Retinal Vessel Segmentation Using Color Image Morphology and Local Binary Patterns

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Abstract: In this paper, an automated retinal vessel extraction algorithm is represented. A multi-scale morphological algorithm is used for local contrast enhancement of color retinal image. This method enhances vessels not only in color image, but also in the three color components of that image. After feature extraction using LBP and spatial image processing, MLP as a classifier segments the pixels into vessels and non-vessels. Finally, in post processing step, we used binary morphologies for noise removing and smoothing. The performance of the proposed algorithm is tested on the images of DRIVE database.

Keywords: Segmentation, multi-scale morphology, LBP, MLP.

1. Introduction

Automated segmentation of the vasculature in retinal images is important in the early detection of many diseases such as diabetic retinopathy, hypertension, arteriosclerosis, etc [1], [2]. However, manual detection and analysis of the retinal images is a time consuming and unreliable task, and as the number of images increases, the study becomes very difficult. Therefore, it is necessary to use automated algorithms for analysis of these images.

For the assessment of retinal images, segmentation of the vessels from the background is an initial requirement. Since the retina images acquired with a fundus camera, it is difficult to detect the blood vessels and quantify changes in geometry due to the low contrast between the blood vessels and retina layer background. Then, we should enhance these images as a preprocessing step before segmentation. Several methods have been developed in case of retinal image enhancement. In [3] a method based on histogram equalization is represented for improving the quality of these images. In [4], [5] contourlet transform and in [6] matched filters are employed to enhance the contrast of blood vessels. In this paper, we use a multi-scale morphological algorithm [7] for local contrast enhancement of color retinal image. The magnitude image constructed from the three color components of red, green and blue is enhanced using multi-scale morphological filters preserving the direction of color vector. This method improves the contrast of vessels in color retinal image and also the red, green and blue channel images of the color image.

Many segmentation algorithms have been presented to provide detection of vascular structure. According to [8] The vessel detection techniques fall into three main categories: kernel-based, tracking-based and classifier-based.

kernel-based methods convolve kernels with different sizes and orientations with the main image based on a specific model. The proposed method in [9] uses Gaussian matched filters for detection of blood vessels in human retina digital images. However it is relatively time consuming when the kernels become quite large and need to be applied repeatedly with different orientations.

Tracking-based methods utilize a certain model to track the vessels. They work by first locating some seed points and then trace the vasculature recursively according to that model [10]. These seed points may be set manually by simple thresholding or automatically by morphological operations.

In classifier-based methods, first, a features vector is extracted for each pixel of retina image and then a classifier uses the vectors and classifies the pixels to vessels and non-vessels [4], [11].

In this paper, we also use a classifier-based method for segmentation and extraction of vessels in retina images. Hence, after the processing step that enhances the retina image quality via a multi-scale morphological algorithm, we extract a feature vector using Local Binary Pattern (LBP) [12] for each pixel of the enhanced image. In the sequel, a Multi Layer Perceptron (MLP) is employed as a classifier for segmentation of blood vessels from background.

Recently, LBP is used in many applications to identify the texture in images. LBP is a technique that describes

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the texture in terms of both statistical and structural characteristics. The generalized form of this operator is gradient and rotation invariant that is beneficial for our application.

The paper is organized as follows: in section 2 the proposed algorithm that is composed of preprocessing, feature vector extraction, segmentation and post-processing steps is explained. Experimental results are presented in section 3 and finally, section 4 concludes the paper.

2. The Proposed Algorithm

The methodology includes the below steps that are described in details in the following section.

I. Preprocessing
II. Feature vector extraction
III. Segmentation of the input image
IV. Postprocessing

2.1 Preprocessing

With the rapid increase in the usage and application of color images, it is essential to develop tools and algorithms for color image processing. The advantages of morphological operations of being sensitive to the shape of the features are combined with the concepts of multi-scale processing to create a very powerful class of filters. We also use a multi-scale morphological algorithm [7] for local contrast enhancement of color retinal images in the preprocessing step.

