AUTOMATED DETECTION OF HARD EXUDATES IN FUNDUS IMAGES USING IMPROVED OTSU THRESHOLDING AND SVM

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ABSTRACT

One common cause of visual impairment among people of working age in the industrialized countries is Diabetic Retinopathy (DR). Automatic recognition of hard exudates (EXs) which is one of DR lesions in fundus images can contribute to the diagnosis and screening of DR.The aim of this paper was to automatically detect those lesions from fundus images. At first,green channel of each original fundus image was segmented by improved Otsu thresholding based on minimum inner-cluster variance, and candidate regions of EXs were obtained. Then, we extracted features of candidate regions and selected a subset which best discriminates EXs from the retinal background by means of logistic regression (LR). The selected features were subsequently used as inputs to a SVM to get a final segmentation result of EXs in the image. Our database was composed of 120 images with variable color, brightness, and quality. 70 of them were used to train the SVM and the remaining 50 to assess the performance of the method. Using a lesion based criterion, we achieved a mean sensitivity of 95.05% and a mean positive predictive value of 95.37%. With an image-based criterion, our approach reached a 100% mean sensitivity, 90.9% mean specificity and 96.0% mean accuracy. Furthermore, the average time cost in processing an image is 8.31 seconds. These results suggest that the proposed method could be a diagnostic aid for ophthalmologists in the screening for DR.

KEYWORDS
Diabetic retinopathy, Fundus images, Hard exudates, Improved Otsu thresholding, SVM, Automated detection.

1. INTRODUCTION

At present, a main challenge of current health care in the world is fast progression of diabetes. The number of people with diabetics would increase to 4.4% of the global population by 2030 expected by the world health organization [1]. However, the fact is that only one half of the patients are aware of the disease. And in the medical perspective, diabetes will lead to severe late complications. These complications are macro and micro vascular changes which would result in heart disease, renal problems and retinopathy. Diabetic retinopathy (DR) which is one of the common complications and it remains the most common cause of blindness among adults greater than 65 years in the developed countries [2]. Although early detection and laser treatment of DR have proved effective in preventing visual loss [3], too many diabetic patients are not treated in time because of inadequacies of the currently available screening programmes [4]. It is now a recognised urgent worldwide priority that institutes an efficient screening programme for the detection of at-risk patients at a stage when they can still be effectively treated because 75% of the blindness due to diabetes can be preventable. International guidelines recommend annual

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fundus examination for all diabetic patients to detect the early stage of DR [5]. Now, it is certain that the most effective treatment for DR is only in the first stages of the disease. So, early detection by regular screening is of paramount importance. Digital image capturing technology must be used because it can lower the cost of such screenings, and this technology enables us to employ state-of-the-art image processing techniques which automate the detection of abnormalities in fundus. DR clinical signs include red lesions and bright lesions. The former include intraretinal microvascular abnormalities (IRMAs) and hemorrhages (HEs), the latter include hard exudates (EXs) and soft exudates or cotton-wool spots (CWs) [6]. EXs are yellowish intraretinal deposits and usually located in the posterior pole of the human fundus which is shown in figure 1. Hard exudates are made up of serum lipoproteins which leak from the abnormally permeable blood vessels, especially across the walls of leaking MAs. It can represent the only visible sign of DR for some patients [6]. Because different lesions have different diagnostic importance and management implications, it is very important to distinguish among lesion types. We did research on EXs detection and their differentiation from other bright areas in fundus images in this paper. EXs detection plays a very important role on DR screening tasks, as EXs are among the common early clinical signs of DR [7]. Additionally, EXs detection could act as the first step for a complete monitoring and grading of DR.

