MLFF: Multiple Low-Level Features Fusion Model for Retinal Vessel Segmentation

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Abstract. Imaging is increasingly used for the diagnosis of retinal normality and the monitoring of retinal abnormalities. Many retinal vessel properties, such as small artery aneurysms, narrowing of incisions, etc., are related to systemic diseases. The morphology of retinal blood vessels themselves is related to cardiovascular disease and coronary artery disease in adults. The fundus image can intuitively reflect the retinal vessel lesions, and the computer-based image processing method can be used for auxiliary medical diagnosis. In this paper, a retinal vessel segmentation model, named as MLFF, is proposed to effectively extract and fuse multiple low-level features. Firstly, there are 25 low-level feature maps of fundus retinal vessel images that are analyzed and extracted. Then, the feature maps are fused by an AdaBoost classifier. Finally, the MLFF is trained and evaluated on public fundus images for vessel extraction dataset (DRIVE). The qualitative and quantitative experimental results show that our model can effectively detect the retinal vessels and outperforms other models including deep learning-based models.

Keywords: Vessel segmentation · Low-level features · Feature fusion · AdaBoost

1 Introduction

The fundus retinal vessels are the parts of the human body vessels that can be directly and non-invasively observed. By observing the changes in the retinal vascular network structure or morphology of retinal vessels, like diameter, branch morphology and angle, lots of ophthalmological and cardiovascular diseases can be diagnosed, such as glaucoma, diabetic retinopathy, hypertension, and arteriosclerosis [1]. Fundus retinal images have been commonly used for screening of diabetic patients. Using computer-assisted methods to automatically generate segmented blood vessel images can effectively help clinicians save their time [2].

In order to facilitate the diagnosis and surgery planning of those diseases, the first thing we have to do is to distinguish between the blood vessels and the background in the fundus images. Since it is labor-intensive and time-consuming

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to perform the segmentation manually by the clinicians, we want to achieve computer-aided automatic segmentation. Hence, the automatic detection and extraction of retinal vascular structure in color fundus images are of great significance. However, retina vessel segmentation (RVS) has been a challenge for long. In the fundus images, the intricacies of retinal vessel network and the changing brightness of the vessels with the extension of the vessels cause the segmentation challenging [3–5]. Furthermore, because of the lack of retinal vessel datasets, the deep learning-based models, which rely heavily on datasets, could be not effective.

In this paper, there are total of 25 low-level features of fundus retinal image are analyzed and extracted. Then, we design a multiple low-level features fusion model (MLFF) for retinal vessel segmentation. The extracted low-level features are fused by an AdaBoost classifier. By training and testing MLFF on the public digital retinal images for vessel extraction dataset (DRIVE) [6], the experimental results show that our model can effectively detect the retinal vessels and outperforms the SOTA models including deep learning-based methods.

2 Related Works

Researchers have worked on the RVS and made some achievements for many years. There are numerous methods of RVS published, which can be roughly classified into supervised and unsupervised methods.

Supervised methods require annotated standard images for training and thus show better performance. Among these methods, the commonly used techniques include Neural Networks, Gaussian Mixture Models, Conditional Random Fields, AdaBoost and Convolutional Neural Networks, etc. [7–9]. Lupascu et al. [10] buildt a RVS method based on Adaboost classifier, constructing the 41-D feature vector including local information, shape information and structural information of each pixel in the fundus image to train a classifier. Yang et al. [11] designed a multi-scale feature fusion model based on U-Net, which included data augmentation and preprocessing. The inception structure was introduced in the multi-scale feature extraction encoder for different sizes in the retina, showing a better segmentation effect on blood vessels. Recently, Wu et al. [12] constructed a NFN+ model, in which the multi-scale information was extracted and deep feature maps was fully used. A unique cascaded networks structure with network connection was designed to improve segmentation accuracy and solve the problem of under-segmenting of faint blood vessels. The models achieved high accuracy on DRIVE [6], STARE [13] and CHASE [14,15] databases. Shi et al. [16] proposed a multi-scale U-Net for RVS, called MSU-Net. Zhang et al. [17] built a pyramid context-aware network (PCANet) for RVS. Besides, a fast and efficient RVS model was proposed by Boudegga et al. [18].

