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ORIGINAL RESEARCH ARTICLE

Diabetic retinopathy feature extraction images based on confusion neural network

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ABSTRACT

The diagnosis of diabetic retinopathy depends on the evaluation of retinal fundus pictures. The current methods have been successful in extracting features from fundus images, but due to the complex blood vessel distribution in these images and the presence of a great deal of noise, simple methods based on threshold segmentation and clustering are vulnerable to feature loss during the extraction process. For example, the small blood vessels in the fundus are lost, and the branches of blood vessels are blurred. In addition, the noise in medical images is mainly distributed in the high-frequency area of the image. The proposed method to segment the retinal fundus vessels in the DRIVE and STARE datasets, the average accuracy of this method is 95.45% and 94.81%, respectively, and the sensitivity and specificity are 73.35%, 75.39% and 97.34%, 95.75%. In addition, compared with related methods, the proposed method has higher segmentation accuracy, and after segmentation, the fundus blood vessels have higher integrity, clear structure, and less loss of small blood vessels.

Keywords: Diabetic Retinopathy; Medical Images; Confusion Neural Network

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1. Introduction

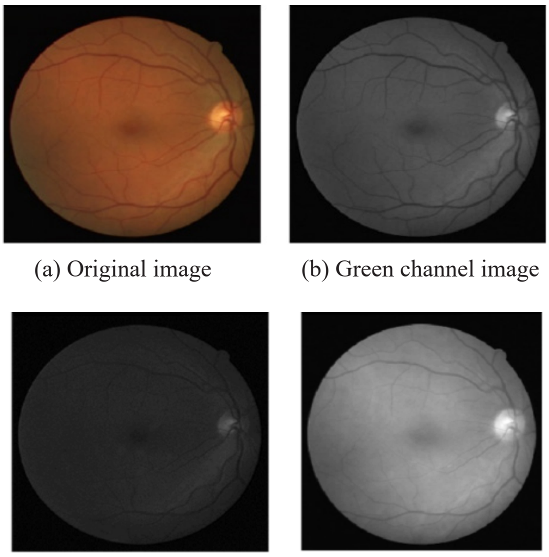
The human retina comprises millions of photoreceptor cells and nerve cells that can respond to light[1]. This photoreceptor transmits impulse signals to optical neurons and converts them into images humans can recognize[2]. A variety of human diseases can indirectly lead to retinopathy, which can cause various visual impairments such as poor vision or blindness. Retinal fundus pictures are frequently utilized to diagnosis clinical retinal illnesses because early detection of retinal diseases can successfully avoid visual impairment. The retinal fundus image is divided into three parts: the optic disc, retina and vascular network[3]. Physicians can detect ocular illnesses, conduct patient screenings, conduct clinical research, and diagnose diseases connected to the retina by analyzing retinal blood vessels[4,5]. Factors such as the width of fundus blood vessels, irregular blood vessel distribution, and narrow blood vessel branches may lead to abnormal blood vessels and cause retina-related diseases[6,7].

