Hierarchical Detection of Hard Exudates in Color Retinal Images

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Abstract-Diabetic retinopathy (DR) is one of the common causes of blindness, and hard exudates (HEs) are the primary and early clinical signs of DR. Thus, a reliable detection of HEs is significant for clinical diagnosis and preventing vision loss of patients. In this paper, a novel method is presented to detect HEs automatically in color retinal images. The method consists of two stages: coarse level and fine level. In coarse level, we extract HEs candidate regions by combining histogram segmentation with morphological reconstruction. While in fine level, we define 44 representative features for each candidate region, and train a support vector machine (SVM) model to classify HEs and non-HEs. We evaluate the proposed method on the public DIARETDB1 database and yield a sensitivity of 94.7% and a positive predictive value of 90.0%. Experiment results show that our method can detect HEs efficiently.

Index Terms—diabetic retinopathy, hard exudates, histogram segmentation, morphological reconstruction, SVM

I. INTRODUCTION

IABETIC retinopathy is one of the leading causes O of vision impairment and blindness throughout the world, and has the steady growth in the prevalence [1]. Hard exudates have been known as the specific marker of DR [2], which are the lipid residues of serous leakage from damaged capillaries. The clinical examination of HEs is essential to the early diagnosis and treatment of DR. The traditional detection of HEs is accomplished manually and is a laborious and time-consuming work. Meanwhile, with population of DR increase, the workload of ophthalmologist aggravate notably and the deficiency of manually check becomes significantly serious, which prevent many patients from receiving an effective treatment in time. Therefore, an automatic and reliable detection of HEs is a significant task in computer aided diagnosis of DR.

HEs appear as yellow-white regions with sharp margins in color retinal images, and often are circinatelike objects, see Fig. 1. However, HEs detection is still an open issue in medical image processing, and the





Figure 1. Illustration of hard exudates. (a) Color retinal image with HEs and (b) enlarge image with parts of HEs marked.

main difficulties for HEs detection are the interference of similar color objects such as cotton wool spots (CWS), optic disk (OD) and circular scars left after pan-retinal photocoagulation treatment (PRP) for DR, and the noise caused by normal macular reflection.

To solve these problems, we hereby present an hierarchical framework for exudate detection in color retinal images. As shown in Fig. 2, this method employs the coarse-to-fine strategy which has two main stages: (a) Coarse level: extraction of the exudates candidate regions with histogram segmentation and morphological reconstruction; and (b) Fine level: final HEs classification by

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Figure 2. The flow chart of proposed method.

means of SVM based on a set of significant features of HEs.

II. RELATED WORKS

Many techniques have been employed to the exudate detection and can be roughly divided into four categories: thresholding based, clustering based, morphology based and learning based methods.

Thresholding based methods dedicate to select a grey level threshold which can be used to segment the HEs from retinal images directly [3], but the automatic selection of proper threshold is difficult due to the uneven illumination of the image [4]. Consequently, the local dynamic thresholding method [5] is proposed to segment HEs automatically which calculates every pixel's threshold according to its local histogram. Another dynamic thresholding is designed in [4] which select the threshold based on the robust estimation of the histogram of the whole image by using a mixture model. Soares *et al.* proposed an innovative threshold computation method based curvature extremes detection in the Gaussian scale space [6] for the localization of exudates.

Clustering based methods segment retinal images based on the spacial contiguity, illumination homogeneity and texture similarity of the HEs. Sinthanayothin *et al.* present a region growing scheme based on these clustering criterion [7]. Dynamic clustering techniques have been used in [8] to automatically and accurately group HEs clusters without prior thresholds and input parameters because there are only two clusters, lesions versus non-lesions.

Morphology based methods as the simple and highly efficient image processing approaches have been widely used in retinal image analysis. After applying some greyscale morphological operators to remove uninterested structures, such as vessels network and optic disk, Walter *et al.* [9] first segment HEs roughly and then locate the contour of HEs by using morphological reconstruction and some post-processing. Welfer *et al.* [10] also advocate an integrated framework to segment HEs by combining the morphological reconstruction and threshold processing.

