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VESSEL ENHANCEMENT OF LOW QUALITY FUNDUS IMAGE USING MATHEMATICAL MORPHOLOGY AND COMBINATION OF GABOR AND MATCHED FILTER

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Abstract:

Fundus images have been widely used in the diagnosis of retinopathy and cardiovascular diseases. However, because of the movement of patients' eyes and limitation of medical equipments, the quality of fundus images may be low sometimes. In this paper, we propose vessel enhancement method for a low-contrast and blurred image based on multi-scale morphological top-hat transformation, and the combination of Gabor and matched filter. The underlying rationale of this proposed method is to make use different kinds of information to improve blood vessels on retinal fundus images with poor quality. Experiments show that vessels enhanced by our proposed method are much clearer than the ones using original multi-scale morphological top-hat transformation, Gabor filter or matched filter. The results confirm that the quality of vessel enhancement can be improved by combining these methods.

Keywords:

Retina; Fundus image; Vessel enhancement; Matched filter; Gabor filter; Morphology;

1. Introduction

Retinal fundus images contain considerable medical information and many diseases, *e.g.,* ocular lesions and systemic diseases, can be diagnosed by fundus examination. However, fundus images may be in poor quality due to incorporated patients and hardware. Noise, low contrast and blur may increase difficulty of diagnose. Moreover, a result of image processing, e.g. fundus image stitching [16], on fundus images with low quality is unsatisfying. Since blood vessels is one of important information in fundus images, this study focuses on vessel enhancement. This technique aims to highlight the vasculature of retinal fundus by increasing the contrast between vessels and non-vessels and restraining the non-vessel features.

There are many image processing approaches [12, 13, 14, 15] devised for vessel enhancement with satisfying performance on public databases. For example, Contrast Limited Adaptive Histogram Equalization (CLAHE) [9], morphological filtering [6, 8] and the Hessian Matrix method [14]. However, in practice, the resolution of retinal images is limited by hospitals' equipments. Furthermore, unpredictable photographing environment, improper illumination, complex pathologic situation of patients' eyeball and the unavoidable movement of patients will affect the contrast of the images. Figure 1 show the quality difference of fundus images from a public database and the ones collected in practice. Therefore, the quality of retinal fundus images may not be as good and stable as the ones in the public databases. The existing vessel enhancement methods may not handle the images with low quality well.

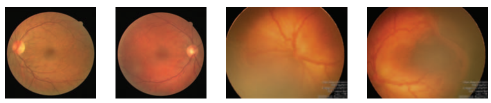

FIGURE 1. Samples of fundus images in the DRIVE public database (the first and second images) and collected in practice (the third and fourth images)

Although the shape of a vessel is an useful feature in vessel enhancement, it is noise sensitive, *i.e.,* it does not have a good performance on blur or noisy images. On the other hand, [1, 2] the Gaussian shape profile assumes that intensity profile along a cross section of a vessel has the shape of Gaus-

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sian. By cooperating with matched and Gabor filter, a blood vessel can be extracted efficiently. These two filters are robust on noisy images but perform badly in low contrast image. Therefore, this article devise a blood vessel enhancement method for fundus images with low quality by considering both shape and shape profile of vessels. Many studies [1][7][4] show that the green channel shows the best contrast between vessels and background. Moreover, the green channel suffers the least from noise in comparison with other channels. Therefore, only the green channel of a retinal image is used in our method. The green channel of an image is firstly processed by morphological filter in order to remove the noise. The contrast of the image is then adjusted by Contrast Limited Adaptive Histogram Equalization (CLAHE) method. Multi-scale morphological top-hat transformation and the filter combined by Gabor and Match filters extract vessel information based on different features. Finally, the results are merged by a weighted sum approach. Experiments show that our proposed method performs averagely higher than original morphological top-hat transformation, Gabor and match filter approaches.

