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Automatic Microaneurysm Detection of Diabetic Retinopathy in Fundus Images

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Abstract:

A serious diabetic complication is Diabetic retinopathy (DR), and the initial lesion in diabetic retinopathy is Microaneurysm (MA), so initial MA detection plays a critical role in diabetic retinopathy diagnosis. In this paper, the Joint Dynamic Sparse Representation (JDSR) algorithm is with multiple-channel multiple-feature dictionaries. For MA candidates are first extracted as small image blocks; then the multiple-channel multiple-feature dictionaries for candidate representation are developed. Next, sparse coefficient can be obtained by the JDSR algorithm which can be used for classification. The group sparsity dictionary selection method is also introduced, to form an optimal dictionary.

Keywords

Diabetic Retinopathy, Microaneurysm, JDSR, Multiple-Channel Multiple-Feature Dictionaries

1. Introduction

Diabetic retinopathy (DR) is a widely spread eye disease and a majority of the people suffering from diabetes mellitus will eventually develop DR. In the early stage of disease, due to the symptoms are not very salient, those patients who have the DR often cannot pay attention to the changes in their vision. However, with disease develops, sufferers may lose their eyesight [1]. Therefore, annual screening of patients for possible DR is recommended. Digital colour fundus photography allows acquisition of fundus images in a non invasive manner which is a prerequisite for large scale screening [2].

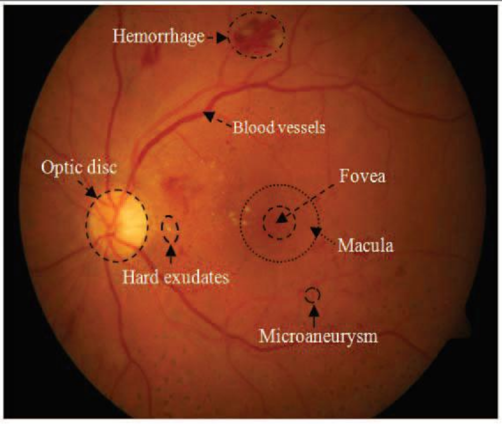

Figure1. A retinal image with different types of lesions and main anatomical features.

There are several different components in retinal images(see Fig.1), such as blood vessels, the fovea, the macula, and the optic disc (OD). In clinical, ophthalmologists classify DR into two major phases namely Non-proliferative DR (NPDR) and proliferative DR (PDR).NPDR can be viewed as the initial phase of DR. During the NPDR, several lesions such as red lesions (microaneurysms and haemorrhages, see Fig.1) caused by blood leakage, yellowish or bright spots (hard and soft ex updates, see Fig.1) in case of fat or protein leakage. The second phase of DR is the PDR, because of the blood vessels cannot obtain the enough oxygen causing blood vessels to grow in different regions of the retina image to maintain the adequate oxygen. Among the lesions, microaneurysms as one of the earliest lesions appear in diabetic retinopathy, which are dark-red round dot filled bulges in the artery walls and their diameters always range from 10μm to 100μm . However, the variations in shape, size and illumination of fundus images play important roles in detection of MA, which make the detection of MA becoming more challenging [3].Therefore, MA detection is importance for automatic retinopathy detection.

Numerous approaches have been proposed for microaneurysm detection using retinal colour

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fundus images. They can be divided into three categories [4], mathematical morphology [5-8], supervised classification [6, 9-10] and template matching [12-14]. However, when the size of MA is much smaller than the length of the structuring elements, the vessel can hardly be removed. Whereas, pixel level classification methods need a reference standard which is mainly from medical experts manually labelling at each image pixel. In this paper, a novel algorithm named JDSRMF is there, which combines joint dynamic sparse representation and multiple-channel multiple-feature into a unified frame work for MA detection.

2. Related Work

MICROANEURYSM DETECTION

The MA detection algorithm based on five main stages: (1) MA candidate extraction; (2) optimal dictionary atoms selection; (3) the formation of multiple-feature dictionaries; (4) sparse coefficient can be obtained by joint dynamic sparse representation with extracted multiple-feature dictionaries; (5) classification.Fig.2 shows the whole working mechanism of microaneurysm detection.

