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Blood vessel enhancement via multi-dictionary and sparse coding: Application to retinal vessel enhancing

Bin Chen [a], Yang Chen [a,*], Zhuhong Shao [c], Tong Tong [d], Limin Luo [a,b]

[a] Laboratory of Image Science and Technology, Southeast University, Nanjing, China
[b] Centre de Recherche en Information Biomedicale Sino-Francais (LIA CRIBs), Rennes, France
[c] College of Information Engineering, Capital Normal University, Beijing, China
[d] Biomedical Image Analysis Group, Department of Computing, Imperial College London, London, UK

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ABSTRACT

Blood vessel images can provide considerable information of many diseases, which are widely used by ophthalmologists for disease diagnosis and surgical planning. In this paper, we propose a novel method for the blood Vessel Enhancement via Multi-dictionary and Sparse Coding (VE-MSC). In the proposed method, two dictionaries are utilized to gain the vascular structures and details, including the Representation Dictionary (RD) generated from the original vascular images and the Enhancement Dictionary (ED) extracted from the corresponding label images. The sparse coding technology is utilized to represent the original target vessel image with RD. After that, the enhanced target vessel image can be reconstructed using the obtained sparse coefficients and ED. The proposed method has been evaluated for the retinal vessel enhancement on the DRIVE and STARE databases. Experimental results indicate that the proposed method can not only effectively improve the image contrast but also enhance the retinal vascular structures and details.

1. Introduction

The human body contains different types of blood vessels, which constitute a network of arteries and veins. The visualization of these blood vessels is important for disease diagnosis and improving the planning and navigation in interventional procedures [1–4]. For instance, retinal vessel images are widely used by ophthalmologists for the disease diagnosis such as diabetes, hypertension, cardiovascular disease and stroke. In case of changes in vessel caliber, branching angle or vessel tortuosity are results of hypertension [5]. The onset of neovascularization is a sign of diabetic retinopathy, and a complication of diabetes which leads to the cause of blindness [6]. However, due to the imperfect imaging condition, the quality of blood vessel images is usually poor, making it hard to recognize the vascular structure clearly. An effective way to overcome these issues is to use the image enhancement technology. The main purpose of blood vessel enhancement is to highlight the vascular structures and details [7–9]. In this paper, we propose a novel method for the blood Vessel Enhancement via Multi-dictionary and Sparse Coding (VE-MSC). The DRIVE[1] and STARE[2] databases are used to evaluate the proposed method. Experimental results demonstrate that the image contrast is effectively improved and the retinal vessel structures and details are well enhanced. A comparison with state-of-the-art methods has also been carried out in the retinal vessel enhancement.

The rest of the paper is organized as follows. In Section 2, the related works about blood vessel enhancement are briefly reviewed. The proposed method VE-MSC and its application on retinal vessel enhancement are presented in Section 3. In Section 4, the performance of retinal vessel enhancement is assessed by experiments on the DRIVE and STARE databases. Finally, a conclusion is given in Section 5.

2. Related works

According to different emphasis on the prior knowledge, blood vessel enhancement methods can be categorized into three groups: histogram based, transformation based and filter based.

(1) *Histogram-based* method [10–14] utilizes the prior information of blood vessel to equal the histogram distribution. For instance, histogram equalization (HE) [15] and contrast limited adaptive histogram equalization (CLAHE) [16] are two basic methods used for the retinal vessel enhancement. However, some retinal vessel details are lost during the equalization. Kuldeep et al. [17] proposed a contrast enhancement method based on the sub-image histogram equalization for low exposure gray scale image. The histogram was clipped using a threshold value as an average number of gray level occurrences to control the enhancement rate, but it was only used for the low exposure gray scale image.

* Corresponding author.
E-mail addresses: cbstudent163@126.com (B. Chen), chenyang_seu@126.com (Y. Chen).

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

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(2) *Transformation-based* method transfers the image to other space [18–21], where the blood vessel can be enhanced. Miao et al. [22] proposed a retinal vessel enhancement algorithm based on multi-scale top-hat transformation and histogram fitting stretching. However, part of the vascular structures were changed through the transformation and histogram stretching. In addition, some parameters utilized in the method were sensitive to the initialization. Li et al. [23] applied the fractional Fourier transformation to the image enhancement. However, it also suffered the blood vessel details lost problem during the selection of image features.

(3) *Filter-based* method utilizes a filter or multiple filters [24–27] to enhance the blood vessel. Fraz et al. [28] proposed a retinal vessel enhancement method based on decision trees and Gabor filter, while it also had the vascular details lost problem. To overcome these weaknesses, a medical image enhancement method using morphology-based homo-morphic filtering technique was developed by Oh et al. [29]. However, the contrast of the blood vessel was low, and the vascular details lost problem was also existed.