Many attempts to detect EXs from fundus images can be found in the literature. Some of them use the high luminosity of EXs to distinguish the lesions from background by the method of thresholding.Ward [8] used shade correcting to reduce the shade variation in the color fundus image. EXs were detected by thresholding. It required the user to select the threshold manually according to the histogram. Phillips [9] detected the large EXs by a global threshold and segmented the smaller, lower intensity ones by local threshold. The thresholds were selected automatically, but the region of interest must be chosen manually. Sinthanayothin[10] applied a recursive region growing segmentation to detect EXs after the color image standardization. Li[11] modified the region growing method by introducing the Luv color space. Walter[12] proposed the approach on EXs detection by their high grey level variation and their contours determined by morphological reconstruction. S´anchez[13] raised the algorithm employing statistical recognition, Fisher's linear discriminant analysis, colour information and the edge sharpness by applying a Kirsch operator to detect hard exudates and based on the detection to perform the classification. Jaafar[14] proposed the algorithm that included a coarse segmentation which is based on a local variation operation to outline the boundaries of all candidates with clear borders and a following fine segmentation which is based on an adaptive thresholding as well as a new split-and-merge technique to segment all bright candidates locally. Other approaches were based on neural network classifiers, such as multilayer perceptrons as well as support vector machines (SVM) [15-18].

In the following section 2, the characteristics of the image database under study is presented. Section 3 describes the detection method. We test the performance of the proposed method and compare our method with other methods in section 4. In section 5, discussion and conclusion of this paper is made.

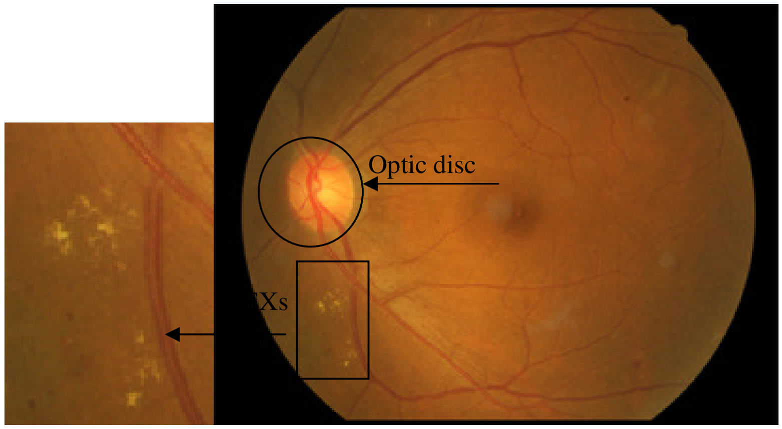

Figure 1. Color fundus image and close-up of EXs

2. MATERIALS

In this work, a total of 120 fundus images which came from department of Ophthalmology, Jiangsu province hospital of TCM were obtained from a non-mydriatic retinal camera with a 45° field of view. The image resolution was 800*600 at 24 bit RGB. An ophthalmologist manually marked all EXs in these images. The results obtained by our automatic method were compared with these hand-labeled ones. According to the ophthalmologist, these images in the database were divided as follows:

(1) 68 of these images belong to patients who suffered from mild to moderate nonproliferative DR. The images from DR patients all contained EXs.
(2) The remaining 52 images belonged to healthy patients.

Drusens were not present in any of these images. The total 120 fundus images were divided at random into two subsets, one is a training set the other is a test set:

(1) The training set contained 70 images of which 40 images were from DR patients. 2560 segmented regions were extracted from these images after the segmentation step of the method named improved Otsu threshold segmentation. They were labeled as EXs, or non-EXs according to the annotation of the ophthalmologist. Consequently, a fully labeled ground truth database was created which would be used to determine the parameters of SVM. The test set contained the remaining 50 images (22 from healthy retinas and 28 from DR patients). It was used to validate the effectiveness of the complete algorithm by comparing our result with the expert annotation.

For this study we have used a Intel(R) Core(TM) Duo E7500 CPU PC with 6.0 GB RAM and the platform of MATLAB R2009a.