In therapeutic treatment, the segmentation and extraction of retinal fundus vessels are extremely important. Based on whether the segmentation findings of blood arteries are manually tagged by medical specialists, the segmentation methods now in use can be classified as unsupervised and supervised approaches. Generally, the segmentation performance of supervised methods is slightly better than that of unsupervised methods. However, the Unsupervised methods do not rely on labelled data, which is their unique advantage. Thangaraj *et al*.[8] proposed a supervised method and designed an automatic segmentation method of fundus blood vessels based on a convolutional neural network. The segmented blood arteries had an appropriate diameter and distinct structure, and they produced positive results on the DRIVE dataset. Park *et al*.[9] proposed a deep convolutional neural network model based on fuzzy logic to automatically segment blood vessels and achieve accurate segmentation results. Yan *et al*.[10] designed a segmental computational loss model based on deep learning, focusing more on the consistency of vessel thickness during model training. Fraz *et al*.[6] proposed a fundus blood vessel extraction method combining blood vessel centreline and plane slicing technology. Then slice the grayscale image after blood vessel enhancement, using morphological operations to obtain the shape and contour of the blood vessel, and compare the centreline with these. The features are combined to obtain the final vessel segmentation result. Mendonca and Campilho[11] unsupervised method used the iterative region growth method to fill the fundus blood vessels based on the blood vessel centreline to realise the automatic segmentation of fundus blood vessels. However, this method not only achieved good results on related datasets but is also close to the average accuracy of manual segmentation by medical experts. Mapayi and Owolawi[12] proposed the adaptive local threshold blood vessel segmentation method based on local spatial relationship variance, which can accurately detect large and small blood vessels, and has a good segmentation effect compared with existing methods. This method converts blood vessels to a one-dimensional domain, which is processed to ensure enhanced images with good segmentation accuracy compared to recent methods[13]. Zhang *et al*.[14] proposed a new matched filtering method for the detection error of non-vessel edges by matched filters. By adjusting the detection threshold, not only the edge detection error is significantly reduced, but many originally missing features are detected. Kushol *et al*.[15] proposed a new and accurate fundus blood vessel segmentation algorithm to achieve blood vessel segmentation of different diameters and achieve good segmentation results in the high-resolution fundus image dataset they provided. Pathan *et al*.[16] proposed a fundus blood vessel and optic disc segmentation method. The optic disc region was removed and segmented after the blood vessel characteristics were first extracted from the image using the image cutting technique. Therefore, an advanced method is urgently needed to improve excellent segmentation performance on multiple datasets. This paper presents characteristics of medical images of a retinal fundus blood vessel segmentation method based on wavelet transform decomposition and reconstruction to realise the segmentation and feature extraction of fundus blood vessels. The proposed method comprehensively evaluates sound's good effect on retinal fundus blood vessel segmentation. By choosing the image datasets DRIVE and STARE, the efficacy of this method is confirmed, and the experimental segmentation results and associated techniques are compared and assessed.

2. Background

Most fundus images in the retinal fundus dataset come from ophthalmology centres or medical institutions. During the shooting process, the images are usually affected by the shooting site environment, which makes the collected retinal fundus images appear uneven grey distribution and low image contrast and other issues. The above problems make the distribution of the blood vessel structure in the retinal fundus image more complicated, and it is not easy to be extracted and detected. In order to improve the quality of retinal fundus images, before performing retinal fundus vessel segmentation, a series of pre-processing operations need to be performed on the retinal fundus images to lay a good foundation for the subsequent fundus vessel segmentation. By analyzing and processing the retinal fundus image, the retinal fundus RGB colour image and its R (red channel), G (green channel), and B (blue channel) monochrome channel images are shown in **Figure 1**.

For retinal fundus images, it can be seen that the green channel has the best vascularity and background contrast. The red channel is the brightest single channel, yet the branching architecture of the vessels are blurry due to the low contrast. The blue channel is dark; overall, the distribution of blood vessels is not obvious, and the dynamic range of grayscale is poor. In conclusion, the green channel in retinal fundus images exhibited the best distribution of vascular structures and had the highest contrast with the retinal background[17,18]. Therefore, in this paper, the channel separation operation is performed on the retinal fundus RGB colour image, and the green channel image of the retinal fundus image is extracted, which is a good choice for fundus blood vessel segmentation. From the original image, a green channel image was recovered with good quality. However, contrast enhancement processing must be applied to the resulting green channel image in order to increase the contrast between the fundus blood vessels and the backdrop in order to further increase the segmentation accuracy of the fundus blood vessels. **Figure 2** displays the final fundus image that was created.



(a) Original image (b) Green channel image

(c) Blue channel image (d) Red channel image

Figure 1. Schematic diagram of the original image channel.

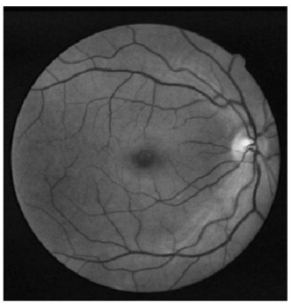


Figure 2. Schematic diagram of contrast enhancement.