The rest of the paper is organized as follows. Next section reviews other published vessel enhancement approaches. Section III explains and illustrates the proposed method for retinal vessel enhancement. Section IV presents its results and compares them to some existing methods. Finally, the authors' conclusions and discussion conclude this paper.

2. Related Works

2.1. CLAHE

With more uniform distribution of the gray-scale histogram, a retinal fundus image is of better contrast. CLAHE is an advanced Histogram equalization (HE), which uniformizes the gray-scale histogram using the probability theory. In CLAHE, an image is processed by patches. The gray-scale histogram of a patch is uniformed by considering itself and its neighborhood patches. CLAHE is defined as follows for an image s:

$$h(s) = \beta h_w(s) + (1-\beta)h_b(s) \tag{1}$$

where $h_w(s)$ and $h_b(s)$ denotes HE of the patch and its neighborhood patches respectively. β is a tradeoff parameter and its range is between 0 and 1.

2.2. Morphology Filter

Morphology filter is introduced briefly in this section. The details can be found in [7]. An image s is defined by a three-dimensional function $F(x, y)$ and K is a structural element. The six basic gray-scale morphological operations, which are dilation, erosion, opening, closing, top-hat and bottom-hat respectively are defined as:

$$Dilation : \epsilon_K(F) = \max_{a,b\in K}\{F_{(m+a,n+b)} + K_{(a,b)}\} \tag{2}$$

$$Erosion : \delta_K(F) = \min_{a,b\in K}\{F_{(m-a,n-b)} - K_{(a,b)}\} \tag{3}$$

$$Opening : \gamma_K(F) = \epsilon_K(\delta_K(F)) \tag{4}$$

$$Closing : \phi_K(F) = \delta_K(\epsilon_K(F)) \tag{5}$$

$$Top-hat : TH = F - \gamma_K(F) \tag{6}$$

$$Bottom-hat : BH = \phi_K(F) - F \tag{7}$$

Dilation operation expands bright areas in an image and reduces its dark areas. On the contrary, erosion operation expands dark areas and reduces bright ones. Opening preserves (attenuate) intensity patterns which are darker (brigter) than its neighborhood, while closing preserves bright patterns and attenuates dark ones. Top-hat and bottom-hat extract bright and dark pattern of a particular structure from an image.

2.3. Matched Filter

Chaudhuri et al[1]. proposed that retinal blood vessels almost never have ideal step edges.

Instead, the intensity profile of a vessel can be approximated by a simplified up-side-down Gaussian curve: f(x) = -exp(-x^2 /($2\sigma^2$)) where σ is the variance. Vessels can be considered as piecewise linear segment, therefore we can match a number of cross sections of identical intensity profile along the vessel's length simultaneously. A 2-D Gaussian kernel is designed as

$$K(x, y, \varphi, L, W) = -exp(\frac{-x^2}{(2\sigma^2)}), \|y\| \leq \frac{L}{2}, \|x\| \leq \frac{W}{2} \tag{8}$$

where L and W are the length and width of the kernel respectively. φ determines orientation of a matched filter kernel. It is assumed that the y-axis of the kernel K(x,y) is aligned along the direction of the vessel. Vessel segments at various orientations are detected by convolving the image with the rotated versions of the matched filter kernel and only the maximum response is retained.

2.4. Gabor Filter

2-D Gabor filter[3, 4, 5] which is a linear filter with orientation and frequency selectivity can be defined as:

$$G(x, y, \varphi) = \frac{1}{2\pi\sigma_x\sigma_y}\exp(-\frac{1}{2}(\frac{X^2}{\sigma_x^2} + \frac{Y^2}{\sigma_y^2}) + j2\pi fX) \tag{9}$$

where j is an imaginary number, $X = x\cos\varphi + y\sin\varphi$, $Y = -x\sin\varphi + y\cos\varphi$, φ denotes the orientation of the filter and f denotes the central frequency of the filter. σ_x, σ_y are the spatial constants of the Gaussian envelope along x-axis and y-axis respectively. When the imaginary part of 2-D Gabor filter is ignored and σ_x=σ_y, the formula of 2-D convolutional Gabor kernel can be simplified as:

$$G(x, y, \varphi, s) = \exp(-\frac{X^2 + Y^2}{\sigma^2}) \cos(2\pi f X) \tag{10}$$

where $f = 1/s$, $\sigma = k * s/\pi$, and s represents the size of the kernel, *i.e.,* the Gabor kernel is a $s * s$ matrix.