3. METHODS

3.1. Improved Otsu thresholding segmentation stage

Pigments contained in the fundus structures have different absorption characteristics, and different wavelength monochromatic lights also have different penetration performance through fundus, so spectral signatures of different layer of fundus structure are different. We found that EXs appear most contrasted in the green channel, and optic disc appears most continuous and most contrasted against the background in the red channel [19]. So we coarsely segmented EXs in the green channel as shown in Figure 2(a), and segmented optic disc in the red channel which was shown in Figure 2(b). In color fundus images, EXs are yellow white lesions with relatively distinct margins, and in the green channel, they are of high luminosity. Consequently, the most direct and simple approach to identify candidate regions of EXs might be to extract the bright pixels from green channel using a threshold. But residual variability in the luminosity or in the pigmentation of the retinal background made the utilization of an approach based on a threshold impractical.So we opted for an improved approach which is called improved Otsu thresholding based on minimum inner-cluster variance [20]. This method combines inner-cluster variance and between-cluster variance of adaptive threshold segmentation, and when the threshold makes the inner-cluster variance minimum and between-cluster variance maximum, it is considered to be the optimal threshold. Optic disc is also masked out as shown in Figure 2(b) using the method developed by Walter T [12] to reduce the computational cost of the classifier because optic disc has similar attributes in terms of brightness, color and contrast. Figure 2(c) is the result after segmentation of the image in Figure 1.

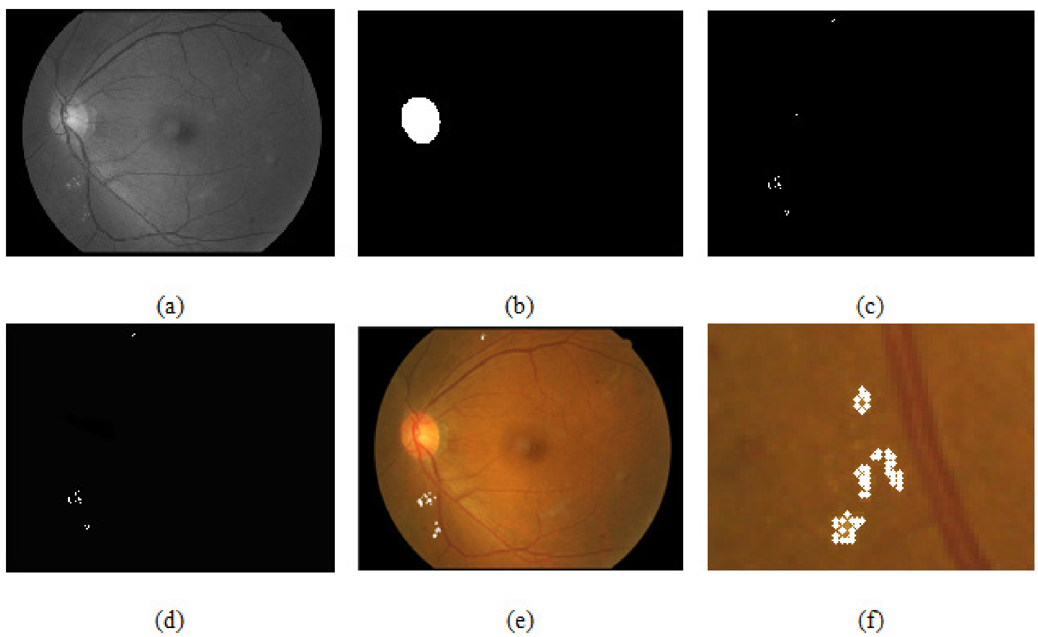

Figure 2. The detection of EX. (a) green channel of original fundus image. (b) segmentation result of optic disc. (c) candidate regions of EXs. (d) classification result of SVM. (e) detection result superimposed over the original image. (f) close-up of detection result

3.2. Feature extraction stage

In order to classify the candidate regions identified in the previous stage as EXs or non-EXs, some significant features which help ophthalmologists to visually distinguish EXs from other types of lesions as well as the background needed to be extracted from each region and to be used as inputs of SVM. In this way, prior knowledge was used to the classification task. We extracted the following 24 features[16]:

(1) Region size A
(2-4) Mean RGB values inside the region μ_R, μ_G, μ_B
(5-7) Standard deviation of the RGB values inside the region σ_R, σ_G, σ_B
(8-10) Mean RGB values around the region μ_R^N, μ_G^N, μ_B^N

(11-13) Standard deviation of the RGB values around the region σ_R^N, σ_G^N, σ_B^N
(14-16) Ratio of the mean RGB values between inside region area and surrounding area P_R, P_G, P_B
(17-19) Homogeneity of the region H_R, H_G, H_B
(20-22) RGB values of the region center C_R, C_G, C_B
(23) Region compactness CP
(24) Region edge strength ES

3.3. Feature selection stage

Many features could be used to design and train the given classifier. However, misclassification probability might be to increase with the number of features and the structure of classifier would much more difficult to interpret [21]. Feature selection tries to avoid these problems by picking out the subset of the extracted features which is most useful for a specific problem.