Unsupervised methods do not need to rely on labeled samples and analyzes similarities or features between images. Such methods include matched filtering, morphological processing, model based approach, thresholding, etc. Image matting was also applied to the retinal vessel segmentation. Zhao et al. [19]

transformed the segmentation problem into a matting task, combining the local matting loss and global pixel loss to discern the ambiguous pixels around small vessels. The method can be either supervised or unsupervised. Ding et al. [20] proposed a new deep neural networks(DNNs) to detect vessels in FA images. Ramos-Soto et al. [21] built an efficient RVS model with optimized top-hat and homomorphic methods. The proposed methodology included previous, main, and post processing stages.

3 Multiple Low-Level Feature Fusion Model

3.1 Multiple Low-Level Feature Extraction

There are various features in the image, but not all of them are useful for improve the performance of different detection or segmentation task. Feature selection improves classification accuracy by identifying the most distinct features. In this work, the multiple low-level features of retinal vessel image, including gray, color, intensity, edge, morphology, texture, and multi-scales linearity, are analyzed and extracted detailedly. There are total of 25 low-level image features are extracted in our work. Specifically, 2 color feature maps on RGB and HSV color space, 1 luminance feature map, 8 edge features by Canny and Scharr operators, 7 morphological feature maps of Dilation, Erosion, Opening, Closing and TopHat operations, 6 texture feature maps by Gabor, Hessian and Frangi filters and 1 multi-scale feature map.

Color. As we know, the color image includes red, green and blue channel features. For retinal vessel image, the color fundus images separated by channels showed the strongest contrast in the images separated by green channels [10]. So, we choose the green gray feature map $\mathcal{F}_{Green}$ as one important low-level feature.

In terms of color feature analysis, HSV color space was selected to extract the colors of black and white. It was found that the whole range of red included the large vessels, while the background and small vessels were orange. We extract the red and orange color feature map $\mathcal{F}_{HSV}$ in the HSV color system. Compared with RGB color space, HSV color space can directly show the type, light and shade of color, and the color distribution of blood vessels and background in the color retinal vessel image is obvious. So, it is convenient and clear to extract the color information by using HSV color space.

Luminance. The luminance value of blood vessels in each area of fundus image is different from that of background. Threshold segmentation can effectively select the blood vessels, so the luminance value is taken as a feature. The brightness of blood vessels and background in different areas is obviously different in the color retinal vessel images. In terms of luminance feature analysis, the luminance value of each pixel is obtained through the calculation method of

extracting luminance value. The luminance feature map of retinal vessel image is extracted by follow formula:

$$\mathcal{F}_{Lum} = \lambda_R * R + \lambda_G * G + \lambda_B * B \tag{1}$$

where λ_R, λ_G and λ_B are the weights of red (R), green (G), blue (V) channels of retinal vessel image on the RGB space, respectively. As mentioned above, the green channel includes the strongest contrast feature information. So, we set the weight of G as the biggest one $\lambda_G = 0.587$, and $\lambda_R = 0.299$ and $\lambda_B = 0.114$. The selection of the weights of each RGB channel are based on our experimental experience.

