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Research paper

Segmenting Retinal Blood Vessels with Gabor Filter and Automatic Binarization

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Abstract

For timely diagnosis of retinal disease, routine retinal monitoring of people with high risk should be put in place. To assist the ophthalmologists in performing retinal analysis efficiently and accurately, numerous studies have been conducted to propose an automated retinal diagnosis system. One of the crucial steps for such a system is accurate detection of retinal blood vessels from retinal image. In this paper, we investigated the use of automatic binarization methods on pre-processed fundus image to detect retinal blood vessels. Three methods for binarization were investigated in this study, namely Otsu's method, ISODATA and K-means clustering method. The resulting binarized output indicated good detection of large vessels but most of the smaller vessels were left undetected. To address this issue, Gabor wavelet filter was used to enhance the small blood vessel structures before binarization of the filter output. Combining the binary images from both binarization with and without Gabor filter resulted in significant improvement of the overall detection rate of the retinal blood vessels. The proposed method proved to be comparable to other unsupervised techniques in the literature when validated using the publicly available fundus image database, DRIVE.

Keywords: *binarization; blood vessel; Gabor wavelet; retinal image; segmentation.*

1. Introduction

Retinal images have been widely used for diagnosing multiple eye diseases through regular screening of patients' retinal health. In some cases, numerous underlying diseases such as diabetes mellitus and hypertension can also be diagnosed using retinal image of the patient. To cater for the increasing number of retinal images that needs to be diagnosed by the ophthalmologists on a daily basis, a lot of research have been conducted in these recent years in order to come up with a computer-assisted retinal diagnosis system. One of the important pre-requisites for such a system is accurate segmentation of the retinal blood vessels from the input retinal image.

Retinal blood vessel segmentation is a step in which the retinal blood vessel network on a retinal image is detected and extracted to allow for a more efficient and accurate diagnosis by physicians. While manual segmentation is possible, this can be time consuming and tedious, requiring specialized personnel which contribute to inter-operator variability. That is why in these recent years large number of researchers have conducted studies into automatic segmentation of retinal blood vessels from retinal image. Some of the challenges in automatic retinal blood vessel segmentation include inconsistent lighting of the retina during the image capture, the low contrast of the vessels against the background, and the presence of noise or pathologies on the image.

In [1] presented a comprehensive review of techniques used to detect blood vessels from retinal images in the recent years. The techniques were generally grouped into five categories including pattern recognition, matched filtering, morphological processing, vessel tracing, and multiscale methods.

For pattern recognition techniques, they can be further divided into two different approaches, i.e. supervised and unsupervised classification. In supervised classification methods, a set of manually segmented vessel images must be made available for training before the pixels can be labeled as either vessel or non-vessel pixels. Classification methods such as neural networks [2], principal component analysis [3], support vector machines [4] have been applied in previous work to classify pixels on retinal image. Unsupervised classification techniques do not require any prior information or the use of manually segmented images in order to classify the pixels, for instance the use of Fuzzy C-Means to cluster pixels in [5].

In [6] proposed the use of matched filtering method to detect retinal blood vessels, which then inspired more work on matched filtering such as in [7-8]. In [9], morphological processing method for blood vessel detection was investigated by [9] while in [10] used morphological processing combined with centerline detection to trace the blood vessels tree. A set of trainable B-COSFIRE filters was proposed by [11] with the objective to better capture the bar-like structures of blood vessels on a retinal image.

Another approach for detecting blood vessels on a retinal image is vessel tracking approach, involving the tracing of the vessels centerline to establish a path that is likely to be part of the retinal blood vessel network. In [12] employed a tracking method using Kalman filter to trace the blood vessels by estimating the next pixel vessel location of the current vessel pixel. A vessel enhancement filter was developed by [13] using multi-scale approach to quantify vesselness measure of structures in retinal images, thus highlighting the retinal blood vessels against the retinal background.

Most of the existing methods that have been proposed to address the challenge of accurate detection of retinal blood vessels involve elaborate algorithms with high computational load and long processing time. It can also be seen that most of the methods that achieved better segmentation performance are almost always supervised methods. In this paper, an unsupervised method performs retinal blood vessel segmentation from retinal images using combined Gabor wavelet filter with automatic binarization is proposed.