Feature analysis for a specific classification task is based on the discriminatory power of the features. This is a measure of the usefulness of each feature in predicting the class of an object. Traditional feature selection methods are classifier-driven, i.e., which rely on the results obtained by a particular classifier for different subsets of features. In addition, it is more appropriate for medical image analysis is that classifier independent feature analysis which collects information concerning the structure of the data rather than the requirements for a particular classifier [21].

Logistic Regression (LR) is a classifier-independent method usually used for feature selection. LR can be used to describe the relationship between a response or dependent variable and one or more explanatory or independent variables [22]. In our study, there were 24 independent variables and the dependent variable was dichotomous. LR could be modelled by function (1) if he possible values of the dependent variable are 0 and 1 [23].

$$Prob(Y=1)=\frac{\mathrm{e}^z}{1+\mathrm{e}^z} \tag{1}$$

where Y is the dependent variable, 1 is the desired outcome, $z=b_0+b_1x_1+b_2x_2+\cdots b_px_p$, p is the number of x_i, $B=[b_0,b_0,\cdots b_p]^{\mathrm{T}}$ is regression coefficient which can be identified by the maximum likelihood method.

Model selection of LR can be carried out by several strategies. A stepwise selection method was adopted because it can provide a fast and effective means to screen a large number of variables, and to simultaneously fit a number of LR equations. Certain criteria are needed to be decided whether an independent variable provides enough valuable information to enter the model or whether, on the other hand, it can be considered redundant. In our study, an independent variable would enter the model if the p-value associated with the result of the score test was lower than 0.05 which was a standard significance level. Accordingly, a variable would remove from the model if the p-value associated with the result of the likelihood ratio test was higher than 0.10.

3.4. SVM classification stage

SVM is a typically statistical learning method based on structural risk minimization [24], and it has been successfully applied to many pattern recognition problems and the reader is referred to for details [25].

Consider a labelled two-class training set $\{x_i, y_i\}$, $i = 1, \cdots, n$, $x_i \in R^d$, $y_i \in \{+1, -1\}$ is the associated "truth". The separating hyperplane must satisfy the following constraint:

$$y_i[(\omega \bullet x_i) + b] - 1 + \delta_i \geq 0 \qquad i = 1, 2 \cdots n \,,\, \delta_i \geq 0 \tag{2}$$

Where ω is the weight vector, b is the bias, δ_i is the slack variable. In order to find the optimal separating hyperplane, function (3) should be minimized subjected to function (2):

$$\phi(\omega, \delta) = \frac{1}{2}(\omega \bullet \omega) + C\left(\sum_{i=1}^{n} \delta_i\right) \tag{3}$$

Where C is a parameter chosen by the user and controls the trade-off between maximizing the margin and minimizing the training error. The classifier can be constructed as:

$$f(x) = \mathrm{sgn}\{\omega^* \bullet x + b^*\} = \mathrm{sgn}\left\{\sum_{i=1}^{n} \partial_i^* y_i (x_i \bullet x) + b^*\right\} \tag{4}$$

Where ω^* and b^* denote the optimum values of the weight vector and bias respectively, and ∂_i^* is the Lagrange multiplier.

SVM will map the input vector x into a high dimensional feature space by means of choosing a nonlinear mapping kernel if a linear boundary being inappropriate. The optimal separating hyperplane in the feature space can be given by function (5):

$$f(x) = \mathrm{sgn}\left\{\sum_{i=1}^{n} \partial_i^* y_i K(x_i \bullet x) + b^*\right\} \tag{5}$$

Where $K(x, y)$ is the kernel function. Gaussian radial basis function is commonly used.