Edge Features. Retinal vessel images have obvious edge features, and the junction between blood vessels and background has obvious changes of gray scale or other characteristic values. The edge features are important for the retinal vessel segmentation. In this case, we extract the edge feature maps $\mathcal{F}_{Edge} = \{\mathcal{F}_{Cany}, \mathcal{F}_{Sobel}, \mathcal{F}_{Scharr}\}$, 2 low-level feature maps are obtained by using Canny operator with 3×3 and 5×5 different cores, and 4 low-level feature maps are obtained by using Scharr operator in X and Y directions with 3×3 and 9×9 different cores. The weighted square of two directions is used to obtain 2 low-level feature maps. The Canny feature map $\mathcal{F}_{Cany}$ can judge whether edge points are edges. In order to extract more edge information of retinal vessel, the Sobel feature map $\mathcal{F}_{Sobel}$ are also considered as another low-level edge feature in this work. However, although the Sobel operation can effectively extract image edges, but cannot extract the unclear edges. Compared with the edge features extracted by Sobel, the edge feature map extracted by Scharr operator $\mathcal{F}_{Scharr}$ can significantly improve the information of small blood vessels.

Morphological Characteristics. The mathematical morphology operation can remove the noise in the image and connect the image area. So, we use the 3×3 structure operator to extract the morphological characteristics by Dilation, Erosion, Opening, Closing and TopHat operations, and obtain the feature maps $\mathcal{F}_{Dila}, \mathcal{F}_{Ero}, \mathcal{F}_{Opening}, \mathcal{F}_{Closing}$ and $\mathcal{F}_{TopHat}$ respectively. Note that, three cores with different structures, i.e. (80,800), (800,80) and (800,800), are selected to perform operation on grayscale images, and 3 TopHat feature vectors are obtained.

Texture. We choose the Gabor, Hessian and Frangi filters to extract the texture features. Gabor feature $\mathcal{F}_{Gabor}$ is extracted with scale equals 1, and Hessian feature map $\mathcal{F}_{Hessian}$ is with stride equals 10, λ equals 10. Furthermore, the sensitivity coefficient of Frangi filter is set to 10, and four scales are selected to filter the retinal images by 0.002, 0.004, 0.008 and 0.01. So, we obtain four Frangi feature maps, $\mathcal{F}_{Frangi_i}$ $(i = 0.002, 0.004, 0.008, 0.01)$.

Multi-scale. In the multi-scale linear analysis, a total of 12 linear detectors were established from 0 to 180° according to the gray distribution of blood vessels, and 1 feature was obtained. By analyzing the transverse information, we can find that the gray distribution of retinal vessels conforms to the Gaussian matched filtering function, that is, the shape of Gaussian matched filtering is similar to the characteristics of retinal vessels in the direction of the bottom of the eye. The Gaussian filter is defined as:

$$\mathcal{G}_\theta(x,y) = -\frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{x^2}{2\sigma^2}\right), f \text{ or } |x| \leq t \cdot \sigma, |y| \leq L/2 \tag{2}$$

where θ is the rotation Angle ($[0°, 180°]$), L and σ represent the length of detectable omental vessels and their cross-sectional stretch, respectively. In this paper, $\sigma = 1.5$, $L = 9$, and 12 directions $[0°, 15°, ...180°]$ were selected to carry out linear retinal vascular Gaussian matched filtering, and operation was carried out on the mask to remove the information outside the mask, and a feature map $\mathcal{F}_M$ was established.

3.2 Multiple Low-Level Feature Fusion

After extracting the low-level features of retinal vessel images, we design a RVS model using the Adaboost learning method (MLFF) in this section. The architecture of MLFF is introduced in Fig. 1. AdaBoost, proposed by Freund and Shapire [22], is an adaptive supervised machine learning technique, which combines a set of low-level classifiers with low discrimination (called weak learners) to construct a powerful classifier. The AdaBoost algorithm is easy to implement and relatively fast, making it popular for computer vision. Furthermore, the AdaBoost can reduce the bias and variance during training phase, which can effectively solve the overfitting problem caused by the small sample learning. The final classifier is a weighted combination of weak classifiers, which is defined as following formula:

$$G(f) = \text{sign}\left(\sum_{t=1}^{T} \alpha_t g_t(f)\right) \tag{3}$$

where $g_t(\cdot)$ is the weak classifier and $G(\cdot)$ is the strong AdaBoost classifier. α_t is the weight of $g_t(\cdot)$. T is the number of weak classifiers. More details are shown in Algorithm 1 and shown in Fig. 1.

