Automatic Detection of Hard Exudates in Retinal Images with Diabetic Retinopathy

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Diabetic Retinopathy

The Diabetic Retinopathy (DR) is a visual complication of diabetes and one of the principal cause of lost vision not recoverable in industrialized countries. The patients with DR do not perceive any symptoms until the visual loss develops in advanced stages when the treatment is less efficient. Hard exudates are the most common lesions in the early stages. In this work, we developed an automatic method for hard exudates detection in DR images with an acceptable level of confidence that can help specialists in the diagnosis and screening of this disease.

Fig. 1: Retina with Diabetic Retinopathy

We propose, to analyze different color components and then to select those that provide greater separability between the structures and the retinal background. Normalize the contrast and luminosity of each selected component and combine them to create an ideal color component where HE can be more accurately segmented.

Luminosity and Contrast Normalization

In order to obtain the undistorted image $\hat{I}^o$, we first compute the background mask, B, consisting of the pixels of I that do not belong to lesions or retinal structures. This can be estimated by using the Mahalanobis distances as follows:

$$B(x,y) = \begin{cases} 1 & \text{If } \left|\frac{I(x,y)-\hat{\mu}_{\mathcal{N}}(x,y)}{\hat{\sigma}_{\mathcal{N}}(x,y)}\right| < \tau \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

where $\tau > 0$ is a experimental threshold and $\mathcal{N}$ a neighborhood of (x, y). Later, we compute the local mean luminosity image $\hat{L}$ and local contrast image $\hat{C}$ corresponding to sites in the background. Finally, the estimate undistorted image $\hat{I}^o$ is computed as follows:

$$\hat{I}^o(x,y) = \frac{I(x,y) - \hat{L}(x,y)}{\hat{C}(x,y)} \quad (2)$$

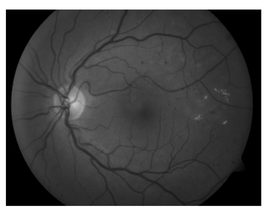


Fig. 2: Original Image

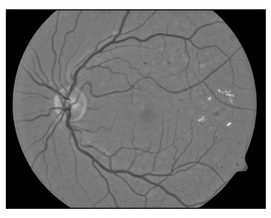


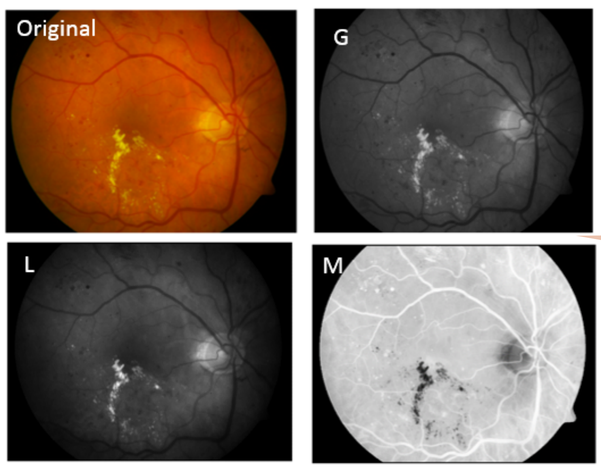
Fig. 3: Normalized Image

Separability in Color Spaces

We study the power of separability between the structures of the retina and the background of the image in each component of color, for different spaces of color. In order to measure which color component highlights the structures and lesions of a retinal image, we apply to each color component the quantitative *Fisher Discriminant Ratio*:

$$\text{FDR} = \frac{(\mu_1 - \mu_2)^2}{\sigma_1^2 + \sigma_2^2}, \quad (3)$$

where μ_1, σ_1^2 belong to pixels of lesions or retinal structures, and μ_2, σ_2^2 to the complement, respectively.



Adaptive Boosting Color

Require: Training dataset $D = \{(x_i, y_i)\}_{i=1}^N$, where $x_i \in \mathbb{R}^M$, and $y_i \in \{-1, 1\}$.

Create the set of weak classifiers $H = \{h_m(x)\}_{m=1,\cdots,M}$
$d = \frac{1}{N}\mathbf{1} \in \mathbb{R}^N$
$\mathbf{w} = \mathbf{0} \in \mathbb{R}^M$
for $t = 1, 2, ..., T$ **do** ▷ Iterations of the algorithm
  for $m = 1, ..., M$ **do** ▷ Loop over the classifiers

$$\epsilon_m = \sum_{i=1}^{N} d_i[y_i \neq h_m(x_i)]; \quad u_m = c_1$$

    if $\epsilon_m > 0.5$ **then** $\epsilon_m = 1 - \epsilon_m$; $u_m = c_2$
  $k = \arg\min_{m \in \{1,\cdots,M\}} \epsilon_m$
  $\alpha = 0.5 \log \frac{1-\epsilon_k}{\epsilon_k}$
  $d_i = d_i e^{-\alpha u_k h_k(x_i) y_i}$
  $d_i = \frac{d_i}{\sum_{n=1}^{N} d_n}$ ▷ Normalization of d
  $\mathbf{w}_t = \mathbf{w} + \alpha u_k \mathbf{e}_k$ ▷ Update weights
return W

Segmentation

In order to obtain hard exudates regions with high intensities we subtract the previous image to the same image filtered by using a median filter. Finally, we apply a threshold to obtain candidate regions for hard exudates.

