

DETECTION AND CLASSIFICATION OF BRIGHT LESIONS IN COLOR FUNDUS IMAGES

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ABSTRACT

Bright lesions including exudates and cotton wool spots are main symptoms in diabetic retinopathy. Early detection and classification of these evidences is essential for an effective treatment. In this paper, a three-stage approach is applied to detect and classify bright lesions. After local contrast enhancement preprocessing stage, two-step Improved Fuzzy C-Means is applied in Luv color space to segment candidate bright-lesion areas. The results are shown to be effective in dealing with the inhomogeneous illumination of the fundus images while reducing the influence of noises. Finally, a hierarchical support vector machine (SVM) classification structure is successfully applied to classify bright non-lesion areas, exudates and cotton wool spots.

Index Terms- Improved Fuzzy C-means (IFCM), support vector machines (SVMs), exudates, cotton-wool spots, fundus images

1. INTRODUCTION

Diabetic retinopathy has become a common eye disease in most developed countries. It occurs in 80% of all diabetic cases and is the leading cause of blindness [1]. Regular screening is the most efficient way of reducing the preventable eye damages. There are two kinds of symptoms in the diabetic fundus images. One is bright lesion that includes exudates and cotton wool spots as shown in figure 1. The other is dark lesion such as hemorrhages and microaneurysms. This paper focuses on the detection and classification of bright lesions. Exudates are yellow-white lesions with relative distinct margins. They are lipid deposits within the body of the retina and are often distributed in a circular pattern peripheral to areas of chronic focal leakage. Cotton wool spots are whitish patches that have no well-defined margins. They are not real exudates but degenerating nerve fibers.

Previous work mainly rely on the detection of the exudates. The accurate classification between bright lesions remains unsolved. Current exudates detection strategies can be grouped into three main categories: thresholding, region growing and classification.

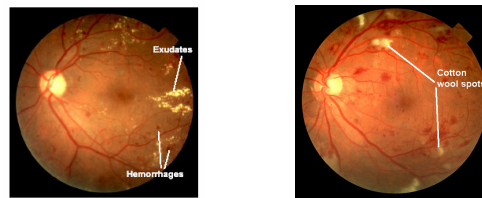


Figure 1. Bright lesions in color fundus image

Thresholding:

Ward [2] used shade correcting to reduce the shade variations in the color fundus image. The exudates were detected by thresholding. It required the user to select the threshold manually based on the histogram. Phillips [3] detected the large exudates by a global threshold and segmented the smaller, lower intensity exudates by local thresholds. The thresholds were selected automatically, but the region of interest must be chosen manually.

Region growing:

Sinthanayothin [4] applied a recursive region growing segmentation to detect the exudates after the color image standardization. However, the limitation of this method is the difficulty in selecting the seed point and the stopping criteria in region growing. Li [5] improved the region growing method by introducing the Luv color space. In the coordinate of $L-u$ histogram, the author suggested that a fixed circular region represents the background region while the northwest region corresponds the bright objects. However, the assumption of the fixed circular background region may not be suitable due to the wide variety of color distribution and inhomogeneous illumination.

Classification:

Wang [6] used color features as feature space. Each pixel was then classified into lesion or non-lesion classes by using a Bayesian statistical classifier. Osareh [7] used Fuzzy C-Means clustering to segment the candidate exudate areas, then a neural network was applied to classify the exudates from non-exudate areas. However, with application of FCM in *RGB* color space and under non-uniform illumination, the detection accuracy would not be very desirable yet. Moreover, classification of cotton wool spots from exudates was not addressed.

In the following section 2, a three-stage approach is presented to detect bright lesions and finally classify them into exudates and cotton wool spots. Experimental results on the local contrast enhancement and lesion classification are given in section 3 to show the effectiveness of the method in dealing with the problem of non-uniform illumination.

