RETINAL VESSEL ENHANCEMENT USING MULTI-DICTIONARY AND SPARSE CODING

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ABSTRACT

A novel retinal vessel enhancement method based on multi-dictionary and sparse coding is proposed in this paper. Two dictionaries are utilized to gain the retinal vascular structures and details, one is the representation dictionary (RD) generated from the original retinal images, and another is the enhancement dictionary (ED) extracted from the corresponding label images. The proposed method represents the input image with RD to get the sparse coefficients via a sparse coding process. Then the enhanced retinal vessel image is obtained from the solved sparse coefficients and ED. Experimental results performed on the DRIVE and STARE databases indicate that the proposed method not only can effectively improve the image contrast but also enhance the details of the retinal vessels.

***Index Terms*—** Image enhancement, multi-dictionary, sparse coding, retinal vessel

1. INTRODUCTION

Retinal image, a kind of two-dimensional biological signal, is widely used by ophthalmologists for the disease diagnosis such as diabetes, hypertension, cardiovascular disease and stroke. For instance, the onset of neovascularization is a sign of diabetic retinopathy, and a complication of diabetes which leads to the cause of blindness [1]. In case of changes in vessel caliber, branching angle or vessel tortuosity are results of hypertension [2]. To quantify these changes for medical diagnosis, accurate vascular structures play a critical role. However, due to the imperfect imaging condition, the quality of retinal vessel images is usually poor and makes it hard to recognize the vascular structure clearly. The main purpose of retinal vessel enhancement is to highlight the vascular structures [3, 4]. Retinal vessel enhancement using histogram equalization (HE) [5] and contrast limited adaptive histogram equalization (CLAHE) [6] are two basic methods, but some retinal vessel details are lost during the equalization. Fraz et al. [7] proposed a retinal vessel enhancement method based on decision trees and Gabor filter, while it also suffered the vascular details lost problem. To overcome these weaknesses, a medical image enhancement method using morphology-based homomorphic filtering technique was developed by Oh et al. [8]. However, its application is limited due to the requirement of corresponding target image. Miao et al. [9] proposed a retinal vessel enhancement algorithm based on multi-scale top-hat transformation and histogram fitting stretching. But part of the vascular structures were changed through the transformation and histogram stretching, moreover, some parameters utilized in the method were sensitive to the initialization.

The classical reported retinal vessel enhancement methods in literature are usually based on histogram distribution, transformation, vessel features or classifier. However, the retinal vascular details are hardly to be completely reserved by these methods, and the retinal vascular contrast is not high enough. For these issues, a novel retinal vessel enhancement method using multi-dictionary and sparse coding is proposed in this paper. To the best of our knowledge, it's the first time to achieve the retinal vessel enhancement via multi-dictionary and sparse coding. In order to gain the retinal vascular structures and details, two corresponding dictionaries are developed, one is the representation dictionary (RD) generated from the retinal images, and another is the enhancement dictionary (ED) extracted from the corresponding label images. The dictionaries are optimized through the label info of patches. Then the input image is represented by RD to get the sparse coefficients via a sparse coding process. Finally, the enhanced retinal vessel image is obtained from the solved sparse coefficients and ED. The experimental results on the DRIVE[1] and STARE[2] databases show that the proposed method can lead to significantly enhanced image contrast of retinal vascular structures. The effect of dictionary patch size is also analyzed in the experiments.

2. METHODS

2.1. RD and ED generation

Dictionary based methods have been studied in medical image processing, which differs in how they form the overcomplete dictionary [12, 13]. The RD and ED in the proposed method are also overcomplete, each patch in RD has the unique and corresponding patch in ED, and they have the same location in respective dictionary. RD is generated from the green channel of the original retinal vessel images, ED is extracted from the corresponding label images with value 0 or 1.