3.5. Postprocessing stage

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In fundus images, there may be bright spots or bright points of physiological structures due to reflection in the human fundus. The biggest difference between such false positive regions as shown in figure 3 and EXs is that it usually exists in isolation, whereas EXs appear in clumps. In order to improve the performance of this system, we regarded those images in which less than 0.01% of the total number of pixels had been detected as EXs as normal fundus. An example of the false positive regions is shown in Fig. 3.

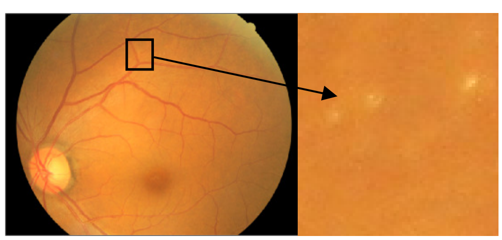

Figure 3. False positive regions

4. Results

4.1. System performance evaluation

Now, there are no publicly available databases which can be used to test the performance of automatic DR detection algorithm on fundus images [26]. The performance of the proposed method was tested using our test set of 50 fundus images. This evaluation requires the parameter of the algorithm to be previously settled using the training set. We varied the parameters and used 10-fold cross validation to assess the generalization ability of SVM. For each combination of the parameters, we measured the mean sensitivity (SE_{val}), specificity (SP_{val}) and accuracy (AC_{val}) obtained for the validation set, defined as follows:

$$SE_{val} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \tag{6}$$

$$SP_{val} = \frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FP}} \tag{7}$$

$$AC_{val} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}} \tag{8}$$

Where TP is the number of classified EXs correctly, TN represents the number of exactly classified non-EXs, FP is the number of non-EXs mistakenly classified as EXs and FN is the number of EXs classified as non-EXs incorrectly.

Once all the parameters of the algorithm were fixed, we assessed the diagnostic accuracy of it on the test set in terms of a lesion-based criterion and an image-based criterion which are defined as follows :

(1) Using a lesion-based criterion, we measured the mean SE_{les} and positive predict value (PPV_{les}) which is given by (9) obtained for the test set. Specificity is not an informative measure for the lesion-based criterion. PPV accounts for the probability that a detected region is really an EX, and it was regarded as a more significant criterion to evaluate the system.

$$PPV_{les} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \tag{9}$$

(2) The image-based criterion accounted for the ability of the algorithm to detect pathological images and separate them from normal ones in the test set due to the presence of EXs. Using the image-based criterion, each images in the test set is classified as belong to a patient with DR or to healthy subject. We used the image-based statistics mean sensitivity (SE_{im}), mean specificity (SP_{im}) and mean accuracy (AC_{im}) to present the final results. The statistics are measured as described in Eqs. (6)-(8).

4.2. Experimental results

We coarsely segmented the training set of 70 fundus images with variable color, brightness and quality using Otsu thresholding based on minimum inner-cluster variance. The segmentation resulted in 2560 candidate regions consisting of 1150 EXs and 1410 non-EXs.

We computed the 24 features for 2560 candidate regions and used SPSS 18.0 to perform LR on these data. The inputs were normalized (mean = 0, standard deviation = 1) to insure that LR was not influenced by the numerical strength of a feature rather than by its discriminatory power. The following 10 features shown in Table 1 were selected and them were with the highest discriminatory power for separating EXs from other non-EX yellowish objects.

Table 1. Result of feature selection

Step	Parameters	Significance	Parameters	Significance
16	A	0.002	CP	0.000
	μ_R	0.000	ES	0.000
	μ_R^N	0.000	H_R	0.000
	C_G	0.001	P_R	0.000
	C_B	0.000	P_G	0.000

SVM was used to classify candidate regions of EXs. At first, it must be specified by the obtained candidate regions with 10 features. It is that specifying a SVM requires two parameters: the kernel function and the regularisation parameter C. For training the SVM classifier, the Kernel-Adatron technique using a Gaussian Radial Basis kernel was used. To obtain the optimal values for the RBF kernel (g) and C, we experimented with different SVM classifiers with a range of values. We apply genetic algorithm combined with 10-fold cross-validation to find the best classifier on the base of validation error. Table 2 shows the optimal parameters of (g) and C with the SVM classification structures. The specified SVM classification result of Fig. 2(c) is shown in Fig. 2(d) which superimposed over the original image is shown in Fig. 2(e), and the close-up of the detection result is shown in Fig. 2(f).