Two main morphological operations i.e. dilation and erosion of gray-scale image g(r,c) by the structuring element of B are defined respectively, as

$$(g \oplus B)(r,c) = \max\{g(r-k, c-l) \mid (k,l) \in B\} \tag{1}$$

$$(g \ominus B)(r,c) = \min\{g(r+k, c+l) \mid (k,l) \in B\} \tag{2}$$

For the sake of features or objects extraction based on both shape and size we add an additional attribute to the structuring element which is its scale. A morphological operation with a scalable structuring element is termed as multi-scale morphology. According this conception, multi-scale opening and closing operations are defined respectively, as

$$(g \circ nB)(r,c) = \big((g \ominus nB) \oplus nB\big)(r,c) \tag{3}$$

$$(g * nB)(r,c) = \big((g \oplus nB) \ominus nB\big)(r,c) \tag{4}$$

Where n is an integer representing scale of the structuring element. If B is convex nB is obtained by dilating B recursively n-1 times with itself.

We can use top-hat and bottom-hat transforms for extracting bright and dark objects that are smaller than size of structuring element. In this method, the features extracted using these multi-scale filters are recombined with each other by assigning large weights to small features.

In the RGB color space the intensity at a pixel location is a 3-component vector which consists of red, green and blue intensity values. The magnitude of this vector at each pixel location (r,c) give rise to a gray-scale image as given by the following equation.

$$g(r,c) = \sqrt{R^2(r,c) + G^2(r,c) + B^2(r,c)} \tag{5}$$

For local contrast enhancing the original image due to presence of bright features, we use the Equation (6) as follows below.

$$\tilde{g}(r,c) = (g \circ B)(r,c) + k[g(r,c) - (g \circ B)(r,c)] \tag{6}$$

Where k is a global amplification factor and is greater than one. So this transformation makes the bright features brighter and, thus, improves the local contrast. By selecting k=2 in the equation, it becomes

$$\tilde{g}(r,c) = g(r,c) + [g(r,c) - (g \circ B)(r,c)] \tag{7}$$

Where $g(r,c) - (g \circ B)(r,c)$ is the top-hat image and if we denote it at scale 1 by $F_B^o(r,c)$, we have Equation (8) as

$$\tilde{g}(r,c) = g(r,c) + F_B^o(r,c) \tag{8}$$

Similarly we denote the bright-feature image at scale n by $F_{nB}^o(r,c)$ and, then, Equation (9) is described as

$$\delta_n^o(r,c) = F_{nB}^o(r,c) - F_{(n-1)B}^o(r,c) \tag{9}$$

It is clear that $\delta_n^o(r,c)$ contains bright features that are larger than (n-1)B, but smaller than nB. Generalizing the equation for a number of scales, we have

$$\tilde{g}(r,c) = g(r,c) + k_1\delta_1^o(r,c) + k_2\delta_2^o(r,c) + \cdots \tag{10}$$

Where k1>k2>..., since we know that smaller the size of a bright feature, more should be its intensity for detectability. Restricting the process up to the scale m we get

$$\tilde{g}(r,c) = g(r,c) + \sum_{i=1}^{m} k_i\delta_i^o(r,c) \tag{11}$$

It's not necessary m to be a large value in this equation because the size of vessels in retina images is small and our purpose is just enhancing these vessels. Now taking $k_{i-1} = k_i + 1$ for all i and choosing $k_m = 1$ we have finally local contrast stretching of bright features as

$$\tilde{g}(r,c) = g(r,c) + \sum_{i=1}^{m} F_{iB}^o(r,c) \tag{12}$$

Similarly for dark features, we have

$$\tilde{g}(r,c) = g(r,c) - \sum_{i=1}^{m} F_{iB}^c(r,c) \tag{13}$$

The enhanced gray-scale image is therefore obtained by assigning equal weights to both dark and bright features.

$$\tilde{g}(r,c) = g(r,c) + \tfrac{1}{2}\sum_{i=1}^{m} F_{iB}^o(r,c) - \tfrac{1}{2}\sum_{i=1}^{m} F_{iB}^c(r,c) \tag{14}$$

The enhancement of the magnitude image is basically either stretching or squeezing (depending on whether it is detected as a part of a bright or dark feature in the color image) the magnitude of the color vector at all pixel locations of the color image preserving its direction. Therefore, the final stretched color image is given by

$$\begin{pmatrix}\tilde{R}(r,c)\\ \tilde{G}(r,c)\\ \tilde{B}(r,c)\end{pmatrix} = \frac{\tilde{g}(r,c)}{g(r,c)}\begin{pmatrix}R(r,c)\\ G(r,c)\\ B(r,c)\end{pmatrix} \tag{15}$$