Let f_g be the green channel of the original retinal vessel

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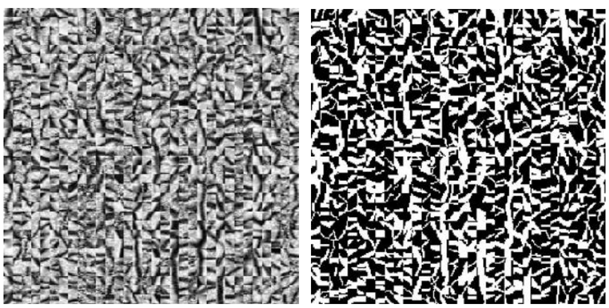
1. http://www.isi.uu.nl/Research/Databases/DRIVE/
2. http://www.ces.clemson.edu/~ahoover/stare/

image f. The image size of f is $M \times M$, and its sequence number in the original retinal vessel image database is k. Then a pixel with the location (x, y) in f_g can be remarked as $f_g(x, y, k)$. Let f_l be the corresponding label image of f, which is the retinal vessel segmentation result delineated manually by an expert. Then the corresponding label value of $f_g(x, y, k)$ in the label image f_l is denoted as $f_l(x, y, k)$. A patch in RD (p^{RD}) or ED (p^{ED}) is defined as:

$$\begin{aligned} &p^{\mathrm{RD}}: f_g(\tau+s, \tau+s, k),\ \tau=-h,-h+1,...h \quad if \sum_{\tau=-h}^{h} f_l \geq t \\ &p^{\mathrm{ED}}: f_l(\tau+s, \tau+s, k),\ \tau=-h,-h+1,...h \quad if \sum_{\tau=-h}^{h} f_l \geq t \end{aligned}, \quad (1)$$

where $\forall s \in \{d, 2d, 3d, ..., md\}$, $\forall k \in \{1, 2, ..., L\}$, h is the patch size, d is a step value used to gain different patches, m is the integer part of M/d, L is the amount of retinal vessel images in database, and t is a threshold value used to optimize the dictionaries. Fig .1 shows parts of the RD and ED with $h=4, t=10$, most of the patches in the dictionaries contain retinal vessels due to the optimization in Eq. (1). The



(a) RD (b) ED

Fig. 1. Part of the RD and ED, $h=4, t=10$

impact of background is mostly eliminated through the ED, and the retinal vascular structures and details are mostly reserved by the two dictionaries.

2.2. Sparse coding and Retinal vessel enhancement

The multi-dictionary (RD and ED) is generated from Eq. (1), in order to describe the dictionary clearly, let p_i^{RD} be the i-th patch in RD, RD = $[p_1^{\mathrm{RD}}, p_2^{\mathrm{RD}}, ...p_n^{\mathrm{RD}}]$, then ED = $[p_1^{\mathrm{ED}}, p_2^{\mathrm{ED}}, ...p_n^{\mathrm{ED}}]$. Let f_o be the original retinal vessel image to be enhanced (only use the green channel). To get the sparse coefficients used in enhancement, f_o is represented as:

$$f_o = \alpha_1 p_1^{\mathrm{RD}} + \alpha_2 p_2^{\mathrm{RD}} + ... + \alpha_n p_n^{\mathrm{RD}}. \quad (2)$$

Since the representation in Eq. (2) is sparse, that is to say, most of the coefficient α_i will be zero, let $\alpha = [\alpha_1, \alpha_2, ...\alpha_n]$, and the α satisfy the restricted isometry property (RIP) [14, 15]. Then the sparse solution can be obtained by solving the following equation [16]:

$$\hat{\alpha} = \underset{\alpha}{min} \|\alpha\|_0 \text{ subject to } \|f_o - \mathrm{RD}\alpha\|_2^2 \leq \varepsilon. \quad (3)$$

where the ε is an error target for the sparse solution ($\varepsilon = 10^{-15}$ in our method), l_0-norm denotes the number of nonzero coefficients, and is the sparse constraint of this equation. Since $n \gg 2h$, the Eq. (3) doesn't have a unique solution. However, when the solution of Eq. (3) is sparse enough, it can be solved efficiently by many sparse coding methods [17-19]. In the proposed method, an efficient batch orthogonal matching pursuit (Batch-OMP) method [20] is used for obtaining the sparse coding coefficients α. Then we reconstruct the enhanced retinal vessel image according to the corresponding relationship from RD to ED:

$$f_e = \alpha_1 p_1^{\mathrm{ED}} + \alpha_2 p_2^{\mathrm{ED}} + ... + \alpha_n p_n^{\mathrm{ED}}, \quad (4)$$

as the values in ED are binary, the gray value of f_e is usually small. Then we rescaled f_e to $[0, 255]$ by the following equation:

$$f_{er} = \frac{f_e - f_e^{\min}}{\max(f_e - f_e^{\min})} \cdot 255, \quad (5)$$

where $f_e^{\min}$ is the minimum in f_e, max is an operator to find the maximum, and f_{er} is the final enhanced image.

Fig. 2 presents the flow chart of our method. In order to enhance the retinal vessels, patches extracted from retinal vessel image database and label image database have the same location (x, y, k). The patches in RD are made up of gray values, and the corresponding patches in ED consist of binary values. Most of the retinal vascular structures and details are obtained through an optimization, which is introduced in Eq. (1). Then a representation to the target image f_o is utilized to solve the sparse coefficients α. After getting the dictionaries (in Eq. (1)) and sparse coefficients (in Eq. (3)), we use the ED and sparse coefficients to obtain the enhanced retinal vessel image with Eq. (4). Finally, the enhanced image is rescaled by Eq. (5).

3. RESULTS

To evaluate the performance of the proposed method, experiments were performed on the DRIVE database and STARE database. The DRIVE database consists of 40 color retinal images, the size of each retinal image is 565×584 pixels. The STARE database contains 20 color retinal images, and the size of each retinal image is 700×605 pixels. In order to evaluate the enhancement quality quantificationally, two objective criterions [8] are used:

(1) C represents the contrast between the retinal vessels and the background (retinal regions except the vessels), which is defined as:

$$C = \left| \frac{Y - G}{Y + G} \right|, \quad (6)$$

where Y is the average gray values of the retinal vessels, G is the average gray values of the background.

(2) CII represents the contrast rate between enhanced image (C_{en}) and the original image (C_{or}), which is defined as:

$$CII = \frac{C_{en}}{C_{or}}. \quad (7)$$

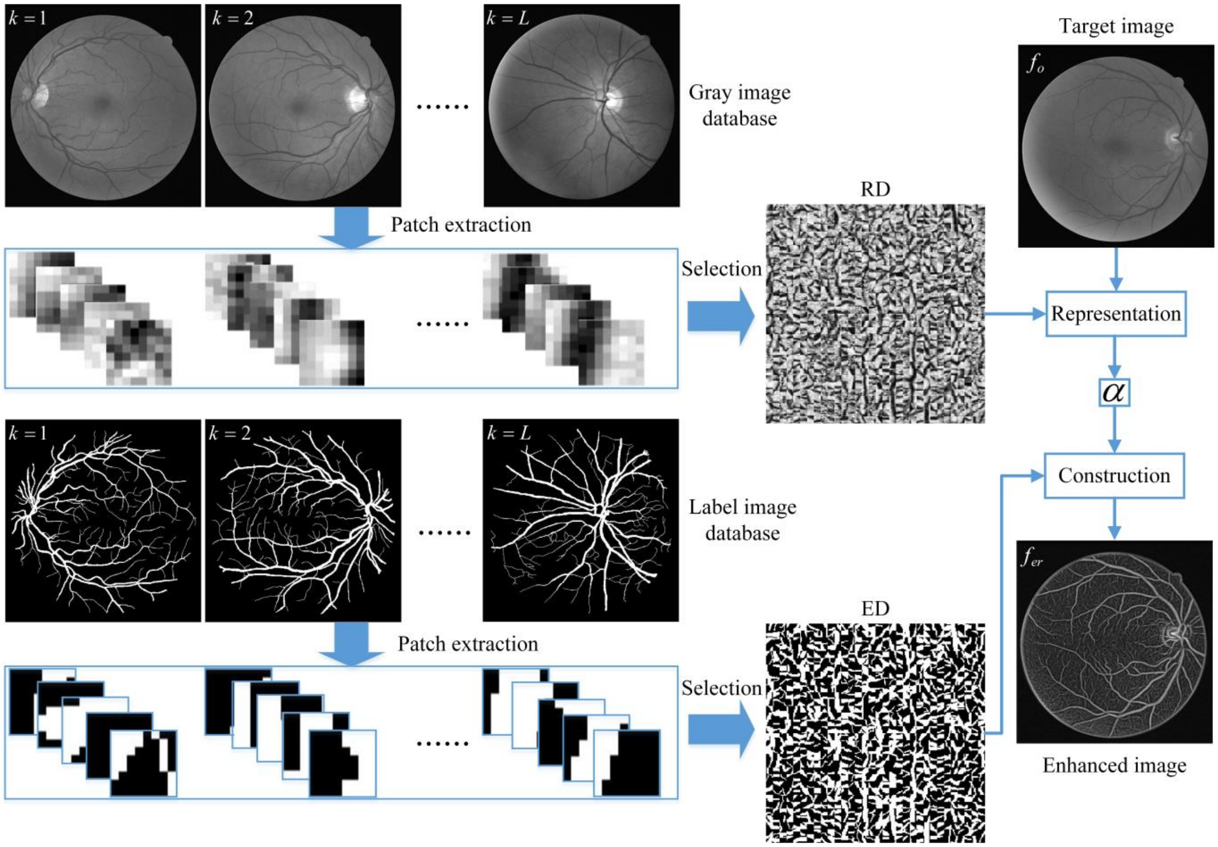


Fig. 2. Flow chart of the proposed retinal vessel enhancement method, $h = 4$, $t = 10$.

The larger the value of C is, the more obvious the difference between the retinal vessels and the background is. Noticed that black background pixels outside the pupil are not calculated in our method. In the experiment, the proposed approach was compared with HE, CLAHE, method in [7], method in [8] and method in [9], and the effect of dictionary patch size was also analyzed.

3.1. Enhancement results

All the RD and ED used in two databases were extracted from DRIVE database (40 images). Fig. 3 shows the comparison of CII values among different methods in DRIVE testing set (image No.1-No.20). It can be observed that the proposed method has the highest CII values. Compared with method in [9] (purple line in Fig. 3), the maximum difference value of CII is 4.7937 (image No.13), and the mean difference value of CII is 2.0842.

Table 1 and Fig. 5 represent part of the retinal vessel enhancement results with different methods. It can be seen that the retinal vascular structures enhanced by the proposed method are clear and complete, and the small retinal vessels are also enhanced efficiently. Compared with HE, CLAHE, method in [7], method in [8] and method in [9], the enhanced retinal vessels by the proposed method are much easier to recognize, and the proposed method has a much better enhancement performance on image contrast, retinal vascular structures, and retinal vascular details due to the contribution of multi-dictionary and sparse coding.

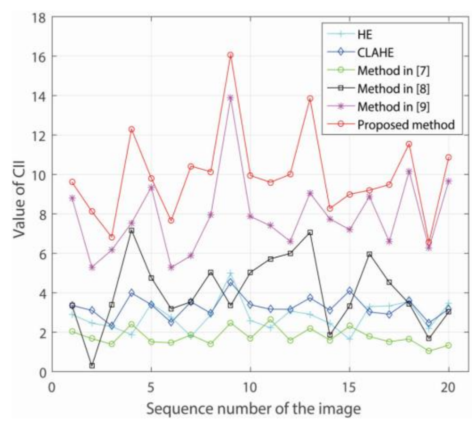


Fig. 3. Values of CII with different methods (DRIVE)

