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Comparative Analysis of Automatic Exudate Detection Algorithms

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Abstract— Exudate detection is important for diabetic retinopathy screening systems. Early detection can help to reduce the incidence of blindness in diabetic patients. In this work we implement and evaluate the performance of different algorithms for automatic exudate detection. These consist of a mathematical morphological technique, a fuzzy c-means clustering technique, a naive Bayesian classifier, a support vector machine and a nearest neighbor classifier. The detection accuracy is defined with respect to expert ophthalmologists' hand-drawn ground-truths and the results are presented and comparatively analyzed.

Index Terms— comparative analysis, diabetic retinopathy, exudate detection.

I. Introduction

Exudates are a visible sign of diabetic retinopathy which is the major cause of blindness in patients with diabetes. If the exudates extend into the macular area, vision loss can occur. Automated early exudate detection could limit the severity of the disease and assist ophthalmologists in investigating and treating the disease more efficiently.

A large number of methods for automatic exudate detection have been published. C. Sinthanayothin et al. [1] propose an automated system of detection of diabetic retinopathy using recursive region growing segmentation (RRGS). A. Osarah et al. [2, 3] use fuzzy c-means (FCM) clustering to segment color retinal images, then a neural network and support vector machines (SVMs) are used to separate exudate and non-exudate areas. Morphological reconstruction techniques to detect the contours of exudates are proposed by T. Walter et al. [4]. D. Usher et al. [5] use a combination of RRGS and adaptive intensity thresholding to detect candidate exudate regions and a neural network is used to classify exudates and non-exudates. X. Zhang and O. Chutatape [6] use local contrast enhancement and FCM to segment candidate bright lesion areas. SVMs are also used to classify exudates and cotton wool spots.

Most techniques mentioned earlier work on images taken on patients with dilated pupils in which the exudates and other retinal features are clearly visible. Good quality images are required to achieve optimal results from the application of the detection algorithms. The examination time and effect on the patient could be reduced if the detection system could succeed on images taken from patients with non-dilated pupils. Automatic exudate detection on images acquired without pupil dilation is investigated in this work with the aim of providing decision support in addition to reducing the workload of ophthalmologists.

In our previous work, we have proposed and separately evaluated methods for automatic exudate detection using a mathematical morphological technique [7, 8], a FCM clustering technique [9], a combination of FCM and mathematical morphology [10], a naive Bayesian classifier [11], a SVMs classifier [12] and a nearest neighbor classifier, yet a descriptive comparative analysis has not been performed. In this paper, a descriptive comparative analysis of these automatic exudate detection methods is presented.

II. Method

All digital retinal images taken of patients with non-dilated pupils were obtained from a KOWA-7 non-mydriatic retinal camera with a 45° field of view. The image size is 752 x 500 pixels with 24 bits per pixel. Pre-processing includes the removal of the optic disc from the images because it has some characteristics similar to exudates [13].

A. *Exudate Detection*

Exudate detection was performed using the traditional methods of mathematical morphology, FCM, a combination of FCM and mathematical morphology. Exudate detection was also performed using the machine learning approaches of naive Bayesian classifiers, SVMs, and nearest neighbor classifiers. These approaches are briefly presented in this section. Further discussion about the topics can be found in our previous publications.

1) *Traditional Methods*

With respect to the mathematical morphological method, the exudates are obtained by thresholding the difference between the original image and the reconstructed image [7]. While the four features of intensity value after pre-processing, standard deviation of intensity, hue and number of edge pixels from an edge image are the result of a numerical experiment. These features are selected as input for FCM clustering [9]. The result from the FCM clustering is then used as a rough

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estimation of the exudates before segmentation using morphological reconstruction is applied for a finer result [10].