Learing based methods are always used to classify the HEs and non HEs as the refined process in the detection procedure. This results from the existing of interference such as other light lesion regions that have same intensities as HEs. After defining some inherent features such as geometry, color, contrast and texture features, many machine learning methods such as k-nearest neighbor classifier and linear discriminant classifier [11], statistical classification [12], neural network [13], [14], Bayesian classifiers [15] and SVM [16] can used to classify the true HEs.

In the light of previous works, our proposed method combine the histogram segmentation, morphology reconstruction and supervised SVM model in a hierarchical framework. The organization of the remaining part of this paper is as follows: Section III and IV contain the details of the proposed HEs detection scheme. Experimental results is described and discussed in Section V, and in Section VI we conclude the paper.

III. COARSE LEVEL: CANDIDATE DETECTION

A. Preprocessing

The fundus image captured in a clinical environment always have an uneven illumination and a local weak contrast, which will degrade the accuracy of candidates detection, especially for some small exudate regions. In order to eliminate these unfavourable imperfections, the preprocessing scheme is advocated before HEs candidate detection.

We first normalize the image illumination as follows, given an input color retinal image I_{rgb} and its illumination component I_{ic} in the HSI colorspace, an illumination normalized image I_{eq} can be calculated according to:

$$I_{eq} = I_{ic} + M - I_{bg} \tag{1}$$

with

$$I_{bg} = I_{ic} * f_m$$

where M is a constant matrice in which all element are set as an empirical value of 0.4. I_{bg} is an estimation of the background illumination which is obtained by using a 30×50 mean filter f_m to smooth I_{ic} , "*" is convolution operator. Let I_{eq} as the new illumination component in HSI colorspace, the color image I_{rgbeq} in RGB colorspace is finally acquired which also has the nomalized illumination.

We next adopted the method proposed in [17] to enhance the contrast between exudate regions and background in I_{rgbeq} . The input image is first smoothed to suppress background noises while preserving HEs edge. Given a lightness channel I_{lc} of I_{rbgeq} in the CIELAB color space. We expect to find a new image I_{eps} which is as close as possible to I_{lc} , meanwhile, is as smooth as possible everywhere except across the edge in I_{lc} . Hereby we use the edge-preserving smoothing (EPS) which is modeled based on a weighted least squares (WLS) optimization framework, and compute the new lightness image I_{eps} by minimizing the following quadratic functional:

$$F = \sum_{q} \left(\left((I_{eps})_q - (I_{lc})_q \right)^2 + \lambda \left(\alpha_x \left(\frac{\partial I_{eps}}{\partial x} \right)_q^2 + \alpha_y \left(\frac{\partial I_{eps}}{\partial y} \right)_q^2 \right) \right)$$
(2)

where q denotes the coordinate of a pixel. The goal of the first term is to minimize the distance between I_{eps} and I_{lc} , while the second term is to smooth I_{eps} . Parameters α_x and α_y are smoothness weights which depend on I_{lc} , while λ is used to balance the effects achieve by the two terms.

The multi-scale edge-preserving decomposition is then constructed in a same manner as [17] by using EPS. Let $I_{eps}^1, I_{eps}^2, \ldots, I_{eps}^n$ denote the smoothed versions of I_{lc} , and the original I_{lc} can be recovered by:

$$I_{lc} = b + \sum_{i=1}^{k} d^i \tag{3}$$

where $b = I_{eps}^{n}$ is the base layer and d is detail layers defined as

$$d^{i} = I_{eps}^{i-1} - I_{eps}^{i}$$
, where $i = 1, ..., n$ and $I_{eps}^{0} = I_{lc}$ (4)

We construct a three-level decomposition (one coarse base level and two detail levels), and let η as the exposure factor of the base layer, δ_0 as the boosting factor for the base layer and δ_1, δ_2 for the medium and fine detail layers. The final enhanced result I_{en} at each pixel q is then given by

$$(I_{en})_q = \mu + S(\delta_0, \eta b_q - \mu) + S(\delta_1, d_q^1) + S(\delta_2, d_q^2)$$
(5)

where μ is the mean value of the lightness range, and S is a sigmoid function.