2. PROPOSED METHOD

There are three types of objects in the retinal images: bright objects, dark objects and retinal background. Bright objects include white or yellow ones such as optic disk, exudates and cotton wool spots. Blood vessels, fovea, hemorrhages and microaneurysms belong to dark-object group. The color of the retinal background is between that of bright objects and dark objects.

The proposed method contains three main stages: firstly, local contrast enhancement is applied as a preprocessing stage. Then, an improved Fuzzy C-Means (IFCM) is proposed and applied in *Luv* color space to segment all candidate bright lesions areas. This segmentation stage is conservative and it segments all possible bright lesions as well as false positives due to cluster overlapping, non-uniformity of color distribution and noises. The final stage is a hierarchical SVM classification stage that aims to distinguish true bright lesions from non-lesions, and to obtain more accurate classification between exudates and cotton wool spots.

2.1. Local contrast enhancement preprocessing stage

Local contrast enhancement [4] depends on the mean and variance of the intensity within the local area. If the variation of the intensity in the local area is high, the algorithm does not significantly increase the local contrast. On the other hand, if the intensity variation in the local area is small, the local contrast is substantially increased.

Consider a sub-image W of size $M \times M$ pixels centered on a pixel. Set the mean and standard deviation of the intensity within W by $\langle f \rangle_W$ and σ_W respectively. Denote f_{\max} and f_{\min} as the maximum and minimum intensities

of the whole image, then the adaptive local contrast enhancement transformation is defined by:

$$g(x, y) = 255 \frac{[\Psi_W(f) - \Psi_W(f_{\min})]}{[\Psi_W(f_{\max}) - \Psi_W(f_{\min})]} \quad (1)$$

where the sigmoidal function $\Psi_W(f)$ is

$$\Psi_W(f) = \left[1 + \exp\left(\frac{\langle f \rangle_W - f(x, y)}{\sigma_W}\right) \right]^{-1} \quad (2)$$

2.2. Improved FCM segmentation stage in *Luv* color space

Fuzzy C-Means is an effective approach of segmenting color image. Unlike hard segmentation methods such as K-means that force pixels to belong exclusively to one class, the FCM allows pixels to be classified into multiple classes with varying degree of membership.

The objective function of FCM [8] is:

$$J = \sum_{i=1}^c \sum_{k=1}^N u_{ik}^p \|x_k - v_i\|^2 \quad (3)$$

where the array $[u_{ik}] = U$ represents a fuzzy partition matrix, it can be used to show the results of classifying the data X to clusters by interpreting each element $[u_{ik}]$ as a measure according to which data vector x_k belongs to cluster i . $\{v_i\}_{i=1}^c$ are the prototypes of the clusters, $p > 1$ is the weighting exponent which controls the fuzziness of the resulting clusters. However, FCM only considers the individual pixels. Therefore, it is sensitive to noise.

Similar to the MFCM proposed by Mohamed *et al* [9], a new improved FCM (IFCM) is proposed as follows:

$$J_I = \sum_{i=1}^c \sum_{k=1}^N u_{ik}^p \|x_k - v_i\|^2 + \alpha \sum_{i=1}^c \sum_{k=1}^N u_{ik}^p \text{Median}_{ik} \quad (4)$$

where $\text{Median}_{ik} = \text{Median}(\|x_r - v_i\|^2)_{x_r \in N_k}$

$$u_{ik} \in [0, 1]; \quad 1 \leq i \leq c; \quad 1 \leq k \leq N$$

$$\sum_{i=1}^c u_{ik} = 1; \quad 1 \leq k \leq N; \quad \sum_{k=1}^N u_{ik} > 0; \quad 1 \leq i \leq c$$

N_k stands for the set of neighbors that exist in a window around x_k . The effect of the neighbor term is controlled by the parameter α .

IFCM use the median filter effect instead of average filter effect, thus it can keep the edge while reducing the noises. The objective function J_I can be minimized in a way similar to the standard FCM.