2.5. Multi-Scale Morphological Bottom-Hat Transformation

Linear dark shapes can be identified efficiently by morphological bottom-hat transformation. The operation of bottom-hat can be divided into two steps. The first step is closing, which preserves the bright regions and attenuates the dark ones. In other words, dark regions become brighter. This step produces a gray-level difference on dark regions between an original image and a processed image. Subtraction is the next step. By subtracting an original image from an processed image, the dark region is extracted. A single structural element can extract dark regions of a single fixed size. Multiple structural elements of different scales can extract dark regions of different sizes. A study shows that multi-scale morphological bottom-hat transformation can efficiently enhance retinal fundus vessels since retinal fundus vessels contains different linear dark shape patterns [8].

3. Proposed Method

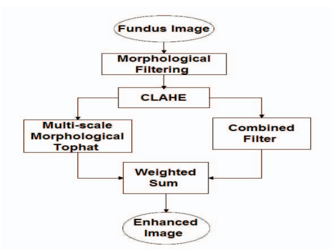


FIGURE 2. Algorithm of the proposed method

In order to enhance blood vessels from fundus images with low quality, our methods consider two types of features, *i.e.,* shape and shape profile of a vessel. The noise of a fundus image is firstly removed by morphological filter [6], which has been shown that this filter is able to remove dark or bright zones without affecting capillaries. CLAHE [9] is then applied to adjust the contrast of the image. After that, the multi-scale morphological bottom-hat transformation [8] and our proposed combined filter the image separately and we take a weighted sum of the results of them to calculate the final result. The detail procedure is illustrated in Figure 2.

3.1. Model Description

The objective of our model is to enhance blood vessels in noisy and low-contrast retinal images. For a given retinal fundus image S_0, only its green channel is applied to our model since green channel is less sensitive to noise other red and blue channels.

Step 1 - Morphological Filter: We firstly apply morphological filter to remove the noise of S_0. Our method considers a group of linear structural elements $L = \{L_i | i = 1, 2, ..., 18\}$ with the same length of 6 pixels and the width of 1 pixel. The angles of the elements in $L = \{L_i | i = 1, 2, ..., 18\}$ are from 0 degree to 170 degree differed by 10 degrees. Infimum of a linear structural element is calculated by morphological closing. The isolated round and the dark zone with a diameter less than 6 pixels have been removed, while most of the capillaries have been preserved. Supremum is then calculated by applying opening to the result of the infimum of closing. Therefore, the round and the bright zone with a diameter less than 6 pixels can be removed.

The result of morphological filter is denoted by S_{opcl}. It is defined as:

$$S_{opcl} = \max_{i=1...12}\{\gamma_{L_i}(\min_{i=1...12}\{\phi_{L_i}(S_0)\})\} \tag{11}$$

Step 2 - CLAHE: The contrast of S'_{opcl} is then adjusted by CLAHE algorithm. Its result is denoted by S_{opcl}.

Step 3 - Multi-Scale Morphological Bottom-Hat Transformation:

Most of retinal fundus vessels contain small curvature. Widths of different regions of a vessel are slightly different. Thus retinal fundus vessel can be treated as piecewise linear segments. Multi-Scale Morphological Bottom-Hat Transformation is applied to extract this information. It is because morphological bottom-hat transformation is good for extracting specific structure pattern [7].