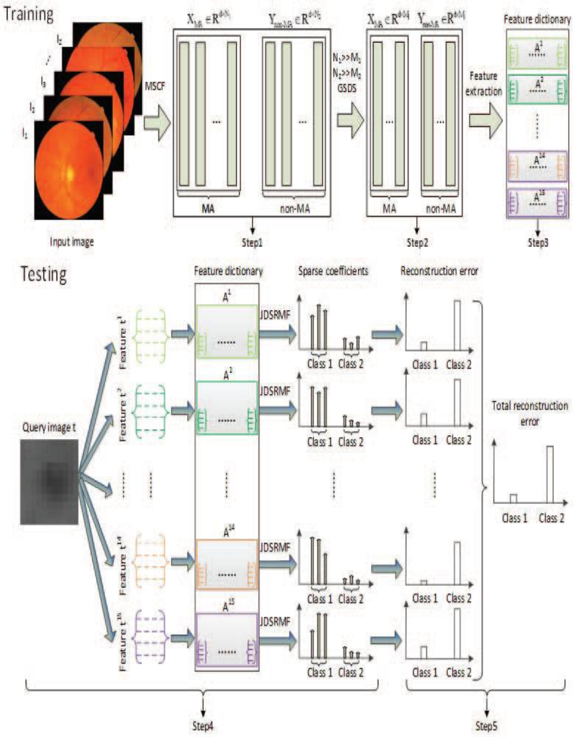

Figure 2. The working mechanism model for MA detection.

2.1 MA candidate extraction

A Multi-scale Gaussian Correlation Filtering (MSCF) method [13] is applied to extract MA candidates. Let I = [I1, I2,…,It,…,Iz] ε Rm×n×z denote Z original colour retinal images with the dimension of m×n in the training set. And for each of the image It training set, MSCF is used to extract 11×11 pixels image blocks, and then concatenate each extracted image patch into a column vector with the dimensionality of121×1.

2.2 The formation of compact dictionary

As the number of extracted MA and non-MA candidates is huge, choosing the important candidates as the final candidates for building dictionary plays an important role in this method, which can improve the efficiency of this model greatly. Here, two optimal subsets from MA and non-MA image blocks are selected to form two compact dictionaries using group sparsity dictionary selection algorithm [15]. As the formation process of the two dictionaries is the same, so the process of MA is illustrated, it can be formulated as below:

$$\min_{W} = \frac{1}{2}\|X_{MA} - X_{MA}W\|_F^2 + \lambda\|W\|_{2,1}$$

Where W ∈ RN1×N1 is a representation matrix; $\|W\|_F = \left(\sum_{ij} W_{ij}^2\right)^{1/2}$ the Frobenius norm; and the $l_{2,1}$norm is represented as $\|W\|_{2,1} = \sum_{i=2}^{N^1}\|W_i\|_2$and Wi denotes the i-th row of W. That is to say, the optimal dictionary atoms can be selected with ||Wi||2≠ 0.After dictionary selection, two compact dictionaries both X’MA and Y’non-MA can be obtained (see step2 of Fig.2).

2.3 Feature extraction

The method of extracting different features in multiple channel for each MA candidate are shown in this paper. Here, ICLAHE is the CLAHE [16] enhanced image preprocessed with original image Ioriginal and Igreen is the green channel image from ICLAHE. Multiple channel images can be described as below:

Channel1: Original green channel image (see Fig.3 (a)).

Channel2: CLAHE enhanced green channel image (seeFig.3 (b)).

Channel3: Hue brightness correction is applied to Igreen for making the brightness unified (see Fig.3 (c).Channel4: IM is the M component image from the enhanced original retinal image of CMYK colour space (seeFig.3 (d)).

Channel5: Using median filtering with a 25×25 pixel kernel to Igreen for calculating background image Ibg and then the Ibg can be removed from Igreen to obtain the shade correlated image Isc . The result of Isc is depicted in Fig.