Finally we convert the color image in CIELAB color space with the contrast enhanced lightness channel I_{en} into the RGB color space, and denoted I_{rgben} . The green channel of I_{rgben} is further applied with a Contrast-Limited Adaptive Histogram Equalization (CLAHE) to enhance the global contrast of the image. Finally we obtain an enhanced green channel image I_{eg} which will be used in the following processes. The preprocessing results is illustrated in Fig. 3 and Fig. 4(a).

B. Candidate Detection

The objective of this step is to coarsely segment all the bright candidate regions, such as optic disk, cotton wool spots, hard exudates, which directly use the intensity feature of the retinal image. We herein integrate





Figure 3. Illustration of the preprocessing: (a) Illumination normalized image I_{npeq} (b) Enhanced color image I_{npen}

histogram segmentation and morphological reconstruction to coarsely segment these candidate regions.

Intuitively, the distribution of grey levels in the histogram of I_{eg} can be modeled as a normal distribution. Fig. 4 illustrates the histogram of I_{eg} and in which the red curve represents the estimated model of the histogram. The normal probability density function (PDF) is defined as in Eq. 6 and its cumulative distribution function (CDF) is computed as in Eq. 7.

$$f(x;\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$
(6)

$$F(x;\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{x} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \mathrm{d}x \qquad (7)$$

We first use the maximum likelihood (ML) to estimate the parameters μ and σ of the normal distribution in our experiments, and we choose the global threshold t_1 as the grey level value at F(x) = 0.97. The initial candidate regions can be segmented from I_{eg} by finding pixels whose grey level value are greater than t_1 . The candidate regions after histogram segmentation will contain hard exudates, CWS and OD and other false positives, such as center reflex on the vessel, as shown in Fig. 7(a).

Then, we apply the morphological reconstruction [18] to remove false positives and obtain the final exudates

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Figure 4. Histogram fitting. (a) Green channel image I_{eg} after applied CLAHE. (b) Histogram of I_{eg} and its fitted normal distribution function.

candidate regions. The morphological reconstruction is given by the following iterative formula:

$$h_{k+1} = (h_k \oplus B) \cap M \tag{8}$$

with

$$(h_k \oplus B)(x) = \sup_{y \in E} [h_k(y) + B(x-y)]$$

where h_k is the marker image at the k^{th} iteration, B is the structuring element, E is a Euclidean space or an integer grid, M is the mask and " \oplus " is the morphological dilation operator. This iterative process repeats until no changes occur in h.

In this paper, we set the image which has the same grey level value as the green channel I_g of I_{rgb} but zero in all candidate regions as the initial marker I_{marker} and let I_g as the mask image, and choose B as a 3×3 square-shaped structuring element. Then we use the morphological reconstruction to obtain the reconstructed image I_{recon} , and segment the HEs candidate regions I_{cand} by converting the difference between I_{recon} and I_g to a binary image with an empirical threshold t_2 .

C. Optic Disk Removal

Furthermore, the optic disk (OD) in retinal images always appears the same intensity and same yellowish

1.	35	120	105	105	90	75	75	60	45
1:	50	135	120	105	90	75	60	45	30
1	65	150	135	120	90	60	45	30	15
1	65	165	150	135	90	45	30	15	15
(0	0	0	0	90	0	0	0	0
1	5	15	30	45	90	135	150	165	165
1	5	30	45	60	90	135	135	150	165
3	0	45	60	75	90	105	120	135	150
4	5	60	75	75	90	105	105	120	135

Figure 5. Vessels' direction template.