3. Proposed method

In the medical world, retina-related disorders such diabetic retinopathy, hypertensive retinopathy, and macular degeneration are frequently diagnosed using the characteristics of blood vessels in retinal fundus pictures[19]. Usually, abnormal blood vessels are about 10–20 microns wide, while normal blood vessels are between 50–200 microns wide. This study offers a retinal fundus blood vessel segmentation approach based on wavelet transform decomposition and reconstruction, as illustrated in **Figure 3**. It does so in light of some features of retinal fundus images as well as the benefits of wavelet transform and morphology in image processing.

The proposed blood vessel segmentation method is processed in the following steps:

Step 1: Extract the green channel from the RGB-colored retinal fundus image to use as the segmentation image. **Figure 1** displays the green channel's schematic representation (b).

Step 2: Perform contrast enhancement processing on the image to be segmented, and the pre-processing result is shown in **Figure 2**.

Step 3: Apply wavelet decomposition to the image that needs to be segmented using wavelet transform multi-scale analysis. As shown in **Figure 4**, acquire the low-frequency region and high-frequency region of the image that has to be segmented based on the various information present in the signal at various scales, and then extract the low-frequency component LL and the four high-frequency components LH, HL, and HH as shown in **Figure 4(a)**.

Step 4: Because the low-frequency component LL contains the main part of the image to be segmented[19], the low-frequency component is processed using morphological correlation operations, as shown in **Figure 4(b)**.

Step 5: Because medical image noise is mainly distributed in the high-frequency region, firstly, image processing methods such as Gaussian filtering and threshold segmentation are used to reduce the large amount of noise contained in the high-frequency region. Then the processed LH, HL and HH high-frequency components are fused to improve the effectiveness of blood vessel segmentation, as shown in **Figure 4(c)**.

4. Result and discussion

In diabetic retinopathy detection, the segmentation of fundus blood vessels is a very challenging scientific research problem, and the segmentation result is an important indicator for evaluating the method's performance. DRIVE and STARE are commonly used retinal fundus vessel segmentation

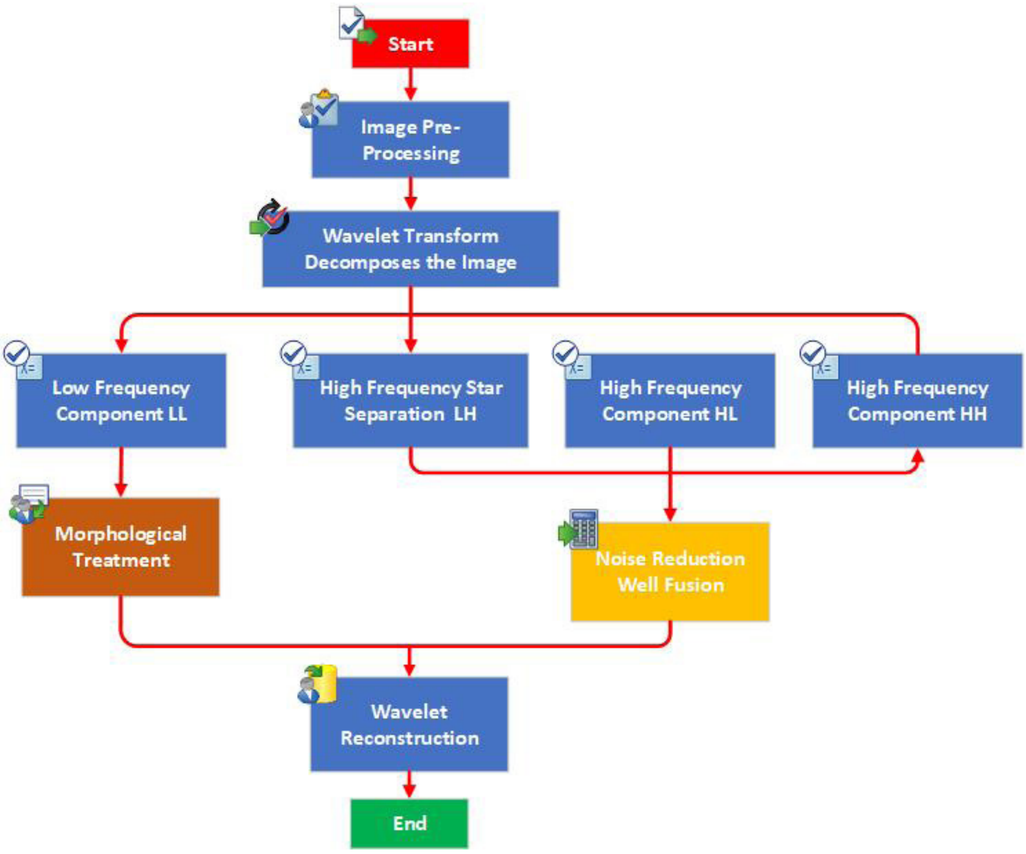
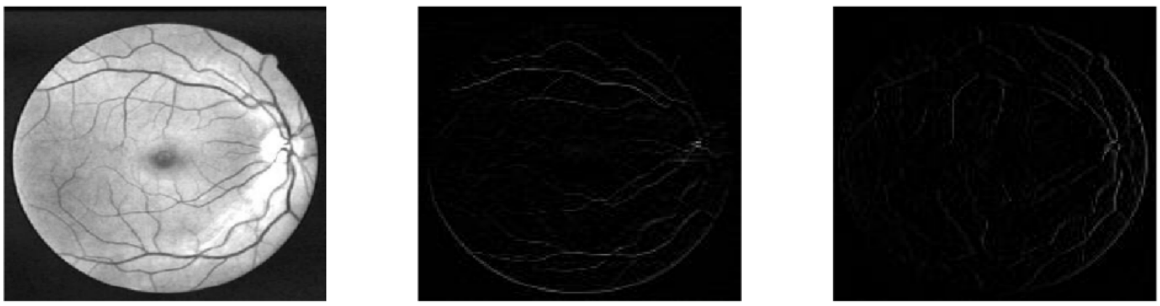


