along $x$ direction is an effective edge detector. We define edge detectors at scale $i$ as

$$E_i^l(p) = -G'_\sigma(x + w_i, \rho_i \cdot y), \forall p \in N^l_i$$

$$E_i^r(p) = G'_\sigma(x - w_i, \rho_i \cdot y), \forall p \in N^r_i$$

with

$$N^l_i = \{(x, y) \mid |x| \leq 3\sigma_l, |y| \leq L_i/2\}$$

$$N^r_i = \{(x, y) \mid |x| \leq 3\sigma_r, |y| \leq L_i/2\}$$

where $\sigma_l$ and $\sigma_r$ are the standard deviation of unscaled Gaussian function, $\rho_i$ controls the smoothness along the $y$ direction, while $L_i$ is the length of filters in $y$ direction at that scale. $D^l_i$ and $D^r_i$ will detect the left and right edge of the vessel at location $x = \mp w$, and the distance between $x - w$ and $x + w$ can be used to estimate the width of vessel. The response of these two edge detector will be both positive for the line while one positive and one negative for the step edge.

To account for the multi-directions and tortuosity of vessel in retinal images, the rotation of $D^l_i$ and $D^r_i$ with angle $\alpha$ is then calculated by

$$E_i^{l,\alpha}(p') = E_i^l(p), \quad E_i^{r,\alpha}(p') = E_i^r(p)$$

with

$$x' = x \cos \alpha + y \sin \alpha + \xi y^2$$

$$y' = y \cos \alpha - x \sin \alpha$$

where the quadratic term $\xi y^2$ is used to fix the bending of some vessels [23] and $\xi$ describes the curvature of the vessel, as shown in Fig. 4 and Fig. 6.

The response of the new line filter at scale $i$ convolved with the input image $I_{eps}$ at location $(u, v)$ can be expressed by

$$R_i(u, v) = \prod_\xi \max_{\alpha} \left( \text{Pos}(R_i^{l,\alpha}(u, v)) \cdot \text{Pos}(R_i^{r,\alpha}(u, v)) \right)$$

(5)
Fig. 2: Illustration of preprocessing: (a) an original color retinal image, (b) the green channel of (a), (c) the shade corrected image and (d) the edge-preserving smoothed image.

Fig. 3: First row: unfavourable factors during the vessel detection. Second row: results of Gaussian matched filtering. Third row: results of the proposed line filter. Fourth row: the phase congruency of the third row. The edge steps are suppressed, and vessels which have low contrast and minor width are detected.
vessels of various widths, and the final response is defined as the maximum of filter responses at all scales. The improved line filter can detect blood vessels with various widths and tortuosity, while suppressing the response to non-vessel edges. The phase congruency developed by Kovesi [19] is a dimensionless quantity that is invariant to changes in image brightness. If the maximum moment of phase congruency at a point is large then that point should be marked as a feature such as a line point, see Fig. 5. Therefore, it can be applied in vessel detection for the low contrast or minor width. Due to the phase congruency, which is processed by the line filter to the multiscale manner [18] which can match the final vessel enhanced image as shown in Fig. 3 and Fig. 7, and on which the final vessel network is segmented by using hysteresis thresholding.

\[ PC(x, y) = \frac{\sum_o \sum_n W(x, y) |A_{o,n}(x, y)\Delta\phi_{o,n}(x, y) - T|}{\sum_n A_{o,n}(x) + \varepsilon} \]

with

\[ \Delta\phi_{o,n}(x, y) = \cos(\phi_{o,n}(x, y) - \bar{\phi}_o(x, y)) - |\sin(\phi_{o,n}(x, y) - \bar{\phi}_o(x, y))| \]

where \( o \) and \( n \) denote the index over orientations and scales respectively, \( \phi_o(x, y) \) is the mean phase angle at orientation \( o \), the term \( W(x, y) \) is the sigmoid function used to weight a phase congruency, \( \varepsilon \) is added to avoid division by zero, \( T \) is a threshold to control the noise influence, the symbols \( | \cdot | \) denote the enclosed quantity is equal to itself iff its value is positive, and zero otherwise.

In our paper the local frequency information is obtained via banks of log Gabor wavelets tuned to different spatial frequencies, and the phase congruency of vessel enhancement image as shown in Fig. 3 and Fig. 7, and on which the final vessel network is segmented by using hysteresis thresholding.

