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Retinal Vessel Enhancement Via Sparse Coding and Dictionary Learning

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Abstract

This paper presents a new method for vessel enhancement in retinal fundus images. In the proposed method, two dictionaries are utilized to gain the vessel structures, including Representation Dictionary (RD) which is generated from the original vessel images and Enhancement Dictionary (ED) generated from the corresponding label images. Then sparse coding technology is utilized to represent the target vessel image. At last, the learned dictionaries is used in the enhancement process. However, the size of the dictionaries increases the computational burden on the sparse coding process, which implies sophisticated data management and memory access. Here we introduce a simplified formulation that reduces the size of the dictionaries. Besides visual validation, quantitative evaluations demonstrate that our strategy is able to yield results that are highly competitive with traditional approaches.

1 Introduction

Retinal fundus images have been widely used for diagnosis, screening and treatment of cardiovascular and ophthalmologic diseases[1]. However, due to the imperfect imaging condition, the quality of retinal vessel image is usually poor, which make it hard to recognize the vessel structures and details clearly. An effective way to overcome these problems is to enhance the poor image. The main purpose of vessel enhancement is to highlight the structures and details[2].

In the past decades, many related works have been done for the enhancement of vessels in retinal fundus images. Histogram-based methods[3, 4] use the prior information of vessels to equal histogram distribution. Contrast limited adaptive histogram equalization (CLAHE)[5] is one basic method for vessel enhancement. Transformation-based methods[6] use other space information of the image. In other spaces, vessel details can be enhanced better. [7] proposed an algorithm based on multi-scale top-hat transformation and histogram fitting stretching. Filter-based methods[8, 9] apply a filter or multiple filters to enhance the blood vessel. Decision trees and Gabor filter are proposed for vessel enhancement in [10].

The details enhanced by these classical methods are hardly to be completely reserved, and the contrast of the enhanced image is not high enough.Algorithms based on Sparse Coding and Dictionary Learning have been widely used. [11] proposed a vessel enhancement method using multi-dictionary and sparse coding to solve these issues. In order to gain the structures and details, the dictionary is generated from the blood vessel images and the corresponding label images directly, which will increase the computation burden on the sparse coding stage and cost much time. In this paper, we utilized the dictionary learning technology to speed-up the enhancement process. Two public databases, DRIVE and STARE, are used to evaluate the proposed method. In order to compare the performance of the proposed method with other state-of-the-art approaches, we collected the results published in the past years in prestigious journals and conferences. We followed the same protocols as in those papers. Experimental results demonstrate that the image contrast is effectively improved and the retinal vessel structures and details are well enhanced by the proposed method.

The rest of the paper is organized as follows. The proposed method and its application on retinal vessel enhancement are presented in Section 2. In Section 3, the performance of retinal vessel enhancement is assessed by experiments on the DRIVE and STARE databases. Finally, a conclusion is given in Section 4.

2 Proposed Method

2.1 Method Overview

Figure.1 presents a flow chart of proposed retinal vessel enhancement method by sparse coding and dictionary learning. In vessel enhancement, patches are extracted from gray image database and label image database. The extracted patches have same location in the gray image and corresponding image. Then we get two large dictionaries, RD and ED. RD is the representation dictionary which have gray values and ED is the enhanced dictionary which have binary values. During dictionary generation process, most structures and details are achieved through patch selection. Due to the large size of RD and ED which will increase the computation burden on the sparse coding process, dictionary learning technology is taken into account to get much smaller dictionaries which will accelerate the construction progress. Then a sparse representation to the target image with RD is utilized to compute the sparse coefficients. After that, we use the sparse coefficients and ED to reconstruct the enhanced target image. At last, we rescale the ehhanced image to get the final result.