2) Machine Learning Approaches

Fifteen features are proposed to distinguish exudate pixels from non-exudate pixels by using a Naive Bayesian classifier. They are 1) the pixel's intensity value after preprocessing, 2) the standard deviation of the preprocessed intensity value, 3) the pixel's hue, 4) the number of edge pixel in a region around the pixel, 5) the average intensity of the pixel's cluster, 6) size (measured in pixels) of the pixel's cluster, 7) the average intensity of the pixels in the neighborhood of the pixel's cluster, 8) the ratio between the size of the pixel's cluster and the size of the optic disc, 9) the distance between the pixel's cluster and the optic disc 10) another six Difference of Gaussian (DoG) filter responses with six different standard deviation values. The best feature set obtained from the Naive Bayesian is optimized by the greedy backward elimination method. The first model is estimated from a training set using all features. Features are iteratively deleted until the average of the precision and recall ("PR," see section III.) stops improving [11].

We use the best feature set as an initial set for SVMs. We then add features back to the SVMs classifier one at a time and compare the PR of each classifier to that of the previous classifier. The sequence of the feature addition is the same with the Naive Bayesian classifier's feature selection process. The feature-adding process is repeated until all features are added back. The best feature set is the set which provides the highest PR [12]. The nearest neighbor classifier with Euclidean and Mahalanobis distance metrics is used as baseline.

III. Results

A data set of 60 retinal images including 40 images with exudates and 20 images without exudates are tested on an AMD Athlon, 1.25 GHz PC using MATLAB for the mathematical morphology, FCM and FCM with morphology techniques. For the naive Bayesian and SVM classifiers, we use 29 images for training and 30 images including 10 images with exudates and 20 images without exudates for testing. All exudate pixels and equal numbers of non-exudate pixels (randomly selected) are included in the training set. Over all 29 training images, we obtained 115,867 examples of positive (exudate) pixels and an equal number of negative (non-exudate) pixels. Our 10 test images together contain 42,909 exudate pixels. The Naive Bayesian classifier is tested on Weka data mining software running on standard PC while the SVMs and nearest neighbor techniques are tested on a 20-node Gnu/Linux Xeon cluster.

Detected exudates are compared with the ophthalmologists' hand-drawn ground-truth images for verification. Example resulting images of exudate detection from all classification methods are shown in Figure 1 and testing and training performances are shown in Table 1 and Table 2 respectively. Sensitivity (Recall) is the percentage of the actual exudate pixels that are detected, and specificity is the percentage of non-exudate pixels that are correctly classified as non-exudate pixels. Precision is the percentage of detected pixels that are actually exudates, and PR is the average of the precision and sensitivity. Accuracy is the overall per-pixel success rate of the classifier.

For the naive Bayesian classifier, the best classifier contained six features: 1. the pixel's intensity after preprocessing, 2. the standard deviation of the preprocessed intensities in a window around the pixel, 3. the pixel hue, 4. the number of edge pixels in a window around the pixel, 5. the ratio between the size of the pixel's intensity cluster and the optic disc, and 6. DoG4.

For the SVMs, the best performance is obtained using 10 features: 1. pixel's intensity after preprocessing, 2. standard deviation of the preprocessed intensities in a window around the pixel, 3. pixel hue, 4. number of edge pixels in a window around the pixel, 5. ratio between the size of the pixel's intensity cluster and the optic disc, 6. distance between the pixel's cluster and the optic disc, 7. DoG1, 8. DoG2, 9. DoG4, and 10. DoG6, with $\nu = 0.002$ and $\gamma = 0.98$.

On the best feature set obtained from the naive Bayesian classifier, the nearest neighbor classifiers have a PR of 61.54% and 61.81%, respectively. On the best feature set obtained from the SVM classifier, the nearest neighbor classifier achieved a PR of 65.15% and 64.99%, respectively. The results indicate that the naive Bayesian and SVM classifiers perform substantially better in PR than the nearest neighbor classifier.