Figure 3. The fundus blood vessel segmentation method.

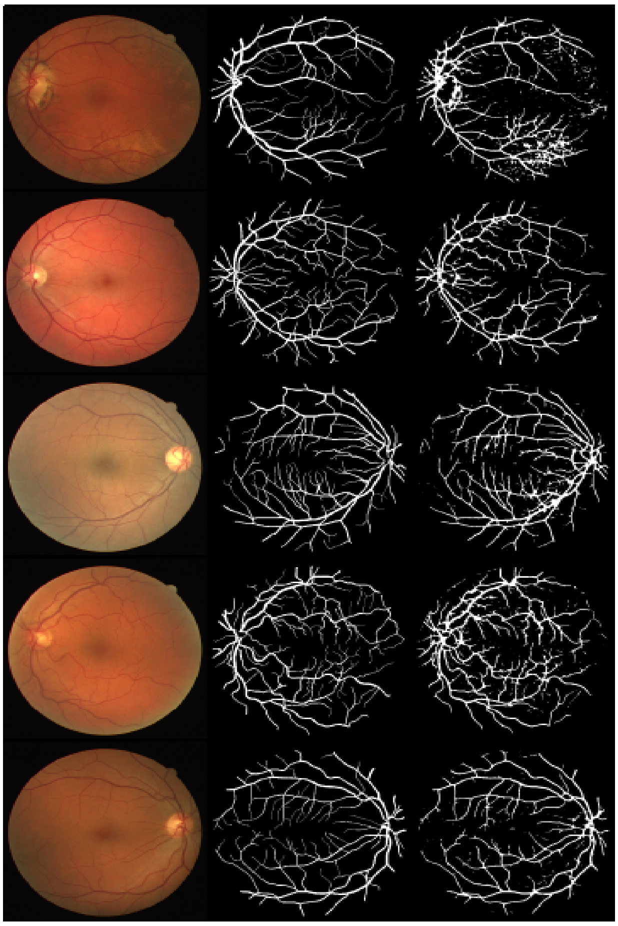


(a) Low-frequency component image (b) Horizontal high-frequency component image (c) Vertical high-frequency component image

Figure 4. Schematic diagram of low-frequency and high-frequency component images.