In studies that have been published in the literature, Gabor wavelet feature was normally combined with supervised classification techniques to detect retinal vessels from an image [14–16]. While these methods worked well in discovering the retinal blood vessel structures, the use of supervised classification techniques normally requires higher overall computational cost and time. The use of simpler method using automatic binarization of pre-processed GCI combined with pre-processes Gabor wavelet feature to efficiently extract retinal blood vessels will reduce the overall processing time while maintaining good segmentation rate. This will be particularly well-suited for mobile diagnosis application considering the smaller computational overhead.

Three methods for automatic binarization of vessel-enhanced image were investigated, namely Otsu's method, ISODATA and K-means clustering. All these methods are simple to implement and thus, more efficient for processing a huge number of retinal images.

2. Methodology

In our proposed method, green channel image (GCI) is extracted from colour retinal image to be used as the input. GCI from the colour retinal image has been consistently chosen as the input for many retinal blood vessel segmentation methods in the literature. This is mostly due to the fact that the green channel better highlights the contrast between vessels and retinal background, as opposed to the other two channels red and blue.

The GCI is later enhanced to emphasize the retinal vessels against the retinal background using Contrast Limited Adaptive Histogram Equalization (CLAHE). Background subtraction is also performed on the contrast-adjusted GCI to further highlight retinal vessels. After all the pre-processing steps done, the image is binarized by applying one of the three binarization methods namely Otsu's method, ISODATA and K-means clustering.

The next step uses the same pre-processed GCI with the blood vessels enhanced from the previous step to extract Gabor feature using Gabor wavelet. The resulting Gabor image is then enhanced using CLAHE and background subtraction too. This Gabor image is then binarized using one of the three automatic binarization methods mentioned earlier, producing another binary image from the same GCI input.

The two binary images, i.e. one from direct binarization of enhanced GCI and another from binarization of Gabor image extracted from the vessel-enhanced GCI are then pre-processed to eliminate most of the false positive pixels. The two images are then combined by applying the logical OR operation, resulting in a single binary image. The resulting binary image is then post-processed using morphological operations to remove most of the remaining pixels that are falsely detected as vessel pixels. Fig. 1 illustrates the block diagram of the proposed method.

2.1. Pre-processing

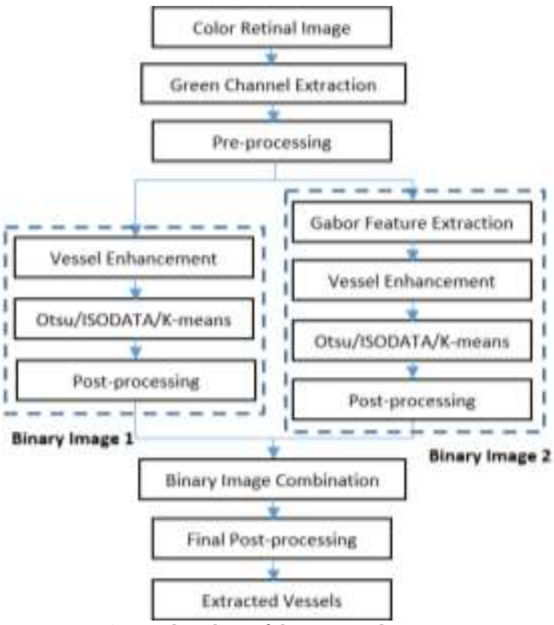


Fig. 1: Flowchart of the proposed system.

Once the GCI has been extracted from the original fundus image, the retinal area in the image referred to as Field of View (FOV) is expanded around the border as proposed by [14]. The objective of FOV expansion is to reduce the false detection rate of vessel pixels close to the original FOV because of the high contrast against the background outside the FOV.