(b)

Figure 6. Illustration of OD removal: (a) the center of the OD with '+' marked; (b) the estimated area of the OD.

color as HEs, it is necessary to remove the OD region from I_{cand} before following process, and obtain the final HEs candidate regions I_{fin} . In this paper, we use the vessels' direction matched filter proposed in [19] to locate the optic disk. First, since the profile of the retinal blood vessel has the similarity with 2-D Gaussian template, a multi-directional Gaussian matched filter is designed to detection the vessel network which is presented by Chaudhuri *et al.* [20]. The convolutional mask in direction *i* is defined as:

$$f'_i(x,y) = f_i(x,y) - m_i \quad \forall \bar{q}_i \in N \tag{9}$$



Figure 7. Coarse segmentation processing: (a) Image obtained with the threshold $t_1 = 0.79$ based on histogram segmentation. (b) Marker image I_{marker} . (c) The reconstructed image I_{recon} . (d) Exudates candidate image I_{cand} obtained with the threshold $t_2 = 0.08$. (e) Final exudate candidate regions I_{fin} after OD removal. (f) I_{fin} superimposed on original color image I_{rgb} .

with

$$f_i(x,y) = -\exp\left(\frac{-u^2}{2\sigma^2}\right) \quad \forall \bar{q}_i \in N$$
$$m_i = \sum_{\bar{q}_i \in N} f_i(x,y)/A$$

where the neighborhood $N = \{(u, v) \mid |u| \leq 3\sigma, |v| \leq L/2\}$, and A is the number of points in N. The corresponding point \bar{q}_i in the rotated coordinate system is determined as

$$\bar{q}_i = [u, v] = \bar{q}r_i \tag{10}$$

with the rotation matrix

$$r_i = \begin{bmatrix} \cos \theta_i & -\sin \theta_i \\ \sin \theta_i & \cos \theta_i \end{bmatrix}$$

We use this convolutional kernel to filter the input image in 12 directions with an angular resolution of 15° , and then Otsu method is adopted to segment the vessel network.

Next, according to all blood vessels originate from the OD, a 9×9 vessels' direction matched filter is designed in the same way as [19], see Fig. 5, and which can be resized using bilinear interpolation to four different sizes. The point has the minimum variation between the responds of



Figure 8. Kirsch operators in different directions.



Figure 9. Multiscale LoG filters.

four templates matched with the binary vessel network, which can be seem as the location of the OD. Then we choose an empirical radius to estimate the OD as a circle region which is ignored in the following processes. The OD region is shown in Fig. 6, and Fig. 7 illustrates the candidate regions extraction in detail.

IV. FINE LEVEL: HES CLASSIFICATION

A. Feature Extraction

The final candidate regions I_{fin} may contain three types of regions, i. e., HEs, CWS and other artifacts. For classifying these regions into HEs or non-HEs, we need to define a set of representative features for each candidate region, which will be used as the input in the following classification. The following 44 features are defined to describe each candidate region:

- Feature 1: Area a = Σ_{j∈Ω} 1, where Ω is the pixels set of the candidate region.
- Feature 2: Circularity $cc = 4\pi a/p^2$, where p and a represent the region perimeter and area respectively.
- Feature 3: Compactness $cm = \sqrt{(\sum_{j=1}^{n} d_j \bar{d})/n}$, where d_j is the distance from the centroid of the region to its convex hull's *j*th vertex pixel, \bar{d} is the mean value of all the distances from the centroid to all the *n* vertex pixels.
- Feature 4: Edge strength $es = \sum_{j \in \Omega} I_{Kirsch}(j)/p$, where I_{Kirsch} is the value of each pixel's response after applying a Kirsch operator on I_{eg} , the template of Kirsch filter is shown in Fig. 8.
- Feature 5-8: The grey-level value of the centroid of the region in $[I_l, I_u, I_v, I_h]$. I_l, I_u, I_v correspond to images of *l* channel, *u* channel and *v* channel in Luv colorspace respectively, I_h represents the image of *h* channel in HSI colorspace.