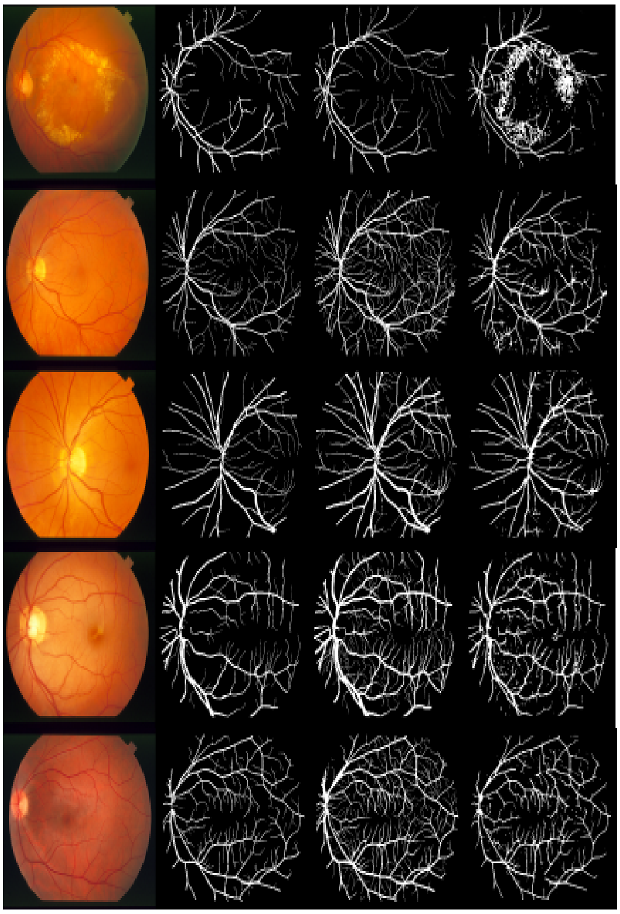
datasets containing disease-free and diseased retinal fundus images. The former corresponds to one segmentation result, while the latter corresponds to two. This paper conducts segmentation experiments on 40 fundus images in the two datasets and selects 5 retinal fundus images to display the segmentation and comparison results, as shown in **Figure 5**. **Figure 6** shows the segmentation results of some retinal fundus images in the DRIVE dataset selected in this paper.

The segmentation findings of the lesions-containing fundus pictures are shown in the first row. As can be seen, the method based on wavelet transform presented in this paper produced good segmentation results of the blood vessels in the retinal fundus compared to the results of expert manual segmentation. The blood vessel structure was generally clear, and there was less loss of small blood vessels. In addition, since there is a small lesion in the fundus optic disc and the lower right corner of the example image, there is noise in the corresponding position in the segmentation result. From the second to the fifth row, the fundus images without lesions are compared with the manual segmentation results. The blood vessel structure is clear, the width is moderate, the small blood vessels are still very little lost, and there is only a small amount of non-vascular noise. The segmentation outcomes of a few retinal fundus images from the STARE dataset used for this work are shown in **Figure 6**. The



(a) Original image (b) Manual segmentation map of experts (c) Segmentation map of our method

Figure 5. Result of DRIVE datasets segmentation experiment.



(a) Original image (b) Manual segmentation map of experts (c) Segmentation map of our method

Figure 6. Result of START datasets segmentation experiment.

fundus photos with lesions are in the first row, and the fundus images without lesions are in the second through fifth rows. The first row is a fundus image of severe retinopathy, which resembles annular maculopathy in the fundus image. By comparing the manual segmentation results of two experts, although the proposed method does not consider the influence of pathological features such as macular degeneration on the segmentation results, the proposed method still performs well in detecting vascular structure and small blood vessels. In conclusion, the proposed retinal fundus vessel segmentation method based on wavelet transform decomposition and reconstruction has good performance. Although the suggested method does not take into account the impact of pathological features like macular degeneration on the segmentation of blood vessels, it is clear from the segmentation findings of the first line of diseased fundus images that this area has to be improved.