Consider a group of disk structural elements D_i, where $i = 1, 2, ..., n$, with various radius from 1 to n. We apply a series of bottom-hat transformations to a retinal fundus image. The i^{th}

transformation works with the i^{th} elements of a disk structural group, and S_{bh_i} is produced. In $S_{bh} = \{S_{bh_i} | i = 1, 2, ..., n\}$, vessels from 3 to $2n$ pixels wide of all directions are extracted. The large homogeneous areas are set to zero since they are unchanged by ϕ_{D_i}. We compute the summation of $S_{bh} = \{S_{bh_i} | i = 1, 2, ..., n\}$ to combine vessels of all scales into one image. Finally by subtracting the sum of S_{bh} from the original fundus image, the final enhanced image is produced.

$$S_{morph} = S_{opcl} - \sum_{i=1}^{10} (BH_{D_i}(S_{opcl})) \tag{12}$$

By observation, widths of retinal fundus vessels fall in the range between 3 pixels to 20 pixels. Therefore, a group of 10 disk structure elements with radius differ from 1 to 10 pixels is chosen.

Step 4 - Combined Filter: Gabor and Matched filter:

According to [1], retinal vessels almost never have ideal step edges. Instead, a gray-level value of a pixel of a vessel is inversely proportional to the distance from the central line of the vessel to the pixel itself. It means a pixel closer to the central line is darker. From this perspective, the gray-level profile of vessels can be modeled by an up-side-down Gaussian curve.

Previous studies [1, 4] show that Gabor and matched filter perform well in detecting and enhancing vessels, especially for vessels with small width. Both of them detect vessels based on a vascular structure feature. Gabor and matched filter are both anisotropic and they obtain the maximum sensitivity only when vessels are aligned to them. Gabor filter is more accurate when capturing small vessels compared with matched filter, but false detection may be easily obtained. Although matched filter is not as accurate as Gabor filter, a vessel output by matched filter is smoother. As a result, we propose a combined filter which contains the advantages of Gabor and matched filter by fusing their outputs.

We convolve S_{opcl} obtained by the step 2 with 18 rotated versions of the Gabor filter and the matched filter separately. The maximum response of each filter is retained. Their outcomes are combined by a weighted sum.

$$S_{Gabor} = \max_{i=1...18} \{S_{opcl} \otimes G(x, y, \varphi, s)\} \tag{13}$$

$$S_{matched} = \max_{i=1...18} \{S_{opcl} \otimes K(x, y, \varphi, L, W)\} \tag{14}$$

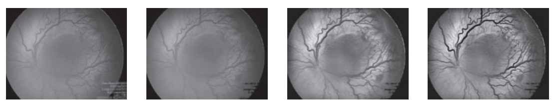
$$S_{combined} = \alpha * S_{Gabor} + (1 - \alpha) * S_{matched} \tag{15}$$

where convolution is denoted by $\otimes$. α is a weight coefficient between 0 and 1 used to adjust the influence of the Gabor and matched filter. By experiment, we found out that the combined filter performs well when α is equal to 0.3. For both the two filter, the parameter φ indicates the orientation of the filter kernel. It is a 18*1 column vector, which is $\varphi^T = [0102030...170]$. φ detects vessels of all angles. The widths of the two filters, which is denoted as s for the Gabor and W for the matched. We set both of these parameter as 5, which is approximately the median value of the width of all vessels. s is set to be 1.3 according to [5]. For the matched filter, L represents the length of the matched kernel. Small L increases the computation time, while if the value of L is large, vessels do not have fixed orientations. In our study, L is set to 5.

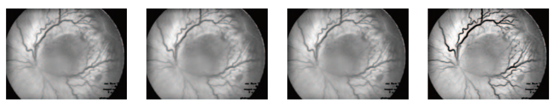
Step 5 - Fusion: We combine the results of the Multi-Scale Morphological Bottom-Hat Transformation and the combined filter by a weighted sum with weights being 0.75 and 0.25 respectively. These two weight coefficients are determined according to experimental results.