• Feature 9-12: Mean grey-level value values of the region in [*I*_l, *I*_u, *I*_v, *I*_h]:

$$\mu_i = \frac{\sum_{j \in \Omega} I_i(j)}{a} \quad i = l, u, v, h \tag{11}$$

• Feature 13-16: Standard deviation values of the region in [*I*_l, *I*_u, *I*_v, *I*_h]:

$$\sigma_i = \frac{\sqrt{\sum_{j \in \Omega} (I_i(j) - \mu_i)^2}}{a} \quad i = l, u, v, h \quad (12)$$

• Feature 17-20: Mean grey-level value values of the surrounding region in $[I_l, I_u, I_v, I_h]$. The surrounding region is obtained by subtracting the candidate region from the region dilated with a disk-shaped structuring element.

$$\mu_i^a = \frac{\sum_{j \in \bar{\Omega}} I_i(j)}{a} \quad i = l, u, v, h \tag{13}$$

with

$$\Omega = \Omega \oplus B - \Omega$$

where " \oplus " is morphology dilate operator and B is structure element.

• Feature 21-24: Standard deviation values of the surrounding region in [I_l, I_u, I_v, I_h].

$$\sigma_i^a = \frac{\sqrt{\sum_{j \in \bar{\Omega}} (I_i(j) - \mu_i^a)^2}}{i = l, u, v, h} \quad (14)$$

• Feature 25-28: Difference of the mean value between the original region and its surrounding region in [*I_l*, *I_u*, *I_v*, *I_h*].

$$DM_i = \sigma_i - \sigma_i^a \quad i = l, u, v, h \tag{15}$$

• Feature 29-32: Homogeneity of the candidate region in $[I_l, I_u, I_v, I_h]$, which are measured by the Shannon's entropy. Taking the *u* channel image I_u for example, the homogeneity H_u of the region is defined as follows:

$$H_u = -\sum_{i=0}^{L_u - 1} P(b_{u_i}) \ln[P(b_{u_i})]$$

$$P(b_{u_i}) = N(b_{u_i})/a, i = 1, ..., L_u - 1$$
(16)

where L_u is the number of grey levels inside of the region in I_u , b_{u_i} represents each grey level and $N(b_{u_i})$ is the number of pixels has the same b_{u_i} inside of the region.

• Feature 33-44: Mean response values of the candidate region in filtered images which are obtained by applying multi-scale 2-D LoG (Laplacian of Gaussian) filter on I_{eg} with $\sigma = \{\sigma_0, 1.5\sigma_0, 2.5\sigma_0\}$, where $\sigma_0 = \{\sqrt{2}, 2, 2\sqrt{2}, 4\}$. The 2-D LoG filter (see Fig. 9) has the form as follows:

$$LoG(x,y) = -\frac{1}{\pi\sigma^4} \left[1 - \frac{x^2 + y^2}{2\sigma^2} \right] e^{-\frac{x^2 + y^2}{2\sigma^2}}$$
(17)

Principle component analysis (PCA) method is then used to reduce the dimension of these features from 44-D to 10-D with a confidence degree of 95%.

B. HEs Classification

We introduce the widely used statistical learning method SVM in the classification stage, which maps the input vector x into a high dimensional feature space by choosing a nonlinear mapping kernel [21].

Take two-class problem for example, let a training set $S = (x_i, y_i, 1 \le i \le n)$ composed of the examples $x_i \in R^n$, each belonging to a class labeled by $y_i \in \{-1, 1\}$. The goal of the SVM is to find the optimal separating hyperplane, i.e., to minimize the following cost function:

$$\min \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n \xi_i \tag{18}$$

s.t.
$$y_i(w^{\mathrm{T}}x_i + b) \ge 1 - \xi_i, \xi_i \ge 0, i = 1, 2, \dots, n$$
 (19)

where ξ_i is slack variable which measures the degree of misclassification of the data, C is penalty coefficient which controls the cost of misclassification, the pair (w, b)defines the hyperplane of equation $w^T x_i + b = 0$. The Lagrangian function associated to the form is defined as

$$L(w, b, \alpha) = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n \xi_i - \sum_{i=1}^n \beta_i \xi_i - \sum_{i=1}^n \alpha_i [y_i(w^{\mathrm{T}} x_i + b) - 1 + \xi_i]$$
(20)

where α_i and β_i is Lagrangian multipliers and according to KKT condition,

$$0 \le \alpha_i \le C, i = 1, 2, \dots, n;$$

$$\sum_{i=1}^{n} \alpha_i y_i = 0$$
(21)

and the optimal separating hyperplane in the feature space is given by [22], [23]:

$$f(x) = \operatorname{sgn}\left(\sum_{i=1}^{l} y_i \alpha_i K(x_i, x) + b\right)$$
(22)

where K is the kernel function. Herein we use a two-class SVM model with a RBF (Radial basis function) kernel to separate those candidate regions into HEs or non-HEs.