The proposed multi-scale enhancement algorithm, presented above preserves the color properties like hue and saturation of the image. The color parameters hue, saturation and the lightness are defined in the following equations.

$$H(r,c) = \begin{cases} 60.h(r,c) & , h(r,c) \geq 0 \\ 60.h(r,c) + 360, & h(r,c) < 0 \end{cases} \tag{16}$$

$$h(r,c) = \begin{cases} \frac{G(r,c)-B(r,c)}{R(r,c)-M_n}, & R(r,c) = M_x \\ 2 + \frac{B(r,c)-R(r,c)}{G(r,c)-M_n}, & G(r,c) = M_x \\ 4 + \frac{R(r,c)-G(r,c)}{B(r,c)-M_n}, & B(r,c) = M_x \end{cases} \tag{17}$$

$$M_n = \min(R(r,c), G(r,c), B(r,c)) \tag{18}$$

$$M_x = \max(R(r,c), G(r,c), B(r,c)) \tag{19}$$

$$S(r,c) = \frac{M_x - M_n}{M_x + M_n} \tag{20}$$

$$L(r,c) = M_x \tag{21}$$

Therefore the hue, saturation and the lightness of the enhanced image are given by

$$\tilde{H}(r,c) = H(r,c) \tag{22}$$

$$\tilde{S}(r,c) = S(r,c) \tag{23}$$

$$\tilde{L}(r,c) = \alpha\, L(r,c) \tag{24}$$

Where $\alpha = \frac{\tilde{\boldsymbol{g}}(\mathbf{r},\mathbf{c})}{\boldsymbol{g}(\mathbf{r},\mathbf{c})}$.

The algorithm makes the bright features brighter and the dark features darker in the images but these operations can increase the noise and create some very small bright and dark objects in the images. So we convolve the image g(r,c) with an average filter of size 3×3 before applying the algorithm to decrease this side effect.

In Fig. 1 a color retinal image and its enhanced image using the proposed algorithm are represented.

As we see, the vessels in the enhanced image are more evident and it improves the results of the segmentation part.

We can compare the three color channels of the original image and the enhanced image in Fig. 2. It is clear that the proposed algorithm enhances the vessels in all the three channels. But the green channel has the highest contrast between blood vessels and the retinal background. Then, we use this channel for detection and extraction of vessels in this paper.

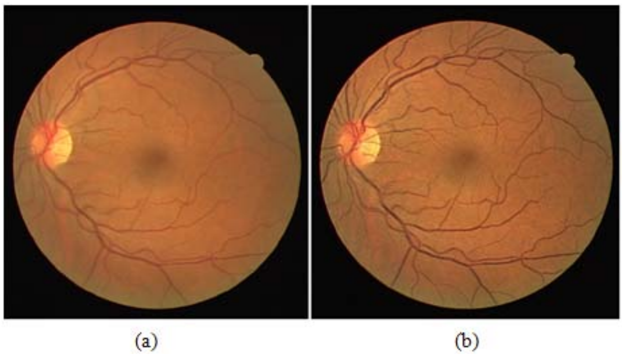

Fig. 1 (a) Color retinal image, (b) the corresponding enhanced image using the proposed algorithm.

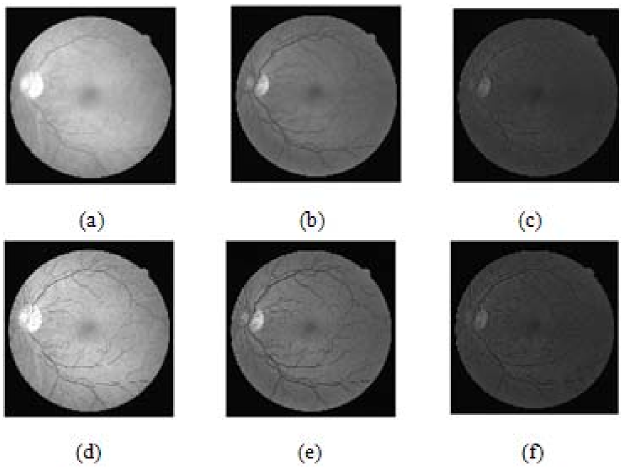

Fig. 2 (a) Red channel of the original image, (b) green channel of the original image, (c) blue channel of the original image, (d) Red channel of the enhanced image, (e) blue channel of the enhanced image, and (f) green channel of the enhanced image.