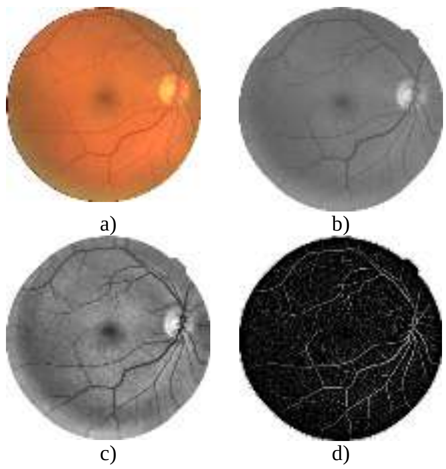


Fig. 2: Sample retinal image from DRIVE and the pre-processed output; a) original colour image, b) padded GCI, c) contrast-adjusted image and d) final vessel-enhanced output.

2.2. Enhancement of Retinal Blood Vessels

Retinal blood vessels on retinal images normally have poor contrast against the retinal background which has almost similar shades of colour with the vessels. This could be made worse by factors like non-uniform illumination and limited dynamic range of imaging sensor in fundus camera. In order to increase the contrast of the blood vessels, the pre-processed GCI undergoes contrast-limited adaptive histogram equalization (CLAHE) process. Then, a mean image is calculated from the image and subtracted from the contrast-adjusted image, producing an image with most of the retinal vessels highlighted since the contrast has been improved.

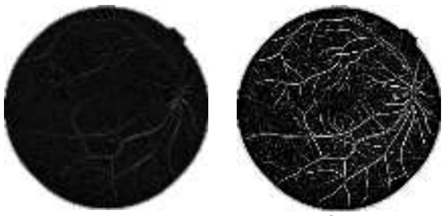
2.3. Gabor Wavelet Filter

Gabor wavelet filters are used in many image processing applications, with the main advantage of performing excellent edge detection with a set of linear filters. A Gabor filter impulse response is produced by multiplying a Gaussian envelope with a sine function, which can be expressed with the following equation:

$$g(x,y) = \exp\left\{-0.5\left(\frac{x'^2+\gamma y'^2}{2\sigma^2}\right)\right\}\exp(i(2\pi\frac{x'}{\lambda} \quad \psi)) \quad (1)$$

where λ represents the wavelength of the sine function, ψ is the phase offset, θ is the orientation, σ is the Gaussian function scale, γ is the aspect ratio, $x' = x\ cos\theta + y\ sin\theta$ *and* $y'^2 = y\ cos\theta + x\ sin\theta$ [14]. Gabor wavelet is especially good in capturing directional signals in images and can also be tuned to capture certain frequencies of interest.

Some of the previous works have demonstrated the effectiveness of using Gabor features extracted from a retinal image to detect the retinal blood vessel network [14–17]. In our proposed method, the parameter values as proposed by [14] are adopted in Gabor feature extraction from the GCI. A sample of image of extracted Gabor feature image and its corresponding pre-processed output are shown in Fig. 3.



a) b)

Fig. 3: Sample of extracted Gabor feature image; a) Gabor feature image extracted from GCI, b) pre-processed and vessel-enhanced Gabor feature image.

2.4. Automatic Binarization

At this point, two vessel-enhanced images are produced from the previous steps. The next step is to convert these grayscale images to binary images using automatic binarization method. With Otsu's method and ISODATA, the binarization is performed by establishing a threshold value so each pixel can be labelled as either a vessel-pixel (value 1) or a non-vessel-pixel (value 0). Where else using K-means, clustering is performed on the image pixels so each pixel can be divided into one of two clusters namely vessel or non-vessel.

2.4.1. Otsu's Method

Otsu's method is one of the classical global thresholding methods that is widely used for segmentation in image processing field. For binary segmentation, the method will choose a threshold value that would optimally segment the input image based on intra-class variance of 2 classes [18]. It works on the assumption that every image contains two classes of pixels, i.e. the background pixels and foreground pixels.

2.4.2. ISODATA

ISODATA is another image thresholding algorithm that can be used to convert an image into a binary image. The principle of the method is to identify the optimal threshold for any image with a two-class histogram by assuming the threshold to be the average of the mean of the two classes [19]. ISODATA is an iterative method since the mean of the two classes are not initially knows, hence the mean image is used initially. The initial threshold will be calculated based on this initial value and will be used to determine the new threshold. This step is repeated until the threshold no longer changes between iteration or until a certain number of iterations is achieved [20].