2.2 Patch Dictionary Generation

Given a gray vessel image I of size $H \times W$, and its sequence number in the gray image database is k , $\forall k \in \{1, 2, ..., L\}$, L is the amount of vessel images in the database. Then a pixel value at the location (x, y) in I can be defined as $I(x, y, k)$. Let I_l be the corresponding label image of I which is the vessel segmentation image delineated manually by an expert. So $I_l(x, y, k)$ can be defined as the corresponding label

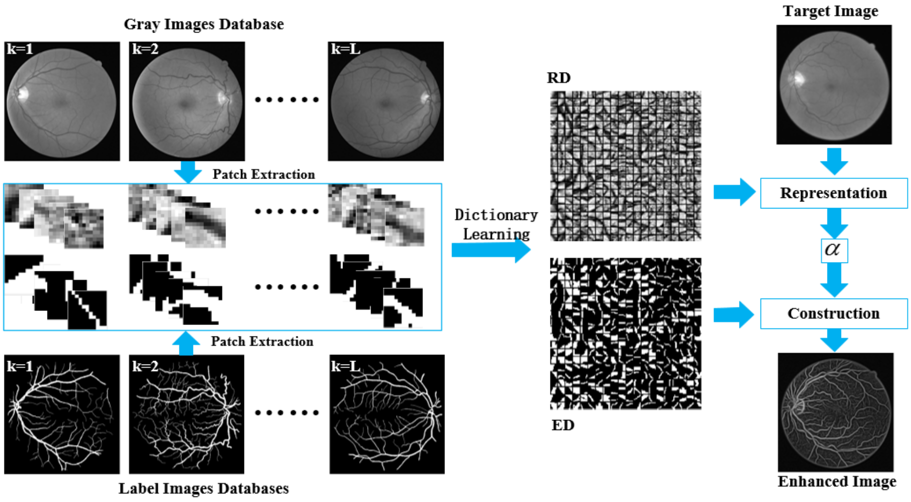


Figure 1: Flow chart of the retinal vessel enhancement method

pixel value in I_l . Then a patch p_{RD} used to generate RD and its corresponding patch p_{ED} which will generate ED can be defined as:

$$\begin{aligned} & p_{RD} : I(\tau + s, \tau + s, k),\ \tau = -h, -h+1, ..., h \\ & p_{ED} : I_l(\tau + s, \tau + s, k), \tau = -h, -h+1, ..., h \\ & \qquad if \sum_{\tau=-h}^{h} I_l \geq t \end{aligned} \tag{1}$$

Where $\forall s \in \{d, 2d, 3d, \ldots, md\}$, h is the patch size, d is a step value used to extract patches from images, m is the integer part of H/d , t is a threshold used to optimize the size of the dictionaries. Most patches that represent the background will be eliminated through t , and the reserved patch can mostly represent the structures and details.

2.3 Dictionary Learning

In the above description, a large number of patches are directly used as the predefined dictionaries which will increase the computational burden on the sparse coding stage. This drawback may be overcome by learning a small size task-specific dictionaries. In this paper, we use a similar idea as described in [12] for our enhancement purpose.

In order to describe the dictionaries clearly, let $P_r = [p_{RD}^1, p_{RD}^2, ..., p_{RD}^n]$ denote the training patch dictionary, containing n patches, p_{RD}^i is the i-th patch in RD. Then its corresponding dictionary is $P_e = [p_{ED}^1, p_{ED}^2, ..., p_{ED}^n]$. A reconstructive dictionary with atoms can be learned from the input library by solving the following problem:

$$\langle D_r, \alpha \rangle = \underset{D_r, \alpha}{\arg\min} \|P_r - D_r\alpha\|_2^2 \text{ subject to } \|\alpha\|_0 \leq T \tag{2}$$

Where $D_r = [d_{r1}, d_{r2}, ..., d_{rK}] \in R^{m\times K}$ is the learned representation dictionary (RD). $\alpha \in R^{n\times K}$ is the sparse coding coefficient matrix of the input patch library, and T is a sparsity constraint parameter. In Eq.(2), the objective function includes the reconstruction error term and the sparsity constraint term without considering the enhancement power. Thus, the learned dictionary is not suitable for our enhancement task. To address problem, the enhancement power was added to the objective function. Then the objective function can be defined as follows:

$$\begin{aligned} \langle D_r, D_e, \alpha \rangle &= \underset{D_r, \alpha}{\arg\min} \|P_r - D_r\alpha\|_2^2 + \beta \|P_e - D_e\alpha\|_2^2 \\ & \text{subject to } \|\alpha\|_0 \leq T \end{aligned} \tag{3}$$

Where $D_e = [d_{e1}, d_{e2}, ..., d_{eK}] \in R^{m\times K}$ is the learned enhancement dictionary (RD). β controls the trade-off between the reconstruction error term and the enhancement error term.