Results from both supervised and unsupervised simulation techniques are included. **Table 1** includes statistical indicators for accuracy, sensitivity, specificity, and average values as well as the experimental results of retinal fundus blood vessel segmentation on the two datasets. **Table 2** compares the proposed strategy to methods that have been used in relevant literature recently on the DRIVE and STARE datasets, respectively. Additionally, pick the statistical indicator that best measures the performance of the method—the average of accuracy, sensitivity, and specificity. Additionally, it should be noted that since the STARE dataset contains blood vessel images that were manually segmented by two experts in order to make it easier to compare experimental results, this paper uses the average of the two groups of statistical indicators in **Table 2** as the experimental data for comparison with alternative techniques.

Table 1. Vessel segmentation performance parameters of the DRIVE dataset

No.	Accuracy	Sensitivity	Specificity
1	0.9624	0.7539	0.9792
2	0.9568	0.728	0.9894
3	0.9475	0.7317	0.9306
4	0.9496	0.7878	0.9905
5	0.9458	0.685	0.9947
6	0.9377	0.7245	0.9572
7	0.9589	0.6514	0.9887
8	0.9524	0.7027	0.9795
9	0.9541	0.7127	0.9762
10	0.9586	0.7686	0.9531
11	0.9653	0.6715	0.9841
12	0.9625	0.6595	0.9895
13	0.9575	0.7439	0.9763
14	0.9691	0.74	0.9663
15	0.9605	0.7437	0.9811
16	0.9508	0.7245	0.9906
17	0.9456	0.7759	0.9618
18	0.9547	0.7793	0.9713
19	0.9511	0.7937	0.9658
20	0.9632	0.7771	0.9784
Average value	0.955205	0.73277	0.975215

Table 2. Vessel segmentation performance parameters of the STARE dataset

No.	Expert 1 manual segmentation map			Expert 2 manual segmentation map		
	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity
1	0.9653	0.849	0.9667	0.9534	0.7909	0.9707
2	0.9542	0.6588	0.9324	0.9647	0.6953	0.9277
3	0.9338	0.8447	0.9163	0.9542	0.7742	0.9603
4	0.9263	0.7408	0.9412	0.9655	0.6723	0.9345
5	0.9614	0.8087	0.9326	0.9561	0.7403	0.9367
6	0.9363	0.8935	0.9234	0.9472	0.7226	0.9423
7	0.9483	0.8797	0.9543	0.9434	0.7163	0.9774
8	0.9561	0.7624	0.9718	0.9555	0.7318	0.9882
9	0.9487	0.8806	0.9546	0.9413	0.7141	0.973
10	0.949	0.7813	0.9637	0.9452	0.7053	0.9773
11	0.961	0.8452	0.9699	0.9468	0.6535	0.9848
12	0.9626	0.9078	0.9673	0.9587	0.7553	0.9854
13	0.9537	0.8396	0.9648	0.9398	0.6657	0.9849
14	0.9465	0.8598	0.9551	0.9377	0.7129	0.9721
15	0.9285	0.8182	0.9389	0.9256	0.7083	0.9568
16	0.9666	0.735	0.9484	0.9416	0.7585	0.9662
17	0.9612	0.8012	0.977	0.942	0.6328	0.9887
18	0.9649	0.7303	0.9774	0.961	0.6573	0.979
19	0.9641	0.7582	0.9734	0.9573	0.6234	0.9797
20	0.9367	0.7203	0.9308	0.9614	0.6215	0.9435
Average value	0.95126	0.805755	0.953	0.94992	0.702615	0.96646

5. Conclusion

This study first summarizes the current techniques for segmenting retinal fundus vessels before discussing and proposing a technique based on wavelet transform image decomposition and reconstruction that takes into account the unique properties of retinal fundus images. Second, DRIVE and STARE datasets are chosen for the investigation of retinal fundus image blood vessel segmentation from a list of six datasets that are often used internationally in the field of retinal fundus pictures and medical imaging. In conclusion, the accuracy of the proposed technique is higher than that of the four supervised methods on the DRIVR and STARE datasets, but only marginally inferior in sensitivity and specificity. The proposed method provides good accuracy, sensitivity, and specificity benefits over the unsupervised method.

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Conflict of interest

The authors declare no conflict of interest.

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