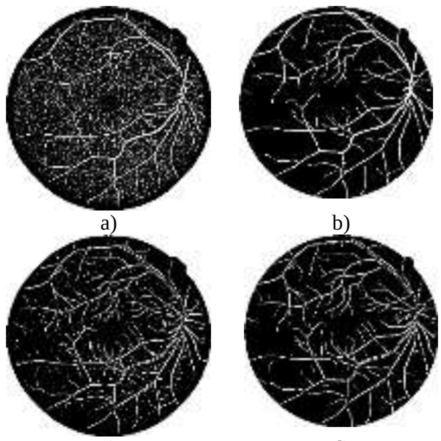
2.4.3. K-means

K-means is an automatic clustering technique that can be used to automatically group observations into clusters [21]. In this study, K-means is used to cluster all the pixels in a retinal image into 2 clusters, namely the vessel-pixel and non-vessel pixel. In K-means implementation, the objective is to partition the observations into *k* clusters in which each observation should be in the cluster with the nearest mean.

2.5. Post-Processing

Once the two images are converted into binary images, these images normally contain a lot of falsely detected vessel pixels, or noisy pixels. During this step, morphological operations opening and closing are applied to the binary images to remove these noisy pixels. Median filter is also applied to smooth the vessels outline on the two binary images. The padding that was added during pre-processing step is also removed, resulting in the original FOV of the retinal region.

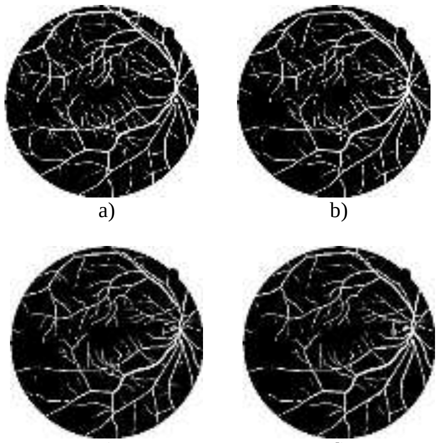
Fig. 4 shows example of the post-processed binary images for both GCI and Gabor feature image.



c) d)

Fig. 4: Sample binary output using K-means; a) binary image from GCI, b) binary image a after post-processing, c) binary image from Gabor feature, and d) binary image c after post-processing.

The final step is to combine the two binary images using a logical OR operation, resulting in one binary image as the final output, as shown in the following figure.



c) d)

Fig. 5: Sample combined binary outputs compared to ground truth image; a) ground truth, b) output with Otsu's method, c) output with ISODATA method, and d) output with K-means method.

3. Results and Discussion

To validate the effectiveness of the proposed method, a publicly available online database is used. The whole procedure described in flowchart in Fig. 1 was applied to the images in the selected database three times with different binarization technique for each run, as described earlier.

3.1. Image Database

The public database used for validation of our proposed method is the DRIVE database [22]. The database has 40 colour retinal images grouped into two sets, training set and test set. The images are in RGB format with 8 bits per colour channel captured using a Canon CR5 non-mydriatic camera with a field of view of 45 degrees. All the images are standard in size, which is 565 by 584 pixels. The database owner provided a mask image and a manually segmented image for each image in the database. A second set of manual segmentation image in addition to the first is also available for the test set. For this study, the test set of 20 images was used for validation using the first set of manually segmented image set as the ground truth and the second manual segmentation set as the target benchmark.

3.2. Performance Evaluation

For performance measure of the proposed method, we only consider the pixels that are within the FOV on the retinal image, i.e. excluding all the pixels in the black background from our calculations for performance metric. A pixel is labelled as true positive (TP) if the algorithm labels it as vessel pixel and the ground truth image also labels it as such. A pixel is labelled as false positive (FP) if the algorithm labels it as vessel pixel but in the ground truth image it is labelled as non-vessel pixel. The same concept also applies to true negative (TN) and false negative (FN).
Once all the pixels within the FOV has been labelled with either TP, FP, TP and TN, a number of performance metrics are calculated to quantify the segmentation performance. We have selected Accuracy(ACC) rate, Specificity (SP), Sensitivity (SN), and Matthews Correlation Coefficient (MCC) performance metrics to measure the performance of our proposed method. Calculations we used for the measures are similar to the ones used by [14].