3.2. Example Illustration

This section illustrate the performance of our model by using a retinal fundus image. The green channel of the sample image is shown in Figure 3(a). Figure 3(b), which is the result of morphological filtering, eliminates pepper-and-salt noise, which is one kind of bright and dark points, in the image. The result of CLAHE is shown in 3(c). Global contrast of the original sample is greatly improved. In Figure 3(d), which is the result of Multi-Scale Morphological Bottom-Hat Transformation, vessels are enhanced while noises are produced simultaneously. From figures 3(e), 3(f) and 3(g), we can observe that the performance of Gabor is a slightly better than that of matched filter. Therefore, the weight of Gabor filter is larger. The final result is shown in Figure 3(h), in which vessels with big size are enhanced greatly while those capillaries are enhanced accordingly.



(a) Original Green Channel (b) morphologically filtered (c) CLAHE (d) multi-scale bottom-hat



(e) Gabor filtered (f) matched filtered (g) combined filtered (h) final result

FIGURE 3. Results of Img # 12 after different operations.

4. Experiment

Our proposed model is evaluated and compared with other exiting methods including 1) Multi-Scale Morphological Bottom-Hat Transformation (MSMBHT), 2) Gabor filter (Gabor), 3) Matched filter (Match), 4) the combination of Gabor and matched filter (Gabor+Match) experimentally in this section. The dataset consists of 20 fundus images collected from Guangzhou Women and Children Medical Center. The resolution of all images are 480×640. Regions of vessels of each image are marked manually.

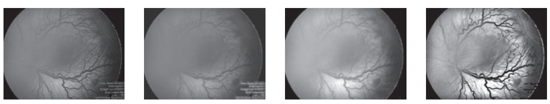
Two evaluation criteria [8], which are the contrast of interesting region and the background (C), and the normalized contrast (CH), are used to indicate the performance of vessel enhancement methods. The criteria are defined as:

$$C = \| \frac{Y - B}{Y + B} \| \tag{16}$$

$$CH = \frac{C_{en}}{C_0} \tag{17}$$

where Y and B represent the mean gray value of pixels in vessel regions and in non-vessel regions. C_{en} and C refers to C of the enhanced and the original image. A larger C is preferable since it indicates the larger contrast between vessels and the background. CH measures the performance of enhanced image relatively to the original one. When $CH > 1$, the image is improved by the enhancement, vice verse. There is no improvement when $CH = 1$.

4.1. Experimental Results and Discussion



(a) MSMBHT (b) Gabor (c) Match (d) Proposed

FIGURE 4. Results of MSMBHT, Gabor filter, Matched Filter and our method on Img #20

The experimental results in terms of C (10^3) and CH of different methods for each samples have shown in Table 1. MSMBHT does not perform well on the images with low quality. Clearness of vessels enhanced by MSMBHT may reduce in many cases. For Img #2, MSMBHT reduces the original C from 1.97 to 0.10. On the other hand, Gabor and Match filter perform better than MSMBHT in our experiment generally. Sometimes their C values are higher then that of our method. Our proposed method achieves the largest C among all methods in 14 out of 20 images. Moreover, C and CH values of our method are significantly higher than others in 9 images. Our proposed method increases the average C value of the original image from 1.25 to 3.64, which is the largest improvement among all methods. The results confirm that our method enhance blood vessels from retinal fundus images with low quality successfully. However, in Imgs #5 and #6, CH of our method is smaller than one which means that vessels are unclearer after the enhancement. As the weight setting between MSMBHT and combined filter is fixed, the setting may not be suitable for these images.