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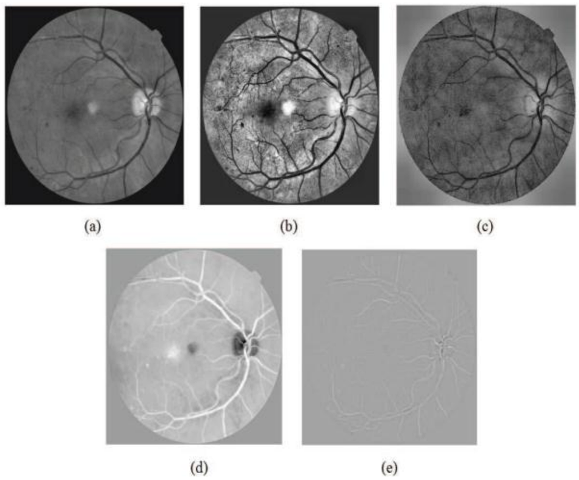

Figure 3. Different channel images. (a) original green image, (b-e)enhanced green channel image Igreen, hue enhanced imageIhue_ enhanced,M component image of CMYK color space IM,shade corrected image Isc, respectively.

With the above mentioned five channel images, three types of features including intensity, histogram equalization and canny edge information are extracted. For each sample, K is extracted (here K=15) different features and then construct its corresponding K different feature dictionaries. (see step3of Fig.2).

2.4 Joint dynamic sparse representation based on multiple features

Given a query candidate image t, K different features extracted from t and then concatenate each extracted feature into a column vector. Thus, t can be represented as t = [t1, t2,…,tk]∈Rd×k in whichtk∈Rd×1(k=1,2,…,k) is the vector of the k-th feature. In order to exploit the correlations among the multiple features, Zhang et al. [17] put forward a novel method named Joint Dynamic Sparse Representation based Classification (JDSRC), which describes the same subject during the multi-mask learning-based sparse representation. Formally, let B = [B1, B2,…,Bk] be the sparse representation coefficients matrix set containing sparse coefficients of K features from t, where Bm is the coefficient vector of the m-th feature. Then, each dynamic active set can be described as a set of row indices of coefficients whose corresponding samples in the training set belong to the same class. The objective function of JDSRC can be listed as below:

$$\min_{B} = \sum_{k=1}^{K} \|t^k - A^k B^k\|_2^2 \quad s.t. \|B\|_G \le T \qquad (2)$$

where T is the sparsity level which denotes the number of non-zero elements in each Bk .The mix-norm

|| B ||G regularization which integrates the indexes from all the feature images coming from the query image t during the sparse representation process and promotes a joint sparsity pattern shared at class-level [17].where

$$\|B\|_G = \left\| \left(\|B_{g_1}\|_2, \|B_{g_2}\|_2, \dots \right) \right\|_0 \qquad (3)$$

$$B_{g_s} = B(g_s) = (B(g_s(1),1), B(g_s(2),2), \dots, B(g_s(K),K))^T \in R^k \qquad (4)$$

is the vector containing a series of coefficients associated with the s-th dynamic active set. Since the regularization term in Eq. (2) contains thel0 -norm. In this paper, an improved Simultaneous Orthogonal Matching Pursuit (SOMP) [18] is adopted to optimize Eq.(2), which contains the following five steps: (i) a series of new candidates can be selected by the current reconstruction error; (ii) integrate the newly selected candidates with the previously chosen atom set to form the new atom set; (iii) the representation coefficients can be obtained based on the new obtained atom set; (iv) utilize the new estimated representation coefficients to prune the new atom set to a specified sparsity level; (v) update the corresponding reconstruction error .This procedure is iterated until meeting the conditions [17].

2.5 Classification

After obtaining the optimal coefficient $\beta = [\beta^1, \beta^2, \dots, \beta^k]$, the reconstruction error can be calculate by the corresponding feature dictionary A_c^k of the c-th class and k-th feature. The error of all K features of each class in t and get the final recognition of the query image t as:

$$Label(t) = \arg\min_c \sum_{k=1}^{K} \|t^k - A_c^k \beta\|_2^2 \qquad (5)$$

3. Conclusion

Combining multiple discriminative features for object recognition has received wide interests in recent years. Extracting diverse modality feature descriptors can be regarded as a good way to enforce the different discriminative power for all classes. Inspired by multiple features and joint dynamic sparse representation, in this paper, the MA detection algorithm named JDSRMF, which integrates joint dynamic sparse representation and multiple channels multiple features in to a framework. In this method not only promotes the multiple features sparse representation vectors belonging to the same test sample shared at class-level, but also allow s varying sparsity patterns within each class to facilitate flexible representation at atom-level. The experiments are carried out on Retinopathy Online Challenge (ROC) dataset, which show favourable results when compared with the state-of-the-art methods.

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