The algorithm has two stages, i.e. Training and Testing. In the training, the low-level feature maps of retinal vessel images are extracted firstly. Then, the feature maps are stacked together as the feature vector for training. Finally, weak classifiers of AdaBoost are combined to a strong classifier. In the testing, the low-level feature maps of test images are extracted as same as the training stage. Then, the features are used to train strong classifier. Finally, the vessel segmentation results are obtained by the post-processing.

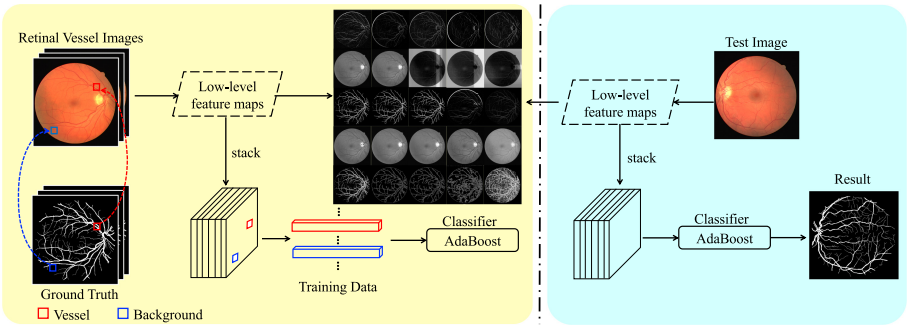

Fig. 1. The architecture of MLFF, including train and test phases.

Algorithm 1: Learning a Multiple Low-level Feature Fusion Using AdaBoost

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Input: Training dataset with N retinal vessel images and ground truth from expert. Testing images I_{test}.

Output: Retinal vessel segmentation map.

Training stage:

1. Extract the the multiple low-level features of fundus vessel images $\mathcal{F}_i$
2. For N retinal vessel images, sample $x_{s(}S=1)^S$ with labels $y_{s(}S=1)^S$. Compute features $f_{s(}S=1)^S = f(x_s)_{(S=1)^S}$.
3. Initialization $w_s = 1/S$.
4. **for** $t = 1, ...T$ **do**

   a. train a weak classifier $g_t : R^d \rightarrow \{-1, 1\}$, by $g_t = \arg\min_{g_n \in \mathcal{G}}$, where

$$\varepsilon_u = \sum_{s=1}^{S} w_t(s) \left[y_s \neq g_u \left(\mathbf{f}_s \right) \right]$$

   b. set the weight of g_t: $\alpha_t = \frac{1}{2} \log \frac{1-\varepsilon_t}{\varepsilon_t}$

   c. update weights

$$w_{t+1}(s) = \frac{w_t(s) \exp\left[-\alpha_t \cdot y_s \cdot g_t \left(\mathbf{f}_s \right) \right]}{Z_t}$$

   where Z is a normalization factor.

end

5. Final classifier is trained $G(f) = \text{sign}\left(\sum_{t=1}^{T} \alpha_t g_t(f) \right)$

Testing stages:

Extract the feature vector $f(x)$ of each location x in I_{test}, obtain the detected vessel segmentation map by the trained strong classifier $g_t : R^d \rightarrow \{-1, 1\}$.

3.3 Post-processing

While a single classifier is used to segment the vessels of fundus image, there will be noise or other impurities in the segmentation results. Therefore, morphological operator $\mathcal{S}$ is established in this paper to calculate the number of blood vessel

pixels contained in the connected region of $\mathcal{S}$. The connected area refers to: from the gray level image, the gray value of one or more of the 8 pixel points around the pixel point or the four pixel points around the pixel point is the same as the gray value of the point, and so forth, until the gray value of no pixel point is the same. In this paper, we select 8 surrounding pixel points, and the structural operator $\mathcal{S}$ judged by the classification model as blood vessel is calculated. The connected area with less than 20 pixel points is changed as the background.