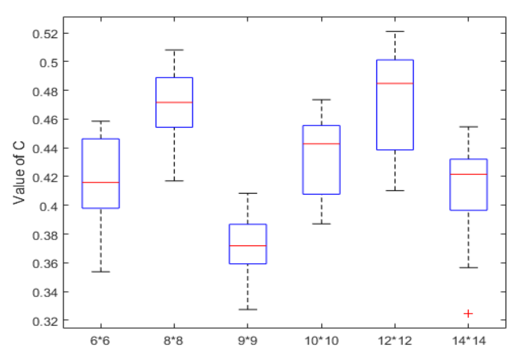
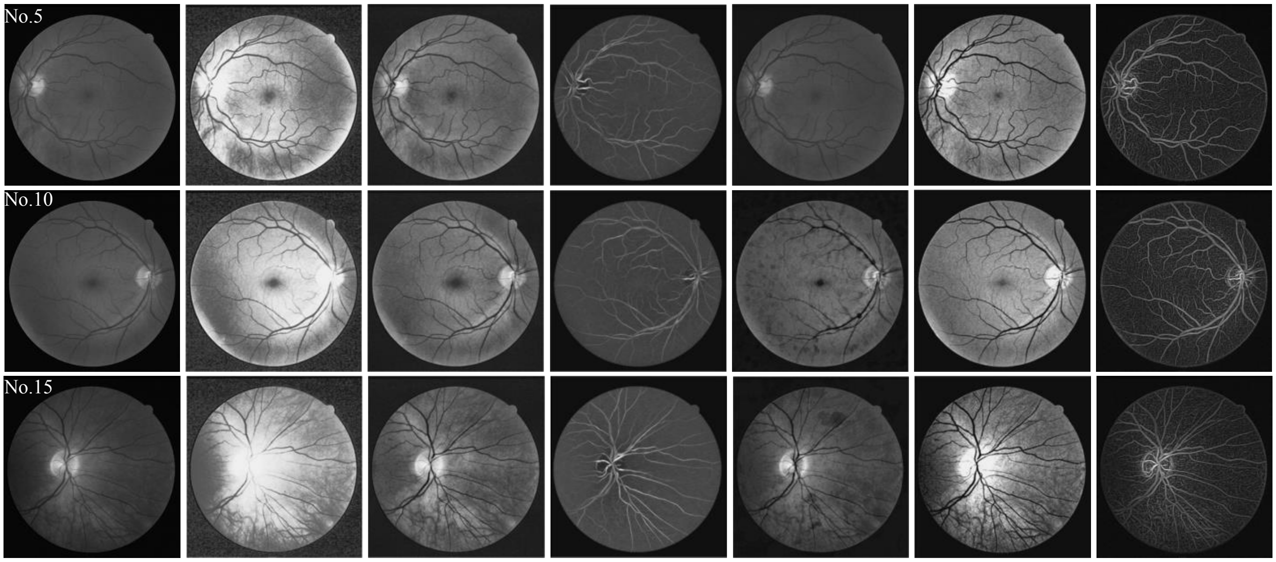
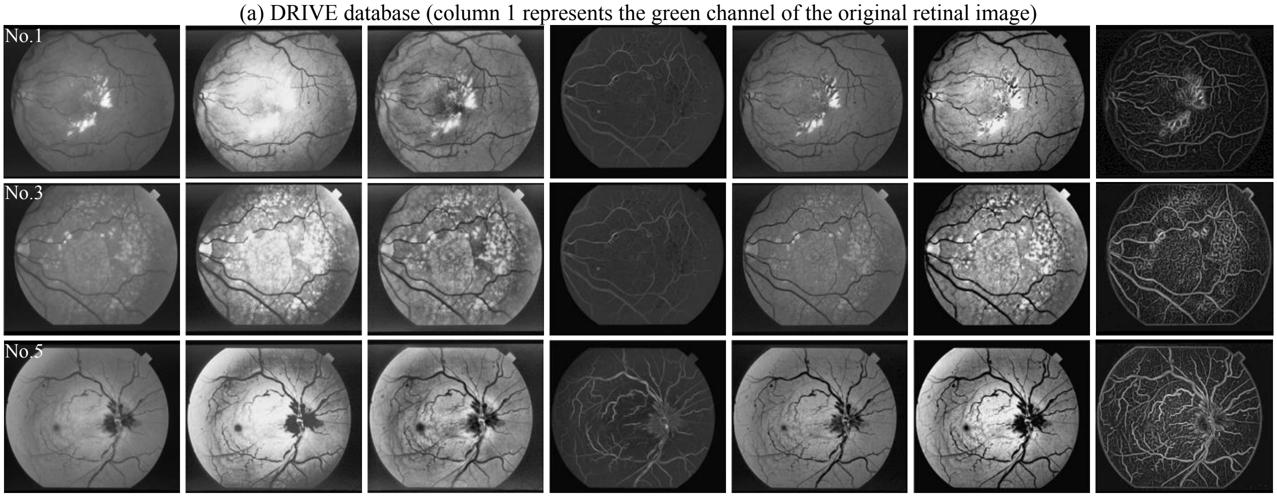