V. EXPERIMENTAL RESULTS AND DISCUSSION

A. Materials

The proposed HEs detection method is evaluated with the publicly available DIARETDB1 database [24], which consists of 89 eye fundus images stored in a PNG image format with a 1500×1200 resolution at 24 bit and 50° field of view. Among all the 89 images, 83 images are abnormal: 47 images contain HEs, 33 images contain CWS and some images do not contain any DR-indicative lesions but show signs of other pathological changes such as microaneurysms and hemorrhages. Referring to the rough ground truth provided by the database, all of these pathological lesions on the images are labeled precisely by our ophthalmologists in the region level. Artifacts interfered regions are also labeled manually for training a accurate classifier.

TABLE I. TRAINING SETS DETAIL IN REGION LEVEL

Region category	Image numbers	Region numbers
Hard exudates(+1) ^{<i>a</i>}	22	941
Cotton wool spots(-1)	17	60
Artifacts interfered(-1) ^{<i>b</i>}	22	649

^a +1, -1 are the labels assigned to train the two-class SVM model.
 ^b Typical artifacts along main blood vessels due to light reflection, noise caused by normal macular reflection, and prominent circular scars left after PRP.

B. Results and Discussion

In our experiments, we use 45 images chose from the database for training and the rest 44 images for testing. There are 941 exudate regions and 709 nonexudate regions in the training set. Table I demonstrates the detail of training sets in region level.

The non-linear RBF kernel function K is chosen as the mapping kernel in SVM model, and the optimal relevant parameters are trained with a 5-fold cross validation [25], and a mean cross validation accuracy = 87.28% is achieved is this step.

Following, we test our proposed method with the left 44 retinal images, which contain 2200 regions in total. And similarly, these 2200 candidate regions also contain HEs, cotton wools spots, and other interfered artifacts. After inputing each region's feature vectors, we obtain a final decision label by using the trained SVM classifier.

Finally, we evaluate the performance of the automated HEs detection approach according to lesion-based criterion [13]. The lesion-based criterion aims at examining the number of exudate lesion detected in the image. Since the specificity criterion is mostly near 100% in many existing literatures which does not represent an informative measurement, we use the sensitivity (SE) and positive predictive value (PPV) instead.

In general, there are four predict outcome in test stage, such as true positive (TP), false positive (FP), true negative (TN) and false negative (FN). The sensitivity can be written as:

$$SE = \frac{\text{number of TP}}{\text{number of TP} + \text{number of FN}}$$
(23)

and PPV can be obtained from the following identity:

$$PPV = \frac{\text{number of TP}}{\text{number of TP} + \text{number of FP}}$$
(24)

where SE is the proportion of candidates that are known to be the HEs the model predicts positive for it, while PPV is the proportion of positive results that are true positives.

Table II shows the performance of our method compared with others methods listed in their papers. Our method achieve a superior performance with sensitivity of 94.7% and PPV of 90.0%. The PPV reported in [9] is higher than our results, but it is worth noting that their test retinal images do not contain CWS, moreover, the method proposed in [9] is typically morphological-based and is not suitable for detecting exudates in retinal images which contain normal macular reflection [10]. We take

COMPARISONS BETWEEN DIFFERENT METHODS AND OUR METHOD								
Detection methods	Database (number of test image)	SE(%)	PPV(%)					
Osareh [26]	67	90.0	89.3					
Zhang and Chutatape [14]	30	88.0	84.0					
Walter et al. [9]	15	92.8	92.4					
Sánchez et al. [27]	58	88.0	-					
García et al. [13]	67	87.61	83.51					
Jaafar et al. [28]	119	93.2	83.7					
Our method	44	94.7	90.0					

 TABLE II.