3.3. Experimental Results

Sample images of post-processed binary images in Fig. 4 b) and d) indicate that the binarization of only the vessel-enhanced GCI may be sufficient in discovering most of the large vessels, but it can also be noticed that most of the smaller vessels were left undetected. This is because the smaller vessels were mostly detected as disconnected pixels of smaller size, which were later removed during the post-processing step. On the other hand, the binary image resulting from binarization of the vessel-enhanced Gabor feature image has smaller vessels detected. However, on a closer look we could see that some pixel along the middle of the large vessels were detected as non-vessel pixels. By combining both the binary images, we could have a better representation of both small and large retinal vessels on the image. Sample output of combined binary images for the three different binarization methods are given in Fig. 5.

Table 1: Comparison of segmentation performance between existing methods and proposed method

Methods	Performance Metric			
	Sn	Sp	Acc	MCC
Supervised Methods				
Niemejer* [23]	0.6976	0.9772	0.9412	0.7294
Staal* [22]	0.7196	0.9784	0.9450	0.7482
Soares [14]	-	-	0.9466	-
Unsupervised Methods				
Chaudhuri* [6]	0.2706	0.9887	0.8969	0.4236
Jiang* [24]	0.6480	0.9623	0.9218	0.6509
Zana* [9]	0.6697	0.9830	0.9429	0.7315
Azzopardi [25]	0.7655	0.9704	0.9442	0.7475
Mendonca [10]	0.7344	0.9764	0.9452	-
Proposed Methods				
Gabor Filter + K-means	0.7206	0.9757	0.9425	0.7400
Gabor Filter + ISODATA	0.7371	0.9757	0.9448	0.7506
Gabor Filter + Otsu	0.7211	0.9785	0.9453	0.7492

Table 1 compares the quantitative segmentation performance of some of existing methods against the proposed methods. The performance for methods proposed by [23] were calculated using the output binary images available on DRIVE database website, while the rest were obtained from the published literatures. It can be seen that the accuracy of the proposed method with Otsu's binarization method (Gabor + Otsu) is 0.9453, which is higher than most of the other methods, except for Soares's. The same is also true with the MCC value of Gabor + Otsu at 0.7492, except when it is compared to the other proposed method Gabor + ISODATA whose MCC value is 0.7506. In terms of sensitivity and specificity values, it can be said that the three proposed methods achieved comparable performance when compared to existing methods.
When comparing the three proposed methods with different binarization methods, it can be seen that Otsu's method achieved the highest performance for two out of the total four performance metrics, namely specificity and accuracy. ISODATA on the other hand achieved highest values for sensitivity and MCC value. K-means consistently has the worst performance across all four performance metrics compared to the other two binarization methods.

4. Conclusion

In this paper, we presented a comparison of three image binarization methods when used together with Gabor wavelet to segment retinal blood vessels on retinal images. The input to the proposed system is the GCI extracted from the colour image, which is then processed to produce two different binary images. One of the binary images are obtained by binarizing the processed GCI while the other is obtained by binarizing the processed Gabor feature image extracted from the same GCI. It is found that by combining the two binary images, the overall detection of both large and small vessels is improved.
Among the three binarization methods proposed to be investigated, Otsu's method demonstrated the best performance in terms of accuracy and spesitivity where else ISODATA exceled in sensitivity and MCC value. Since accuracy is normally regarded as the most significant indicator for segmentation performance, therefore we can conclude that Otsu'd method will be the best method to be used for binarizing the processed images to detect blood vessels. Comparing the performance of the best proposed method, i.e. combined Gabor filter and Otsu's method, to other methods in literature indicated comparable performance, with much shorter processing time. A single image requires on average 3 seconds to process using the proposed methods. The use of simplistic and unsupervised methods in the proposed method can be very well-suited for an efficient and accurate retinal diagnosis system with lower computational load.

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