4 Experiments

The DRIVE dataset [6] is used often in RVS. It includes 20 training and 20 testing fundus images with 584×565 resolution and JPEG-compressed. We evaluated the performance of MLFF on DRIVE dataset.

4.1 Qualitative Evaluation

Figure 2 presents a visual comparison of our model and other models, such as 2D matched filtering, Random Forest learning method. The results indicate that MLFF can much more accurately detect the retinal vessels than others. Furthermore, the comparison of local segmentation results is showed in the third row of Fig. 2. As expected, our model can detect more vessel information than others.

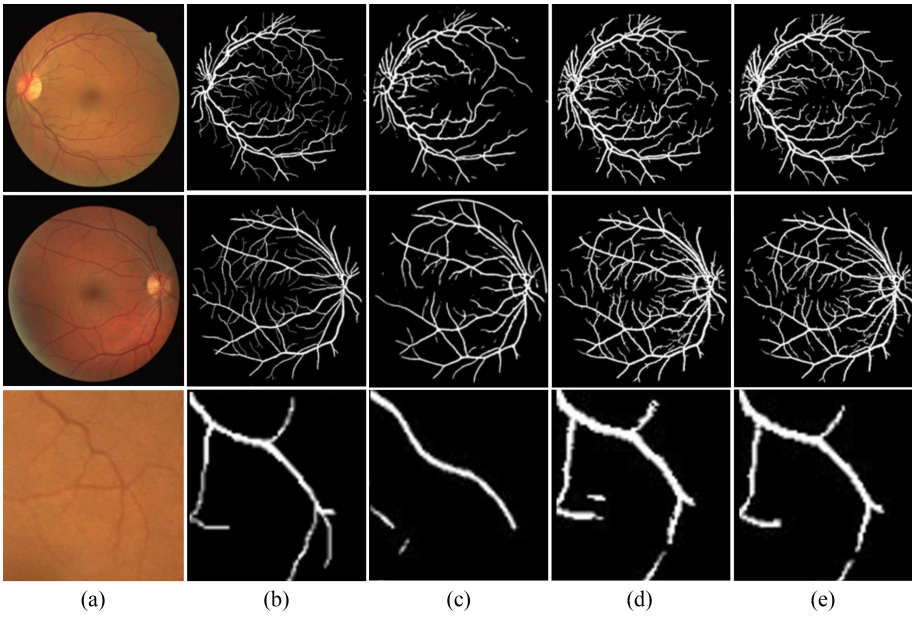

Fig. 2. Qualitative comparison our model with other method. (a) Retinal vessel images. (b) Ground truth. (c) Results of 2D matched filtering. (d) Random Forest. (e) Ours.

Table 1. Comparisons of our model on DRIVE dataset.

	Models	ACC(%)	SP(%)	SE(%)
Classical method	Random Forest	94.70	95.67	84.82
	Azzopardi (2015)	94.42	97.04	76.55
	Orlando (2017)	/	96.84	78.97
	Li (2016)	95.27	98.16	75.69
Deep learning-based	Liskowski (2016)	95.35	98.07	78.11
	Yan (2018)	95.42	98.18	76.53
	Wu (2018)	95.67	**98.19**	78.44
	NFN+ (2020)	95.82	98.13	79.96
Ours (MLFF)		**96.17**	96.77	**87.83**

4.2 Quantitative Evaluation

In this work, we employ the accuracy (ACC), sensitivity (SE) and specificity (SP) [12] to quantitatively compare the performance of our model.