2.4 Sparse Coding and Vessel Enhancement

Let I_t be the target vessel image to be enhanced, and p_{I_t} is a patch extracted from I_t . To get the coefficients which will be used in the enhancement stage, p_{I_t} is represented as:

$$p_{I_t} = \alpha_1 d_{r1} + \alpha_2 d_{r2} + ... + \alpha_n d_{rK} \tag{4}$$

Since the representation in Eq.(4) is sparse, most of the coefficients will be zero. Let $\alpha = [\alpha_1, \alpha_2, ..., \alpha_n]$, and the α satisfy the restricted isometry property (RIP). Then the sparse solution can be obtained by solving the following equation:

$$\hat{\alpha} = \underset{\alpha}{min} \|\alpha\|_0 \text{ subject to } \|p_{I_t} - D_r\alpha\|_2^2 \leq \varepsilon \tag{5}$$

Where the ε is an error target for the sparse solution, l_0-norm denotes the number of nonzero coefficients, and α is the sparse constraint of this equation. Since $K >> 2h$, the Eq.(5) does not have a unique solution. However, where the solution of Eq.(5) is sparse enough, it can be solved efficiently by many sparse coding methods. In the proposed method, an efficient Batch Orthogonal Matching Pursuit (Batch-OMP) method is used for obtaining the sparse coding coefficients in Eq.(5). Then we reconstruct the

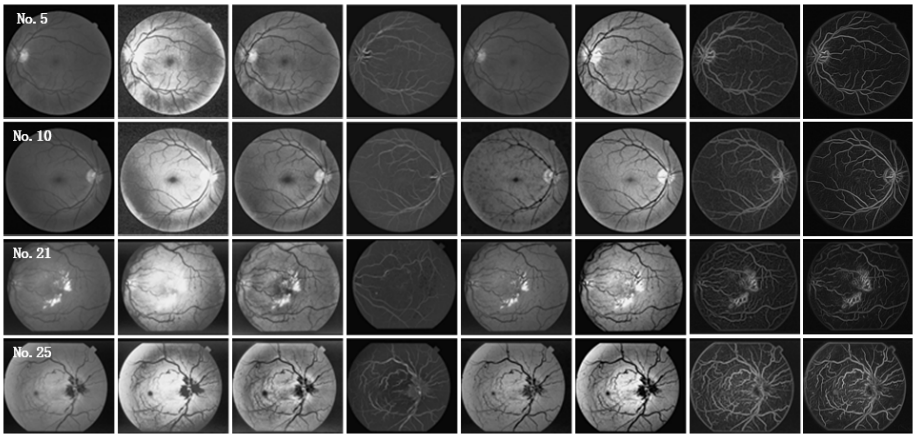


Figure 2: Enhancement results with HE[4], CLAHE[5], methods in[7, 10, 13],VE-MSC[11], column from left to right respectively

enhanced patch according to the corresponding relationship from RD to ED:

$$p_{I_e} = \alpha_1 d_{e1} + \alpha_2 d_{e2} + ... + \alpha_n d_{eK} \tag{6}$$

Where I_e is the enhanced vessel image made up of patches p_{I_e} , and the sparse coding coefficients α in Eq.(6) are the same as in Eq.(5). As the values in ED are binary, the gray value of I_e is usually small. Then we rescale I_e to [0,255] by following equation:

$$I_{er} = \frac{I_e - I_e^{\min}}{\max(I_e - I_e^{\min})} \cdot 255 \tag{7}$$

Where $I_e^{\min}$ is the minimum in I_e , max is an operator to find the maximum, and I_{er} is the final enhanced image.

3 Experiments and Results

To evaluate the performance of the proposed method, a series of experiments are performed on DRIVE and STARE databases. The DRIVE database consists of 40 color retinal images. Among them, the first 20 images are served as the testing set (image index No.1-20) and the rest constitute the training set. The STARE database contains 20 color retinal images (image index NO.21-40). Hereinafter, only the green channel of the RGB original image is used as it offers the best vessel background contrast. In order to evaluate the enhancement quality quantificationally, two metrics[11] are used. C represents the contrast between the retinal vessels and the background, CII represents the contrast rate between enhanced image and the original image

The larger the value of C and CII are, the more obvious the difference between the retinal vessels and the background is. In the experiment, the proposed method was compared with HE[4], CLAHE[5], methods in[7, 10, 13],VE-MSC[11]. Meanwhile, the effects of dictionary size and time are also provided.