Table 1 Testing performance

Classifier	SE (%)	SP (%)	Precision (%)	PR (%)	Acc (%)
Mathematical morphology	80.00	99.46	51.78	65.89	99.29
Fuzzy c-means (8 clusters)	97.29	85.43	51.62	5.94	85.62
Fuzzy c-means (8 clusters) + Morphology	87.28	99.24	42.77	65.02	99.11
Naive Bayesian	93.38	98.14	47.51	70.45	98.05
Support vector machines	92.28	98.52	53.05	72.67	98.41
Nearest neighbor on best feature set for naive Bayesian (Euclidean)	90.48	96.62	32.60	61.54	96.51
Nearest neighbor on best feature set for naive Bayesian (Mahalanobis)	90.44	96.71	33.18	61.81	96.60
Nearest neighbor on best feature set for SVMs (Euclidean)	91.44	97.40	38.86	65.15	97.29
Nearest neighbor on best feature set for SVMs (Mahalanobis)	91.11	97.41	38.87	64.99	97.30

*SE = Sensitivity, SP = Specificity, Acc = Accuracy

TABLE 2 TRAINING PERFORMANCE

Classifier	SE (%)	SP (%)	Precision (%)	PR (%)	Acc (%)
Naive Bayesian	94.53	89.19	89.74	92.13	91.86
Support vector machines	92.06	94.92	94.77	93.41	93.49

*SE = Sensitivity, SP = Specificity, Acc = Accuracy

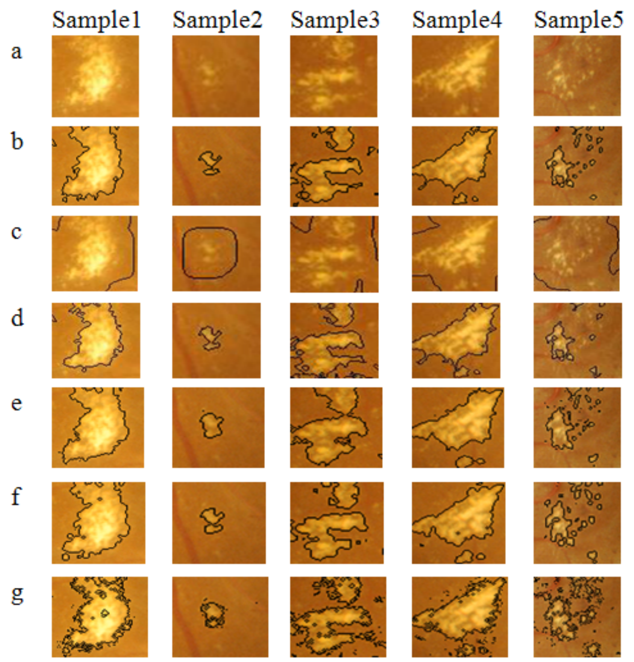

Figure 1 Example of exudate detection results. (a) Original images. (b) Morphological classification results. (c) FCM classification results. (d) FCM with Morphological classification results. (e) Naive Bayesian classification results. (f) SVMs classification results. (g) Nearest Neighbor (Euclidean distance) classification results on best feature set obtained from naive Bayesian.

IV. CONCLUSION AND DISCUSSION

We have implemented many automated exudate detection algorithms and we report the comparison results and the result analysis in this paper. Further result discussion and analysis can be found in this section.

A. *PR and Precision Values*

Among all the classifiers, our experimental results show that the mathematical morphology method achieves the highest specificity and accuracy with 99.46% and 99.29%, respectively. On the other hand, the mathematical morphology method achieves the lowest sensitivity with 80%.

As shown in the result images of exudate detection, Figure 1, using the FCM classifier, most of the exudates are detected. The FCM classifier achieves the highest sensitivity of 97.29 %, but the lowest specificity and accuracy of 85.43% and 85.62%. Rough exudate detection using only the FCM classifier achieves very low PR because of high false positive values. The PR value is improved when fine exudate detection using the mathematical morphology technique is combined with the FCM classifier. SVMs achieved the highest PR and precision values with 72.67% and 53.05% respectively, as shown in Figure 2.

Although the diagnostic PR of the FCM classifier with morphology, the naive Bayesian classifier and the SVMs classifier are close, the superiority of SVMs is very clear in the images. It can detect most of the exudates including their borders and fewer false positive pixels at the same time.

B. *Classifier Selection Factor*

The weakness of traditional exudate detection is that they require many predetermined parameters or features. Those features have to be optimized and may be suited to specific datasets. The performance of the algorithms may change significantly if the dataset is changed. The algorithms may also be camera dependent.