### 3. Experimental Results and Discussion

#### 3.1 Materials

We have evaluated our approach on two publicly available databases DRIVE and STARE which were collected by Staal et al. [24] and Hoover et al. [25] respectively for testing the algorithm of vessel detection. The DRIVE database consists of 40 images captured by Canon CR5 3CCD camera with a 45° FOV which were digitized at 24-bits with a spatial resolution of 565 × 584 pixels and divided into a training set and a test set. The ground truths segmented manually for two sets and the mask images clearly marking the interior of FOV are also provides by the authors of the database. The STARE database consists of 20 images captured by TopCon TRV-50 fundus camera with a 35° FOV which were digitized at 24-bits with a spatial resolution of 700 × 605 pixels and in which there are 10 healthy fundus images and the other 10 unhealthy. The author of the database also provides ground truths for the performance evaluation of vessel detection.

#### 3.2 Experimental Results

To compare the proposed approach with other retinal vessel detection algorithms, we use the sensitivity (SE), specificity (SP) and accuracy (ACC) as the performance measures. In general, there are four predict outcome in testing stage, such as true positive (TP), false positive (FP), true negative (TN) and false negative (FN). The sensitivity

![Fig. 4: Examples of vessel segment with no curvature in (a) and with some curvature in (b).](image)

![Fig. 5: The phase congruency of line feature.](image)
Table 1: Performance measures of vessel detection for each test image on DRIVE database

<table>
<thead>
<tr>
<th>No.</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>No.</th>
<th>Sensitivity</th>
<th>Specificity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.7126</td>
<td>0.9660</td>
<td>11</td>
<td>0.6398</td>
<td>0.9752</td>
</tr>
<tr>
<td>2</td>
<td>0.7176</td>
<td>0.9655</td>
<td>12</td>
<td>0.6178</td>
<td>0.9779</td>
</tr>
<tr>
<td>3</td>
<td>0.6422</td>
<td>0.9598</td>
<td>13</td>
<td>0.6194</td>
<td>0.9794</td>
</tr>
<tr>
<td>4</td>
<td>0.5511</td>
<td>0.9908</td>
<td>14</td>
<td>0.7042</td>
<td>0.9672</td>
</tr>
<tr>
<td>5</td>
<td>0.5874</td>
<td>0.9899</td>
<td>15</td>
<td>0.7150</td>
<td>0.9712</td>
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<tr>
<td>6</td>
<td>0.6267</td>
<td>0.9780</td>
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<td>0.7023</td>
<td>0.9756</td>
</tr>
<tr>
<td>7</td>
<td>0.6176</td>
<td>0.9807</td>
<td>17</td>
<td>0.7108</td>
<td>0.9731</td>
</tr>
<tr>
<td>8</td>
<td>0.5541</td>
<td>0.9854</td>
<td>18</td>
<td>0.7200</td>
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<tr>
<td>9</td>
<td>0.6375</td>
<td>0.9786</td>
<td>19</td>
<td>0.7108</td>
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</tr>
<tr>
<td>10</td>
<td>0.6523</td>
<td>0.9784</td>
<td>20</td>
<td>0.6606</td>
<td>0.9779</td>
</tr>
</tbody>
</table>

Table 2: Performance comparison with different vessel detection methods on DRIVE database

<table>
<thead>
<tr>
<th>Method</th>
<th>Accuracy</th>
<th>Sensitivity</th>
<th>Specificity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Second observer</td>
<td>0.9473</td>
<td>0.7761</td>
<td>0.9725</td>
</tr>
<tr>
<td>Chaudhuri [3]</td>
<td>0.8773</td>
<td>0.3357</td>
<td>N.A.</td>
</tr>
<tr>
<td>Amin [26]</td>
<td>0.9191</td>
<td>N.A.</td>
<td>N.A.</td>
</tr>
<tr>
<td>Vlachos [27]</td>
<td>0.9285</td>
<td>0.7468</td>
<td>0.9551</td>
</tr>
<tr>
<td>Zhang [22]</td>
<td>0.9382</td>
<td>0.7120</td>
<td>0.9724</td>
</tr>
<tr>
<td>Staal [24]</td>
<td>0.9441</td>
<td>0.7193</td>
<td>0.9773</td>
</tr>
<tr>
<td>Mendonça [14]</td>
<td>0.9452</td>
<td>0.7344</td>
<td>0.9764</td>
</tr>
<tr>
<td>Proposed method</td>
<td>0.9347</td>
<td>0.6542</td>
<td>0.9759</td>
</tr>
</tbody>
</table>

and specificity can be written as:

\[
SE = \frac{TP}{TP + FN} \quad (8)
\]

\[
SP = \frac{TN}{TN + FP} \quad (9)
\]

and accuracy can be obtained from the following identity:

\[
ACC = \frac{TP + TN}{TP + TN + FP + FN} \quad (10)
\]

where SE is the proportion of pixels that are known to the vessel the approach detects positive for it, while SP the proportion of pixels are known to the non vessel the approach detects negative for it. The ACC represents the proportion of the total number of correctly classified pixels relative to the total number of pixels.