Fig. 3 shows the vessel enhancement results of the green channel of a color retinal image using methods of histogram equalization, contourlet transform as represented in [4] and the proposed algorithm. There is a clear improvement in enhancement using the proposed algorithm in this paper and no relevant noise amplification has been generated during the enhancement process.

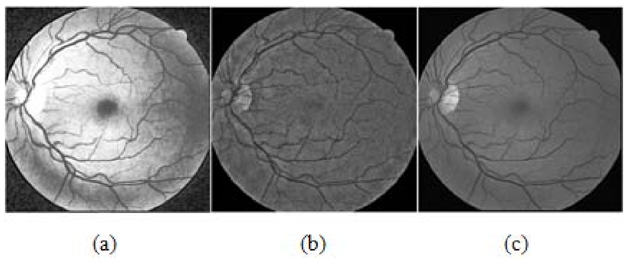

Fig. 3 The enhanced green channel of a color retinal image using (a) histogram equalization, (b) contourlet transform, and (c) the proposed algorithm.

2.2 Feature Vector Extraction

For feature extraction, we used LBP operator which is precisely described in next section. Extracted features are discussed in section 2.2.4.

2.2.1 Local Binary Pattern (LBP)

Local Binary Pattern is a method for texture description that uses values of neighbour pixels to replace gray level of current pixel with a new value [12].

New values of pixels or gray level histogram of photo (after applying LBP operator) can be used as feature vector for texture analysis. LBP has some variations for different applications. First, basic LBP operator will be described and then modified version of LBP that was used to analyse retina images.

2.2.2 Basic LBP Operator

The original LBP labels the pixels of an image by thresholding the 3×3 neighbourhood of each pixel with the center value. First a starting pixel and a direction is selected for traversing neighbours of the center pixel. Each pixel represents a bit in an 8 bit string, while the value of bit is measured with respect to gray level of the current neighbour pixel and pixel at the center of cliché. If value of neighbour is greater than center pixel, corresponding bit is set to 1, otherwise 0. The resulting 8 bit string replaces gray level of center pixel. The basic LBP operator is shown in Fig. 4.

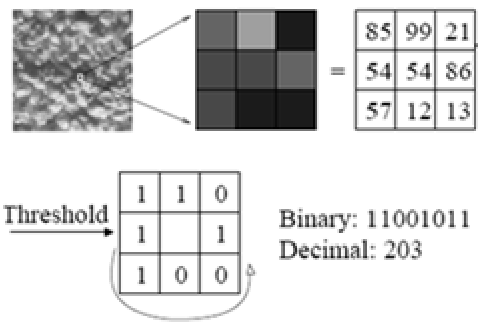

Fig. 4 Basic LBP operator.

2.2.3 Modified LBP Operator

One of limitations of basic LBP operator is that it just describes a small neighbourhood and could not express features in large scales. So a circular operator suggested, so that it could cover larger area using larger diameter.

Some neighbour sets are shown in Fig. 5. (P,R) represents P sample point in a circle with radios R. We will consider this P points as neighbours of center pixel with distance R. The rest of the process is the same as the basic operator. Now if we calculate histogram of new image, it contains information about distribution of local micro patterns like edges and uniform areas.

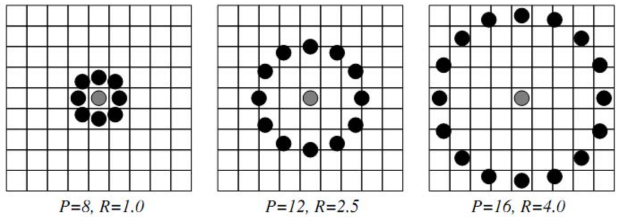

Fig. 5 Circularly neighbour sets for different (P,R).

Further extension of LBP is to use uniform patterns. A Local Binary Pattern is called uniform if it contains at most two bitwise transitions from 0 to 1 or vice versa when the binary string is considered circular. For example, 00000000, 001110000 and 11100001 are uniform patterns. It is observed that uniform patterns account for nearly 90% of all patterns in the (R,P) = (8,1) neighbourhood and for about 70% in the (R,P) = (16,2) neighbourhood in texture images.