3.1 Experimental Results

We utilize the DRIVE testing set and STARE as the evaluating data. Fig.2 represents part of the retinal vessel enhancement results with different methods. In Figure.2 , it can be seen that the retinal vascular structures enhanced by the proposed method are clear and complete, and the small retinal vessel are also enhanced efficiently. The C and CII in Fig.3 are the corrseponding values of Fig.2. It can be observed that the proposed method has the largest C and CII values.

Compared with other methods, the enhanced retinal vessels by the proposed method are much easier to recognize. Based on the above results, it can be concluded that the proposed method has a much better enhancement performance on image contrast, vessel structures and details. The superiority of our method is mainly contributed of the adoption of dictionary learning and sparse coding.

3.2 Effect of Dictionary Size

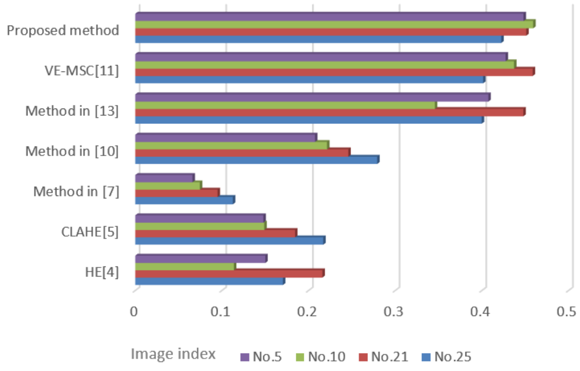
The effect of using different dictionary size is analyzed in this section. Fig.4 shows the C values of DRIVE testing set with different dictionary size. It can be observed that the best overall performance on the image contrast is achieved when the dictionary size is set to 1350. The size has the best overall performance on the image contrast.

3.3 Computation Time

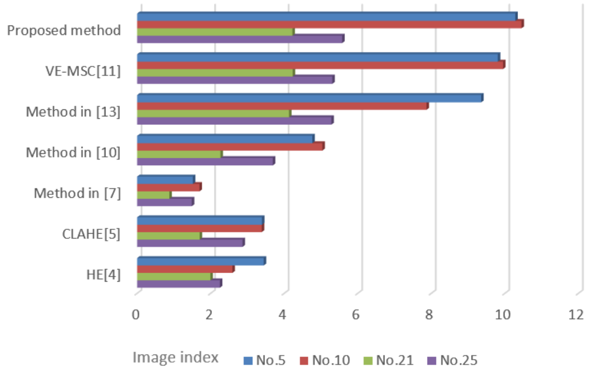
Figure.5 presents the average running time of one image compared with VE-MSC. Codes have been written in Matlab, and run on [CPU i7, 16GB RAM]. As expected, the proposed method is significantly faster than VE-MSC. This reflects the advantage of using dictionary learning technology in the vessel enhancement procedure.

4 Conclusions

A novel vessel enhancement method via dictionary learning and sparse coding has been proposed in this paper. We have evaluated the proposed method for the retinal vessel enhancement on the DRIVE and STARE databases. Experimental results show that the proposed method can not only improve the image contrast effectively but also enhance the retinal vascular structures and details. The superiority of our method is



(a) C



(b) CII

Figure 3: values of C and CII

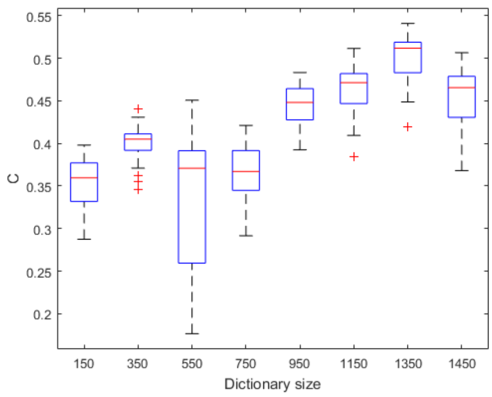


Figure 4: values of C with different dictionary size

Figure 5: comparasion of computation time(s) with VE-MSC

mainly contributed of the adoption of dictionary learning and sparse coding. By using the dictionary learning technology, we can not only achieved better results but also save much more time for the patients. Further work includes: (1) improving the enhancement performance with a larger database; (2) applying on 3D blood vessel enhancement problems.

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