The vascular details enhanced by these classical reported methods in literatures are hardly to be completely reserved, and the contrast of the enhanced vascular image is not high enough. To solve these problems, a novel blood vessel enhancement method using multi-dictionary and sparse coding is proposed in this paper. To the best of our knowledge, this is the first time to achieve the blood vessel enhancement via multi-dictionary and sparse coding. In order to gain the blood vascular structures and details, two corresponding dictionaries are generated. One is the representation dictionary (RD) generated from the blood vessel images, the other one is the enhancement dictionary (ED) extracted from the corresponding label images. The patches in RD and ED are selected through the information of the label images to optimize the multi-dictionary. Then the input target image is represented by RD to get the sparse coefficients via a sparse coding process. Finally, the enhanced blood vessel image is obtained from the solved sparse coefficients and ED. The effect of dictionary patch size and dictionary patch selection are analyzed in the experiments.

3. Vessel enhancement via mlti-dictionary and sparse coding (VE-MSC)

3.1. RD and ED generation

Dictionary based methods have been studied in medical image processing [30–33], which differs in how they form the overcomplete dictionary. For instance, Chen et al. [34] proposed a Low-Dose CT (LDCT) image processing method based on artifact suppressed dictionary learning, where an overcomplete global dictionary was included. Li et al. [35] used the group-sparse representation with dictionary learning for medical image denoising and fusion, and the dictionary utilized was also overcomplete. In the proposed method, both the generated RD and ED are overcomplete, which are then used for enhancing the blood vascular structures and details.

Each patch in RD has the unique and corresponding patch in ED, and they have the same location in the respective dictionary. RD is generated from the original blood vessel images, ED is extracted from the corresponding label images with value 0 or 1. Let f be a 2D gray image in a blood vessel image database. The image size of f is $M \times M$, and its sequence number in the blood vessel image database is k. Then a pixel with the location (x, y) in f can be remarked as $f(x, y, k)$. Let f_l be the corresponding label image of f, which is the blood vessel segmentation result delineated manually by an expert. Then the corresponding label value of $f(x, y, k)$ in the label image f_l is denoted as $f_l(x, y, k)$. A patch in RD (p^{RD}) and its corresponding patch in ED (p^{ED}) are defined as:

$$p^{\mathrm{RD}} : f(\tau+s, \tau+s, k), \quad \tau = -h, -h+1, \ldots h \quad if \sum_{\tau=-h}^{h} f_l \geq t$$

$$p^{\mathrm{ED}} : f_l(\tau+s, \tau+s, k), \quad \tau = -h, -h+1, \ldots h \quad if \sum_{\tau=-h}^{h} f_l \geq t, \tag{1}$$

where $\forall s \in \{d, 2d, 3d, \ldots, md\}$, $\forall k \in \{1, 2, \ldots, L\}$, 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 blood vessel images in the database, and t is a patch selection threshold value used to optimize the dictionaries. Fig. 1 shows some patches in the RD and ED with $h = 4$, $t = 10$. The red boxes in Fig. 1 marked the corresponding

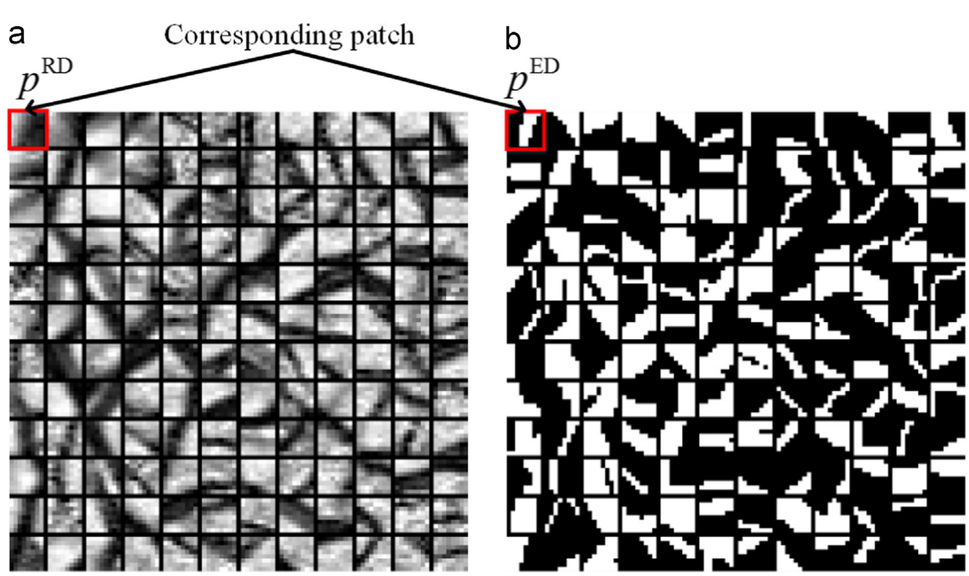

Fig. 1. Patches in the RD and ED, $h = 4$, $t = 10$. (a) RD, the patches are extracted from the DRIVE training set, only use the green channel, (b) ED, the patches are extracted from the corresponding retinal vessel segmentation results (label images from the first expert).