We will denote LBP operator with P points on a circle with radios R and uniform rotation invariant codes with $LBP^{riu2}_{R,P}$.

2.2.4 Feature Vector

We need a set of features to classify image pixels to “vessel” or “background”. For feature extraction image is scanned with 5×5 and 3×3 masks. Mask moves pixel to pixel and for each pixel, six features are extracted. These 6 features are calculated using two LBP operators with radios 1 and 2, and number of neighbour pixels equal to 8 and 16 respectively. For each operator (operators with (R,P) = (1,8) and (R,P) = (2,16)), $LBP^{riu2}_{R,P}$, binary representation of P neighbour points on circle with radios R (that are thresholded with center pixel value) and $VAR_{R,P}$ (the variation of gray-scales in that region) are calculated as features. Final feature vector is constructed by concatenation of these 6 values for each pixel.

2.3 Segmentation Using Multi Layer Perceptron (MLP)

Artificial neural networks are proved to be helpful tools in classification and clustering problems and are widely used in nowadays’ intelligent systems. Multi Layer Perceptron is one of neural networks variations that has a great power in classification.

We used a Multi Layer Perceptron with one hidden layer and 5 neurons in this layer. Output layer has one neuron. MLP generates one output for each 6 features corresponding to a specific pixel. This output is 1 if network classify pixel as vessel, otherwise -1 (showing that pixel belongs to background).

2.3 Postprocessing

So far output of the MLP is a binary image with 1 value on vessel segments. This image may have some noise or artefacts due to misclassification. For eliminating noise and smoothing image, we used morphological operators. First, image is eroded with a circular operator with radios 1. Then all regions with area less than a specified threshold are deleted. Finally, image is dilated using operator with the same size and radios as operator used for eroding image.

3. Results

Proposed algorithm was tested on DRIVE database. This database has 40 colourful shots of retina images from different people. These images were divided to two groups of 20 pictures, one for training the MLP network and the other one test. This database also contains 40 binary images, each represent ideal segmentation output that is produced using human expertise. These images are used to evaluate algorithm's performance. In pre-processing section, we used a circular operator with radios 3 and m equal to 5. To evaluate the algorithm, we calculated True Positive Ratio (TPR) and False Positive Ratio (FPR). TPR is number of pixels of resulting image which are correctly classified as vessel (according image generated by human expert) to total number of pixels of human-expert generated image that are labelled as vessel. FPR is number of pixel of resulting image which are incorrectly classified as vessel to total number of pixel of human-expert generated image that are labelled as background. A sample of a segmented retina image using the proposed algorithm is presented in Fig. 6 along with manually segmented version of the image.

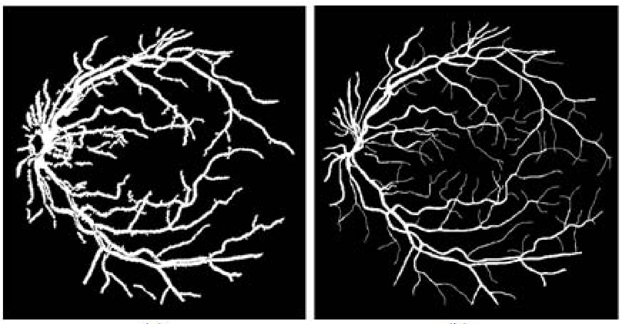

Fig. 6 Final result. (a) segmentation using the proposed algorithm, (b) manually segmented image.

TABLE I compares performance of presented algorithm versus 2nd human observer and presented method in [4] which used contourlet for image enhancement and MLP for segmentation.

TABLE I: Results of proposed algorithm on vessel segmentation

Algorithm	TPR	FPR
2nd human observer	0.7761	0.0275
Proposed Algorithm	0.7751	0.0342
Presented method in [4]	0.7223	0.0289

4. Conclusion

In this paper we presented a new method for automated vessel detection in retinal image, which can be used for diagnosis of some diseases like diabetes. For contrast enhancement of retinal images, we used multi scale morphological operators that outperform similar approaches with other contrast enhancement methods. For feature extraction, we used LBP, a powerful texture descriptor that is new to medical image analysis field. Finally MLP network was used to label pixels as vessel or background.

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