1) Fuzzy partition matrix updating

The constrained optimization in (4) will be solved using one Lagrange multiplier

$$F_I = \sum_{i=1}^c \sum_{k=1}^N (u_{ik}^p d_{ik} + \alpha u_{ik}^p \xi_i) + \lambda (1 - \sum_{i=1}^c u_{ik}) \quad (5)$$

where $d_{ik} = \|x_k - v_i\|^2$, and $\xi_i = \text{Median}(\|x_r - v_i\|^2)_{x_r \in N_k}$.

Taking the derivative of F_I with respect to u_{ik} and setting the result to zero, we get

$$\left[\frac{\partial F_I}{\partial u_{ik}} = p u_{ik}^{p-1} d_{ik} + \alpha p u_{ik}^{p-1} \xi_i - \lambda \right]_{u_{ik}=u_{ik}^*} = 0 \quad (6)$$

Solving for u_{ik}^* we have

$$u_{ik}^* = \frac{1}{\sum_{j=1}^c \left(\frac{d_{ik} + \alpha \xi_i}{d_{jk} + \alpha \xi_j} \right)^{\frac{1}{p-1}}} \quad (7)$$

2) Cluster prototype updating

Taking the derivative of F_I with respect to v_i and setting the result to zero, we can obtain:

$$\left[\sum_{k=1}^N u_{ik}^p (x_k - v_i) + \sum_{k=1}^N u_{ik}^p \alpha (x_M - v_i) \right]_{v_i=v_i^*} = 0 \quad (8)$$

$$v_i^* = \frac{\sum_{k=1}^N u_{ik}^p (x_k + \alpha x_M)}{(1 + \alpha) \sum_{k=1}^N u_{ik}^p} \quad (9)$$

where $\|x_M - v_i^*\|^2 = \text{Median}(\|x_r - v_i^*\|^2)_{x_r \in N_k}$

Approximately, we use

$$\|x_M - v_i\|^2 = \text{Median}(\|x_r - v_i\|^2)_{x_r \in N_k}$$

3) IFCM algorithm

Step 1) Select initial class prototypes $\{v_i\}_{i=1}^c$.

Step 2) Update the partition matrix using (7).

Step 3) Update the prototypes of the clusters using (9).

Repeat Step 2)—3) till termination. The termination criterion is as follows:

$$\|V_{new} - V_{old}\| < \epsilon \quad (10)$$

where $V = [v_1, v_2, \dots, v_c]^T$

Although the retinal image consists of three types of objects, directly using FCM to segment the image into three classes in *RGB* color space usually cannot achieve the desired result. The main reason is the non-uniform illumination in retinal images. After investigating the *Luv* color space, it was found that the *u* component of *Luv* is good in classifying three kinds of objects in most regions of the image except the dark regions near the image perimeter. So in this proposed method, IFCM is applied in two stages, first in *L* that represents luminance, then in *u* and *v* that represent chrominance. In *L*, three types of

intensity clusters are classified. By using the local contrast enhancement, the intensities of bright lesions are within the brightest class. However, some bright background regions are also classified into the brightest class. Then in the second stage, two classes are classified using the chrominance components *u* and *v* to distinguish bright lesions and bright background. Thus by decomposing intensity and chrominance, the problem of non-uniform illumination was more effectively solved.

2.3. Support vector machines classification stage:

SVM is a statistical learning method based on structural risk minimization (SRM). It can map the input vector x into a high dimensional feature space by choosing a nonlinear mapping kernel. The optimal separating hyperplane in the feature space is given by [10]:

$$f(x) = \text{sgn} \left(\sum_{i=1}^l y_i \alpha_i K(x_i, x) + b \right) \quad (11)$$

where y_i are the labels, K is the kernel function, b is the bias, and α_i are the Lagrange multipliers.