 Comparisons between different methods and our method

SE: mean lesion-based sensitivity, PPV: mean lesion-based positive predictive value.

advantage of HEs's multi-features and successfully use them to distinguish HEs from CWS, scars left by PRP treatment and noise caused by normal macular reflection. These interference objects usually act as FPs and thus degrade the HEs classification rate. We demonstrate three of our HEs detection results in Fig. 10, in which the optic disk region are firstly removed before the classification. The first row in Fig. 10 demonstrates that our method can distinguish HEs from CWS effectively. The scars left by PRP treatment and normal macular reflection can be excluded by our method which are illustrated in the second and third row in Fig. 10.

VI. CONCLUSION

This paper proposed an effective hierarchical framework to automatically segment hard exudates in color fundus images, which is significant for the early clinical diagnosis of DR. The undesirable affects produced in image capturing are removed by preprocessing strategy. The candidate region of HEs with accurate contour are extracted by combining the histogram segmentation and morphology reconstruction, and on which a set of distinctive features is defined on the basis of its shape, color, contrast and texture. After employing PCA to reduce the redundance dimension, the feature vector is used to train a SVM classifier to recognize the HEs and non HEs. The experimental results showed that our method can detect HEs effectively and distinguish HEs accurately from orther interferences. Further tests should be carried out on the proposed algorithms with different database have a variety of lesions. In future, we intend to extend the proposed method to segment CWS and build an integrated diagnosis system of DR which can detect dark lesion such as microaneurysm and hemorrhage.

REFERENCES

- J. Olson *et al.*, "A comparative evaluation of digital imaging, retinal photography and optometrist examination in screening for diabetic retinopathy," *Diabetic Med.*, vol. 20, no. 7, pp. 528–534, 2003.
- [2] S. Bjørvig, M. Johansen, and K. Fossen, "An economic analysis of screening for diabetic retinopathy," *J. Telemed. Telecare.*, vol. 8, no. 1, pp. 32–35, 2002.
- [3] D. Kavitha and S. Shenbaga Devi, "Automatic detection of optic disc and exudates in retinal images," in *Intelligent Sensing and Information Processing*, 2005. Proceedings of 2005 International Conference on. IEEE, 2005, pp. 501– 506.

- [4] C. Sánchez et al., "Retinal image analysis based on mixture models to detect hard exudates," *Med. Imag Anal.*, vol. 13, no. 4, pp. 650–658, 2009.
- [5] Z. Liu, C. Opas, and S. Krishnan, "Automatic image analysis of fundus photograph," in *Engineering in Medicine* and Biology Society, 1997. Proceedings of the 19th Annual International Conference of the IEEE, vol. 2. IEEE, 1997, pp. 524–525.
- [6] I. Soares, M. Castelo-Branco, and A. Pinheiro, "Scalespace curvature detection of retinal exudates with a dynamic threshold," in *Image and Signal Processing and Analysis (ISPA), 2011 7th International Symposium on.* IEEE, 2011, pp. 523–528.
- [7] C. Sinthanayothin *et al.*, "Automated detection of diabetic retinopathy on digital fundus images," *Diabetic Med.*, vol. 19, no. 2, pp. 105–112, 2002.
- [8] W. Hsu *et al.*, "The role of domain knowledge in the detection of retinal hard exudates," in *CVPR*, vol. 2. IEEE, 2001, pp. II–246.
- [9] T. Walter *et al.*, "A contribution of image processing to the diagnosis of diabetic retinopathy-detection of exudates in color fundus images of the human retina," *IEEE Trans. Med. Imaging*, vol. 21, no. 10, pp. 1236–1243, 2002.
- [10] D. Welfer, J. Scharcanski, and D. Marinho, "A coarse-tofine strategy for automatically detecting exudates in color eye fundus images," *Comput. Med. Imag. Graph.*, vol. 34, no. 3, pp. 228–235, 2010.
- [11] M. Niemeijer *et al.*, "Automated detection and differentiation of drusen, exudates, and cotton-wool spots in digital color fundus photographs for diabetic retinopathy diagnosis," *Invest. Ophth. Vis. Sci.*, vol. 48, no. 5, pp. 2260–2267, 2007.
- [12] K. Goh et al., "Adris: an automatic diabetic retinal image screening system," *Studies in Fuzziness and Soft Computing*, vol. 60, pp. 181–210, 2001.
- [13] M. García *et al.*, "Neural network based detection of hard exudates in retinal images," *Comput. Meth. Prog. Bio.*, vol. 93, no. 1, pp. 9–19, 2009.
- [14] X. Zhang and O. Chutatape, "Top-down and bottomup strategies in lesion detection of background diabetic retinopathy," in *CVPR*, vol. 2. IEEE, 2005, pp. 422–428.
- [15] K. Narasimhan, V. Neha, and K. Vijayarekha, "An efficient automated system for detection of diabetic retinopathy from fundus images using support vector machine and bayesian classifiers," in *Computing, Electronics and Electrical Technologies (ICCEET), 2012 International Conference on.* IEEE, 2012, pp. 964–969.
- [16] A. Osareh, M. Mirmehdi, B. Thomas, and R. Markham, "Comparative exudate classification using support vector machines and neural networks," *Medical Image Computing and Computer-Assisted InterventionMICCAI 2002*, pp. 413–420, 2002.
- [17] Z. Farbman *et al.*, "Edge-preserving decompositions for multi-scale tone and detail manipulation," *ACM Transactions on Graphics*, vol. 27, no. 3, Aug. 2008.