TABLE 1. C and CH enhanced by different approach

Img	$C * 10^3$ and (CH) of Different Approach				
	origin	*MSMBHT*	*Gabor*	*Match*	*Proposed*
♯1	1.84(-)	0.56 (0.30)	4.17 (2.27)	**5.09 (2.77)**	2.80 (1.53)
♯2	1.97(-)	0.10 (0.05)	3.17 (1.61)	**3.67 (1.86)**	2.85 (1.45)
♯3	0.38(-)	1.41 (3.75)	0.97 (2.58)	1.36 (3.62)	**3.39 (8.99)**
♯4	0.25(-)	2.33 (9.51)	0.12 (0.49)	0.51 (2.08)	**4.51 (18.43)**
♯5	1.79(-)	1.02 (0.57)	3.13 (1.75)	**3.39 (1.89)**	0.92 (0.52)
♯6	3.08(-)	2.01 (0.65)	5.89 (1.91)	**6.36 (2.06)**	1.93 (0.93)
♯7	0.62(-)	0.49 (0.79)	0.91 (1.48)	1.62 (2.64)	**3.28 (5.32)**
♯8	1.62(-)	0.17 (0.11)	3.09 (1.90)	3.67 (2.26)	**3.81 (2.35)**
♯9	1.13(-)	0.02 (0.01)	2.28 (2.03)	**2.65 (2.36)**	2.50 (2.22)
♯10	1.76(-)	0.80 (0.45)	4.00 (2.28)	**4.43 (2.52)**	3.23 (1.84)
♯11	0.99(-)	0.04 (0.03)	2.60 (2.63)	3.01 (3.04)	**3.60 (3.63)**
♯12	0.81(-)	0.79 (0.97)	1.58 (1.95)	1.96 (2.43)	**3.07 (3.80)**
♯13	2.50(-)	1.41 (0.56)	6.17 (2.46)	**7.05 (2.81)**	3.22 (1.28)
♯14	1.15(-)	0.96 (0.83)	2.34 (2.03)	2.96 (2.56)	**4.43 (3.83)**
♯15	2.13(-)	2.50 (1.17)	2.35 (1.11)	2.60 (1.22)	**12.00 (5.64)**
♯16	0.40(-)	1.19 (2.99)	1.39 (3.49)	2.14 (5.38)	**4.44(11.15)**
♯17	0.48(-)	1.26 (2.57)	0.93 (1.90)	1.17 (2.40)	**3.49 (7.14)**
♯18	0.79(-)	2.42 (3.05)	0.58 (0.73)	0.35 (0.44)	**4.31 (5.44)**
♯19	0.77(-)	0.21 (0.27)	1.20 (1.56)	1.41 (1.83)	**2.38 (3.08)**
♯20	0.46(-)	1.45 (3.13)	0.93 (2.00)	1.20 (2.60)	**2.64 (5.69)**
Ave.	1.25(-)	1.06 (1.59)	2.39 (1.91)	2.83 (2.44)	**3.64 (4.70)**

Figure 4 shows the vessel enhanced by different methods. Although the image backgrounds processed by Gabor and Matched filters are brighter than the original one, their performance on vessel enhancement is worse than that of MSMBHT, which shows tiny vessels more clearly. However, MSMBHT generates fake vessels and the background is still dark. On the other hand, our proposed method performs more satisfying vessel enhancement than others. The vessels are displayed much clearer than the ones of other three methods.

5. Conclusion

This study proposes an vessel enhancement method based on Morphological filter, CLAHE, multi-scale morphological bottom-hat transformation, and the combination of Gabor and matched filter.The experiment was carried out using the database containing retinal fundus image collected from the hospital. Our proposed method increase the average CH value from 1.25 of the original images to 4.70, which is much higher than multi-scale morphological bottom-hat transformation (1.59), Gabor filter (1.91) and matched filter (2.44). One of the reasons why our proposed method achieves significantly better than other methods is several kinds of information of fundus images are considered in order to extract accurate vessel information.

The experimental results indicate that vessels cannot be enhanced in some cases due to unsuitable weight setting between MSMBHT and combined filter. One possible solution of this problem may be a dynamic fusion method. The weight values are determined for an image according to its characteristics, *e.g.,* noise level.

Acknowledgements

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