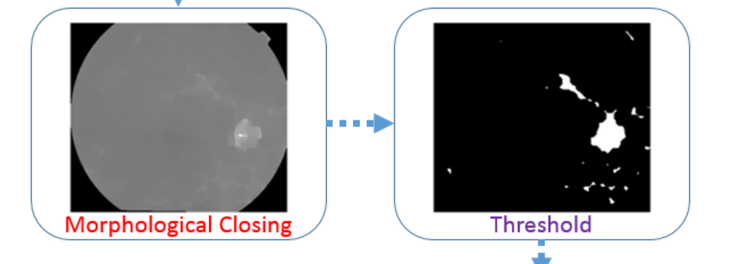


Fig. 5: Segmentation of Hard Exudates Regions

Optical Disk Detection

	Results of Metric FDR			
	C	M	Y	K
Mean	0.4672	**2.4881**	0.1794	0.9437
	R	G	B	
Mean	0.9496	**2.4865**	0.7802	
	L	U	V	
Mean	**1.9694**	0.0653	0.2497	

Features Selection

We carried out a detail analysis about the features of shape and color:

- Mean of RGB values within the region (1-3),
- St. dev. of RGB values within the region (4-6),
- Average of RGB values around the region (7-9),
- St. dev. of RGB values around the region (10-12),
- RGB value of the centroid of the region (13-15),
- Area of the region (16),
- Compactness of the region (17),
- Edge strength in the region (18),
- Homogeneity of the region (19-21),
- Color difference of RGB values (22-24).

Then, the above features are extracted for each detected region followed by a feature selection step.

Scalar Selection

We first calculate the FDR, for each features and we then rank them down according to the discrimination capability of each feature. The feature with greatest FDR is assigned the index i_1 and in order to determine the following significant feature i_k , we solve:

$$i_k = \max_j \left\{ a_1 C_j - \frac{a_2}{k-1} \sum_{r=1}^{k-1} |\rho_{i_r,j}| \right\}, j \neq i_r, r = 1, ..., k-1, \quad (4)$$

with $\rho_{i_r,j}$ as the cross-correlation between the i_r feature and the $j \neq i_r$ feature. The parameters a_1 y a_2 have been experimentally determined.

Vectorial Selection

From the results obtained in the scalar selection, we take the features that preserve 95% of the explained variance, and we analyze different combinations of subsets of features by the method of *Forward Floating Selection* (FFSS) with criterion of separability of classes $J_3 = trace\{S_w^{-1} S_m\}$ where:

$$S_w = \sum_{i=1}^{M} P_i E[(x - \mu_i)(x - \mu_i)^T] = \sum_{i=1}^{M} P_i S_i \quad (5)$$

$$S_m = E[(x - \mu_0)(x - \mu_0)^T] \quad (6)$$

with M the number of classes, S_i the covariance matrix of the class i, and P_i the probability *a priori* of the class i. With $P_i \simeq n_i/N$, where n_i is the number of samples in class i and N the total number of samples.

For selecting the best feature subset, we perform a **10-Fold Cross-Validation**, based on the vector selection results, using as a classification model a Vector Support Machine with Linear kernel and metric the area under the ROC curve.

The best subset have 14 features and are: (1, 2, 5, 7, 8, 9, 10, 12, 15, 16, 18, 22, 23, 24).

Experimental Results

We will use the public database of images DIARETDB1 which contains images with conditions that can be found in any hospital.

Classifier	ACC	SE	PPV	AUC
Nearest Neighbors	0.9330	**0.8452**	0.8073	0.9493
Linear SVM	0.9183	0.7275	0.8177	0.9551
RBF SVM	0.8770	0.4146	**0.8566**	0.9510
LDA	0.9055	0.6464	0.8122	0.9536
Neural Network	**0.9412**	0.8351	0.8562	**0.9782**

A comparison of our results with the state of the art is presented:

Classifier	SE	PPV	AUC
Osareh	0.90	0.893	–
Zhang and Chutatape	0.88	0.840	–
Walter et al.	0.928	0.924	–
Sánchez et al.	0.902	0.968	0.952
María2009 MLP	0.8814	0.8072	–
María2009 SVM	0.8761	0.8351	–
Proposed Method	0.8351	0.8562	0.9782

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