Figure 10. Exudates detection results: left column: Original images; right column: Detection results superimposed on the original images.

- [18] P. Soille, *Morphological image analysis: principles and applications*. Springer-Verlag New York, Inc., 2003.
- [19] A.-H. Abdel-Razik Youssif, A. Ghalwash, and A. Abdel-Rahman Ghoneim, "Optic disc detection from normalized digital fundus images by means of a vessels' direction matched filter," *IEEE Trans. Med. Imaging*, vol. 27, no. 1, pp. 11–18, jan. 2008.
- [20] S. Chaudhuri *et al.*, "Detection of blood vessels in retinal images using two-dimensional matched filters," *IEEE transactions on medical imaging*, vol. 8, no. 3, pp. 263–269, 1989.
- [21] C. Jin, Y. Huang and L. Zhao, "A semi-supervised learning algorithm based on modified self-training svm," *Journal of Computers*, vol. 6, no. 7, pp. 1438–1443, 2011.

- [22] K. Muller *et al.*, "An introduction to kernel-based learning algorithms," *IEEE Trans. Neural NetWor.*, vol. 12, no. 2, pp. 181–201, 2001.
- [23] L. Yang, C. Ding and S. Liao, "Parameter tuning via kernel matrix approximation for support vector machine," *Journal* of Computers, vol. 7, no. 8, pp. 2047–2054, 2012.
- [24] T. Kauppi *et al.*, "Diaretdb1 diabetic retinopathy database and evaluation protocol," *MIUA*, pp. 61–65, 2007.
- [25] D. Li, X. Yang and J. Wu, "SVM optimization based on bfa and its application in ae rotor crack fault diagnosis," *Journal of Computers*, vol. 6, no. 10, pp. 2084–2091, 2011.
- [26] A. Osareh, "Automated identification of diabetic retinal exudates and the optic disc," Ph.D. dissertation, Department of Computer Sciene, University of Bristol, January 2004.

- [27] C. Sánchez *et al.*, "A novel automatic image processing algorithm for detection of hard exudates based on retinal image analysis." *Med. Eng. Phys.*, vol. 30, no. 3, p. 350, 2008.
- [28] H. F. Jaafar, A. K. Nandi, and W. Al-Nuaimy, "Decision support system for the detection and grading of hard exudates from color fundus photographs," *Journal* of Biomedical Optics, vol. 16, no. 11, pp. 116001–1– 116001–10, 2011.

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