After the two-step IFCM clustering stage, the candidate bright lesion areas are segmented. Due to the influence of cluster overlapping, non-uniformity of color distribution and noises, some non-lesion areas among the candidate areas need to be classified. Moreover, the bright lesion areas that consist of exudates and cotton wool spots also need to be classified. There are several schemes of using binary SVM to deal with multi-class problem such as “one versus the rest” and “one versus one”. However, a two-level SVM classification structure is applied in this paper. The first classification stage aims to classify bright lesions versus bright non-lesion areas while the second classification stage classifies exudates from cotton wool spots. The advantage is that unlike other schemes, user can access the results of each classifier for clinical consideration.

In order to classify three kinds of candidate bright lesion areas: non-lesion areas, exudates and cotton wool spots, relevant features need to be selected properly.

1) Region edge strength

$$|\nabla f(x, y)| = \sqrt{\left(\frac{\partial f}{\partial x} \right)^2 + \left(\frac{\partial f}{\partial y} \right)^2} \quad (12)$$

2) Color difference between inside region area and surrounding area

$$Cd = \frac{u_{inside}}{u_{surrounding}} \quad (13)$$

By using above two features, non-lesion areas and lesion areas can be linearly classified. However, in

order to further classify exudates and cotton wool spots correctly, the following features are added.

3) Region size

4) u and v of Luv color space

All the color values such as u and v we use here are relative values. The standard reference color is the color of optic disk region.

3. EXPERIMENTAL RESULTS

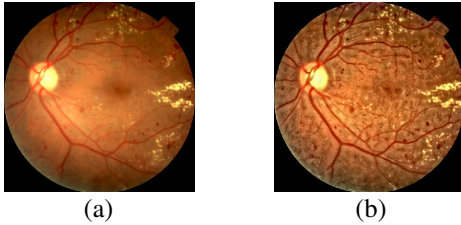


Figure 2. An example of local contrast enhancement. (a) Original image. (b) After local contrast enhancement with a window size of 32×32 .

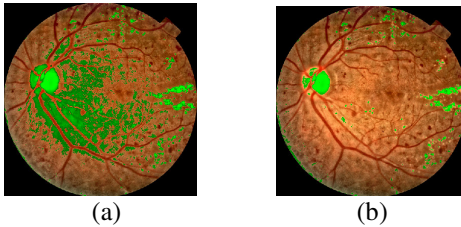


Figure 3. Comparison of segmentation results. (a) Application of FCM in RGB color space. (b) Application of two-step IFCM in Luv color space.

Figure 2 shows the result of local contrast enhancement. Figure 3(a) is the result of applying FCM in RGB color space. It is not satisfactory due to the non-uniform illumination. Figure 3(b) demonstrates the greatly improved result of the two-step IFCM applied in Luv color space. In SVM classification stage, a training set obtained from 30 images consists of 983 segmented bright non-lesion areas, 457 exudates and 54 cotton wool spots. A testing set consists of 432 bright non-lesion areas, 213 exudates and 47 cotton wool spots. The model selection including the type of kernel function and the regularization parameter C are carried out by 5-fold cross validation. Figure 4 shows the Receiver Operating Characteristic (ROC) curves of the following two SVM classifiers.

Stage 1: Classification between bright lesions and bright non-lesion

Linear kernel, $C=10$, sensitivity=97%, specificity=96%, Ratio of SVs=17%.

Stage 2: Classification between exudates and cotton wool spots

Polynomial kernel, $d=2$, $C=6$, sensitivity=88%, specificity=84%, Ratio of SVs=24%.

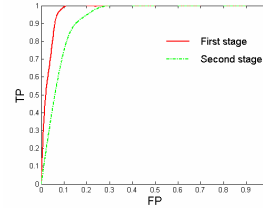


Figure 4. ROC curves of two SVM classifiers

4. CONCLUSION

In this paper, a three-stage approach is applied to detect and classify bright lesions in color fundus. IFCM is proposed to reduce the influence of noises. Applying two-step IFCM in Luv color space can effectively solve the problem of non-uniform illumination. A hierarchical SVM classification structure is applied to classify bright non-lesion areas, exudates and cotton wool spots.

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