Fig. 4. Values of C with different patch sizes (DRIVE)



(a) DRIVE database (column 1 represents the green channel of the original retinal image)



(b) STARE database (column 1 represents the green channel of the original retinal image)

Fig. 5. Enhanced results with HE, CLAHE, methods in [7, 8, 9] and proposed method (column 2 to 7, respectively).

Table 1. Comparisons of C and CII with different methods in Fig. 5.

Image / Method	C (Fig. 5 (a) DRIVE)			CII (Fig. 5 (a) DRIVE)			C (Fig. 5 (b) STARE)			CII (Fig. 5 (b) STARE)		
	No.5	No.10	No.15	No.5	No.10	No.15	No.1	No.3	No.5	No.1	No.3	No.5
HE	0.1500	0.1138	0.0809	3.4435	2.5908	1.6247	0.2159	0.2640	0.1704	1.9917	2.5167	2.2510
CLAHE	0.1478	0.1489	0.2021	3.3947	3.3898	4.1067	0.1844	0.2601	0.2169	1.7011	2.4795	2.8653
Method in [7]	0.0660	0.0745	0.1138	1.5142	1.6949	2.3172	0.0950	0.1066	0.1126	0.8764	1.0162	1.4875
Method in [8]	0.2074	0.2213	0.1638	4.7632	5.0362	3.3286	0.2458	0.2762	0.2792	2.2675	2.6330	3.6882
Method in [9]	0.4074	0.3457	0.3543	9.3537	7.8691	7.1975	0.4478	0.5795	0.3998	4.1310	5.5243	5.2814
Proposed method	**0.4273**	**0.4371**	**0.4429**	**9.8094**	**9.9483**	**8.9985**	**0.4586**	**0.5854**	**0.4017**	**4.2306**	**5.5806**	**5.3065**

3.2. Effect of dictionary patch size

The effect of dictionary patch size was analyzed in this subsection. Fig. 4 shows the C values of DRIVE database testing set with different patch sizes. In order to optimize the dictionaries, we set the parameter $t = 5$, 10, 14, 18, 25, 36. respectively. In Fig. 4, it can be observed that the patch size 12×12 has the best overall performance on the image contrast (C). The dictionary patch size is related to the retinal vascular local geometry, and it leads to a bad enhancement performance when the patch size isn't suitable for the retinal vascular width.

4. CONCLUSION

A novel retinal vessel enhancement method via multi-dictionary (RD and ED) and sparse coding is introduced in this paper. The RD is utilized to gain the sparse coefficients (α), then the enhanced retinal vessel image is reconstructed by α and ED. Experimental results show that the proposed method improves the image contrast, which also enhances the retinal vascular structures and details effectively. Further work includes: (i) improving the enhancement performance with a larger database; (ii) applying on other vessel enhancement problems.

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