Table 2. Validated parameters

Parameters		Result		
C	g	SE_{val} /%	SP_{val} /%	AC_{val} /%
2.39	1.25	95.13	98.01	96.72

The proposed method was tested using a new set of 50 unseen fundus images: 28 belonged to patients in early stages of DR and 22 corresponded to healthy retinas. The test set contained 50 images which were with variable color, brightness and quality. Using the specified SVM to classify the candidate regions segmented by improved Otsu thresholding based on minimum inner-cluster variance from 50 fundus images, the performance is shown in Table 3. And it is stated that post processing excluded 2 images of false positive. In addition, the detection results of these fundus images processed by the method proposed by Jaafar [14] are also shown in Table 3. It is found that the automated detection performance including accuracy and efficiency of the method proposed in this paper is obviously superior to the one proposed by Jaafar.

To assess the performance of the SVM we also classified our segmented candidate regions using other classifiers including RBF classifier and Bayes classifier. In order to estimate the generalisation error of all classifiers, a 10-fold cross-validation technique was used again. The results were summarised in Table 4 which are the best results from a selection of configurations used for training the classifiers. These results indicate that the diagnostic accuracy of SVM is the best in RBF classifier and Bayes classifier.

Table 3. Detection result

Method	Image-based criterion			Lesion-based criterion		Efficiency /s
	SE_{im} (%)	SP_{im} (%)	AC_{im} (%)	SE_{les} (%)	PPV_{les} (%)	
Proposed method	100	90.9	96.0	95.05	95.37	8.31
Jaafar [14]	96.43	90.9	94.0	89.7	90.12	13.58

Table 4. Performances of different classifiers

Classifier	Image-based criterion			Lesion-based criterion	
	SE_{im} (%)	SP_{im} (%)	AC_{im} (%)	SE_{les} (%)	PPV_{les} (%)
SVM	100	90.9	96.0	95.05	95.37
RBF	100	90.9	96.0	93.9	95.5
Bayes	96.43	90.9	94.0	90.15	92.06

5. CONCLUSIONS AND DISCUSSION

Digital imaging is becoming available as means of screening for diabetic retinopathy because it can provide a high quality permanent record of the retinal appearance which can be used for monitoring of progression or response to treatment, and can be reviewed by an ophthalmologist. In other words, digital images have the potential to be processed by automatic analysis system.

In this study, we developed a totally automatic method to detect EXs in fundus images taken from diabetic patients or healthy people with non-dilated pupils. The fundus images were segmented by improved Otsu thresholding based on minimum inner-cluster variance to obtain candidate regions of EXs. In order to distinguish EXs from retinal background, the effectiveness of a set of 24 features of the candidate regions were examined and the subset with maximum discriminatory power were selected , according to a LR analysis of our data.The optimum subset was used to train a SVM classifier. The algorithm was tested on 22 images from healthy retinas and 28 images of retinas with DR, with variable colour, brightness and quality. Furthermore, the result was compared with the method proposed by Jaafar [14].

The SE_{im} in Table 3 shows that we detected all images with signs of DR. We also detected some false positives in the images of healthy subjects, as the image-based SP_{im} demonstrates. However, the impact of wrongly classifying a person suffering from DR as a healthy subject is more important than the converse. Javitt et al. suggested that a sensitivity of 60% or greater maximized cost-effectiveness in screening for diabetic retinopathy in their health policy model [27]. It means that increasing sensitivity of screening from 60% to 100% can not provided additional benefit because of the frequency of screening as well as the likelihood that retinopathy cases missed at one visit will be detected at the next.

That means efficiency of automated detection is more important when detection accuracy is adequate. For DR patients, the retinal lesions will be influenced by treatment, control and progression of diabetes, i.e.. Therefore, only higher detection frequency is guaranteed, related lesions of fundus can be founded in time. Higher detection frequency is guaranteed by efficient automatic detection algorithm. The Efficiency in Table 3 of the proposed method is obviously superior to the one proposed by Jaafar [14]. However, it may not yet be appropriate for clinic. So it is significant that develop more efficient EXs automatic detection algorithm in the future.

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