In our experiments \( w = 1.5\sigma \) and our line detector are rotated into 12 direction, and we choose minor values of \( \xi \) to fix the bending of vessels since filters have small scales. The experimental results are demonstrated in Fig. 6 and Fig. 7, our proposed method can enhance the vessel with some curvature and detect the whole vessel network availably. The performance measures of each test image in DRIVE database are listed in Table 1, while Table 2 presents the performance of different methods on the DRIVE database. Our experimental results on the DRIVE database show that the proposed method performs better than the original Gaussian matched filter and the method in [26] which use the phase congruency measure directly. The results of each image in STARE database are shown in Table 3.

Table 3: Performance measures of vessel detection for each image on STARE database

<table>
<thead>
<tr>
<th>No.</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>No.</th>
<th>Sensitivity</th>
<th>Specificity</th>
</tr>
</thead>
<tbody>
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<td>0.7411</td>
<td>0.9692</td>
</tr>
<tr>
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<td>0.5263</td>
<td>0.9613</td>
<td>12</td>
<td>0.7424</td>
<td>0.9729</td>
</tr>
<tr>
<td>3</td>
<td>0.6398</td>
<td>0.9534</td>
<td>13</td>
<td>0.6498</td>
<td>0.9753</td>
</tr>
<tr>
<td>4</td>
<td>0.6050</td>
<td>0.9774</td>
<td>14</td>
<td>0.6567</td>
<td>0.9755</td>
</tr>
<tr>
<td>5</td>
<td>0.6323</td>
<td>0.9729</td>
<td>15</td>
<td>0.6597</td>
<td>0.9680</td>
</tr>
<tr>
<td>6</td>
<td>0.6266</td>
<td>0.9828</td>
<td>16</td>
<td>0.5955</td>
<td>0.9813</td>
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<tr>
<td>7</td>
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<td>0.9648</td>
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<td>0.7287</td>
<td>0.9800</td>
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<tr>
<td>8</td>
<td>0.7238</td>
<td>0.9665</td>
<td>18</td>
<td>0.6226</td>
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<td>0.6664</td>
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<tr>
<td>10</td>
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<td>0.9669</td>
<td>20</td>
<td>0.5825</td>
<td>0.9760</td>
</tr>
</tbody>
</table>

Table 4: Performance comparison with different vessel detection methods on STARE database

<table>
<thead>
<tr>
<th>Method</th>
<th>Accuracy</th>
<th>Sensitivity</th>
<th>Specificity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Second observer</td>
<td>0.9348</td>
<td>0.8951</td>
<td>0.9384</td>
</tr>
<tr>
<td>Hoover [25]</td>
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<tr>
<td>Fraz [28]</td>
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<td>0.6849</td>
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<tr>
<td>Mendonça [14]</td>
<td>0.9440</td>
<td>0.6996</td>
<td>0.9730</td>
</tr>
<tr>
<td>Staal [24]</td>
<td>0.9516</td>
<td>0.6970</td>
<td>0.9810</td>
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<tr>
<td>Proposed method</td>
<td>0.9392</td>
<td>0.6503</td>
<td>0.9722</td>
</tr>
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</table>

Table 3, and Table 4 compares the performance of different methods on the STARE database. Our experimental results on the STARE database show that the proposed method also achieves a competitive performance compare to the listed methods.

4. Conclusions

In this paper we propose a novel method for retinal blood vessel detection. The method is based on an multiscale line detector which integrated with the phase congruency. The performance of our method achieves competitive results compared to the existing solutions. However, our method yields a lower sensitivity that is mainly because of the width of vessel is not accurate and an high threshold value applied to reduce the noises introduce by the phase congruency. Our following work is devoted to overcome these problems by extracting the feature set of the vessel and training a optimal classifier to identify the vessel pixels and non vessel pixels. Meanwhile, the performance of vessel segmentation from images which have pathological changes will be improved in the future work.

Acknowledgment

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Fig. 6: The enhanced results of blood vessels with some tortuosity. (a) original vessel segment, (b) enhanced result without tortuosity fixed, (c) enhanced result with tortuosity fixed.

References

Fig. 7: Detection results for DRIVE and STARE database: (a) original color retinal images, (b) vessel enhancement images, (c) the phase congruency images of (b), (d) the final segmentation results.