The machine learning approaches of the naive Bayesian and SVMs classifier may take a longer time to learn in the training process but they can automatically search for the best feature set. A summary of the classifier selection factor is shown in Table 3.

The pre-defined numbers of clusters are also the limitation of FCM clustering. The suitable number of clusters is dependent on the requirements of the ophthalmologist and the application. If the application requires a high PPV or PLR, such as an application where an automatic quantitative measurement of exudates is made, then a higher number of clusters is preferred. However, if the application does not require such a high accuracy, such as an application for a visual aid for ophthalmologists to assist exudate detection where the computer enhances the image quality and shows the approximate location of the exudates (the final decision is still made though by an expert ophthalmologist), then a smaller number of clusters is recommended. Also, with a smaller number of clusters, the system runs faster.

The naive Bayesian and SVMs classification require a learning phase which takes time. Many parameters are also used in the SVMs classification and they can affect the classification accuracy. Computational costs for the SVMs are very expensive.

C. *Time Complexity Analysis*

The time complexity for each algorithm is analyzed and summarized in Table 4. In the testing phase, the time complexity for the traditional algorithm approach is higher than that for the machine learning approach. However, for the machine learning approaches, a training phase is also required so extra computational costs must be included. In the case of SVMs, for example, the training time is related to the number of support vectors, which depend on the dataset and on the non-linear mapping from input space to the feature space. The time complexity of the SVMs classifier is equal to the time complexity of the nearest neighbor classifier if the numbers of support vectors are equal to number of training points.

D. *Overall Evaluation*

Mathematical morphology is a simple method and computationally low cost but it does not achieve good sensitivity. FCM clustering can detect most of the exudate regions; however, the false positive rate is high. Additionally, sensitivity and specificity are dependent on the number of clusters which has to be predefined. Using FCM clustering followed by mathematical morphology reconstruction, gives a higher accuracy with a lower false positive value. Even though, naive Bayesian and SVMs, which are supervised classifiers, do not require predefined features, they are

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computationally expensive during the training process. The SVMs classifier is also sensitive to parameter modification but it gains a higher precision value.

Many techniques implemented and evaluated in this paper have different characteristics and should be applied in different situations. In medical decision support applications, for example, the mathematical morphology method has an advantage over others as it can analyze the retinal image very quickly. It could be used for the implementation of real-time assistant application.

On the other hand, the SVMs classifier has an advantage over others as they achieve a high level of diagnostic accuracy in terms of PR. If the application needs precision for quantitative analysis of exudates, SVMs could be a better choice. Furthermore, SVMs allow further control on the generalization ability of the system in the case of unbalanced accuracy results that cannot be improved using traditional approaches. This means that the user has more control on the application implemented based on the SVMs algorithm. However, SVMs are very complex and require training. So, it depends on the purpose of application to be implemented.

TABLE 3 CLASSIFIER SELECTION FACTOR

Classifier	Parameters sensitive	Learning phase	High Computation Cost	High specification computer system
Mathematical morphology	Yes			
Fuzzy c-means	Yes			
Fuzzy c-means + Morphology	Yes			
Naive Bayesian		Yes		Yes
Support vector machines	Yes	Yes	Yes	Yes
Nearest neighbor				Yes

TABLE 4 TIME COMPLEXITY (FOR ONE IMAGE)

Classifier	Training Time complexity	Testing Time complexity
Mathematical morphology	-	$O(n^2 i)$
Fuzzy c-means	-	$O(nfc^2 i)$
Fuzzy c-means + morphology	-	$O(nfc^2 i) + O(n^2 i)$
Naive Bayesian	$O(mf)$	$O(nf)$
Support vector machines	$O(m^2 f^2)$	$O(nfs)$
Nearest neighbor	$O(mf)$	$O(nft)$

* m is number of training data (number of training pixels), n is number of testing data (number of testing pixels), i is number of iteration, c is number of cluster, f is number of features, s is number of support vectors and t is number of training points.

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