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

$$SP = \frac{TN}{TN + FP}, SE = \frac{TP}{TP + FN} \tag{5}$$

where SP denotes that the manually annotated non-vessel pixels that are correctly classified as non-vessel pixels divided by the total number of non-vessel pixels (TN) in the gold standard. Similarly, the SE is determined by dividing the number of pixels correctly classified as vessel pixels (TP) by the total number of vessel pixels in the ground truth.

In Table 1, the performance of our model is compared with other classical model and deep learning model, such as Random Forest [23], some retinal vessel segmentation model (proposed by Azzopardi [24], Liskowski [25], Li [26], Orlando [27], Yan [28] and Wu [29] et al., respectively) and NFN+ [12] model. The comparison results show that the ACC and SE scores of our model are the highest one. Moreover, our model outperforms some deep learning-based vessel segmentation models, such as Liskowski, Yan, Wu and NFN+.

4.3 Ablation Study

To investigate the effects of the proposed MLFF with and without post-processing, the qualitative and quantitative comparisons are shown in Fig. 3 and Table 2, respectively. As shown in Fig. 3 (b) and (c), we can see that the noise and some irrelevant information of retinal vessel are eliminated after the post-processing. In addition, the segmentation results with post-processing are very close to the ground truth visually (Fig. 3 (d)). Furthermore, the quantitative comparison is discussed in Table 2. As expected, we can find that the

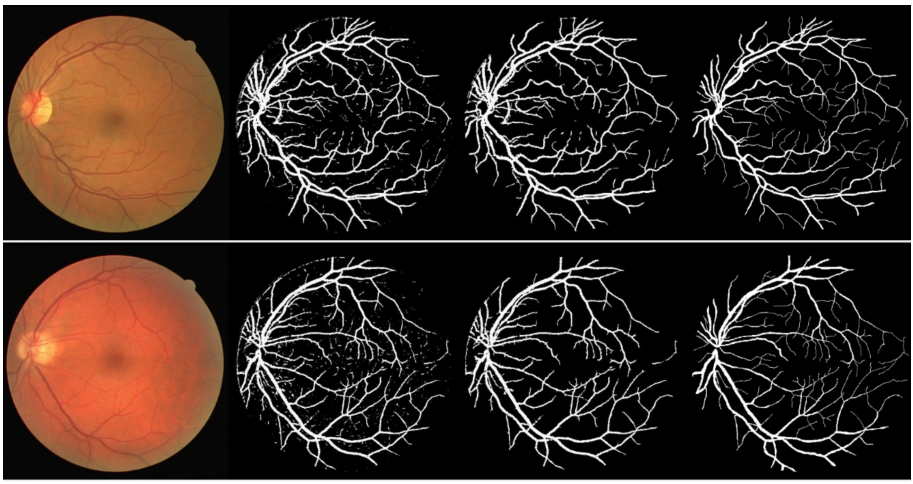

Fig. 3. Qualitative comparison of the proposed MLFF with and without post-processing. (a) Retinal vessel images. (b) Segmentation results without post-processing. (c) Segmentation results with post-processing. (d) Ground truth.

Table 2. Performance of MLFF with and without post-processing.

Models	ACC(%)	SP(%)	SE(%)
MLFF without post-processing	95.12	96.24	83.59
MLFF with post-processing	**96.17**	**96.77**	**87.83**

evaluation scores of MLFF with post-processing are all higher than the without post-processing. Therefore, we can conclude that the post-processing is effective for RVS.

5 Conclusion and Discussion

In this work, we analyze and extract total of 25 low-level features of the fundus retinal images. A multiple low-level features fusion model (MLFF) is proposed for retinal vessel segmentation. The extracted multiple low-level features are fused by an AdaBoost classifier. By training and testing the MLFF on DRIVE dataset, the results show that our model can precisely detect the retinal vessels and outperforms other SOTA models including deep learning-based methods. However, due to the lack of retinal vessel segmentation datasets, the proposed model is only verified on DRIVE. In the future, the proposed model will be trained and tested on more fundus vessel datasets.

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