Classification of Retinal Images Based On Statistical Moments and Principal Component Analysis

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***Abstract*—early diagnosis of Diabetic Retinopathy (DR) has been suggested as a good measure of preventing blindness associated with Diabetes. Some of the reported methodologies of Retinal Images (RI) classification for early diagnosis of DR have been shown to involve several steps and approaches for effective and accurate diagnosis. Thus, this paper investigates the classification of RI using a two-stage procedure. The first stage includes the extraction of blood vessels from RI belonging to healthy and diabetes retinal images using a modified local entropy thresholding algorithm. In the second stage, different features are extracted including statistical moments and principal components. The set of extracted features is combined into one feature vector and fed into a Sequential Minimal Optimization (SMO) classifier. The obtained result is encouraging with an average accuracy of 68.33 %.**

Keywords-Classification; Order moments; Retinal images; Principal Component Analysis (PCA); Sequential Minimal Optimization (SMO)

I. INTRODUCTION

Diabetes is a disorder of metabolism whereby insufficient insulin is produced by pancreas for the body system [1-3]. The imbalance in insulin causes increase in body's blood sugar level as well as damage to various body organs. Early detection of this disorder is of key importance to reduce the risk of blindness [1-6]. Monitoring and detection of diabetes is still predominantly conducted manually by ophthalmologists via observation of the key features in Retina Image (RI). Some of the features usually observed include Retina Vasculature (RV), Optic disk, Macula thus making it difficult for self-monitoring by diabetic patients and the Ophthalmologists [1-6]. In addition, manually diagnosing DR has been shown to be time consuming, tedious, and rigorous [1-5]. However, application of Machine Learning (ML) for automatic diagnosis of DR, have been shown to provide an automatic and low cost analysis of the collected images [1-5]. Such analysis can reveal hidden information that is crucial for final decision such as cross over detection, Bifurcation detection, Fovea and other features. The relatively low performance of various automatic approaches reported in the literature give rooms to improve the current state-of-the-art and consequently to provide adequate treatment to these abnormalities and therefore to reduce the risk of blindness.

In [1], Vascular Intersection (VI) in RI using Combine Crosspoint Number was proposed. The method which was able to detect both vascular bifurcation and crossovers point using two public databases. Though the proposed method gives a very high precision and true positive rate the technique still give a very small false error rate. In addition, the work is a four-stage technique for VI detection.

The use of Artificial Neural Networks (ANN) and Fuzzy Logic system (FLS) for VI in RI was reported in [4]. Though success in detection of VI was reported however the use of ANN involves almost a three-stage approach with pre-training of the system. Application of Speed-Up Robust Features algorithm (SURF) for detecting points of interest in RI was reported in [6]. A visual dictionaries technique was then applied in deriving a vector of characteristics of the extracted points before the use of multiple classifiers for classification into normal and pathological images. Application of two features extraction methods for VI was reported in [10]. The work hypothesized that that different disease affects the blood vassal width, thus diagnoses can be detected based on that assumption. The dimension of the extracted feature vector was then reduced using Principal Component Analysis (PCA) and classified using two classification methods, Support Vector Machines (SVM) and ANN. Several other studies have attempted to develop Computer-Aided Medical Diagnosis systems (CAMDS) for DR. The use of Digital Signal Processing (DSP) was reported in [5]. The DSP approach also involves a three stage technique for total abnormality detection. Hence, the objective of this work is to develop a simple but accurate technique for VI detection.

The remaining part of this paper is organized as follows: Section II is a description of the proposed methodology while Vascular Tree extraction is presented in Section III. In Section IV, feature extraction methods including order moments and PCA are discussed. Results and discussion of the performances of the proposed algorithm are given in Section V and Section VI offers the conclusion.

II. DESCRIPTION OF THE PROPOSED METHODLOGY

In order to differentiate healthy RI from the affected RI, a two-stage approach has been proposed in this work. The first stage includes the extraction of blood vessels from RI. In this paper this first stage is accomplished using a modified local entropy thresholding algorithm. In the second stage, different features are extracted from the extracted blood vessels. Here these features are statistical moments and principal components. The set of extracted

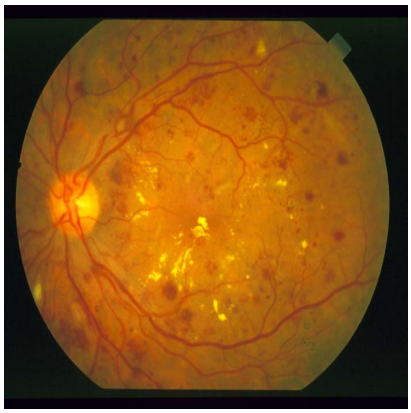
978-1-4799-7635-5/14 $31.00 © 2014 IEEE
DOI 10.1109/ICCCE.2014.37

features is combined into one feature vector and fed into a classifier. The Sequential Minimal Optimization (SMO) classifier has been chosen due to its good performance. Executing aforementioned stages is enough in order to separate healthy retinal images from diabetes ones. However as the applied classifier is sensitive to irrelevant attributes, proper feature selection can further increase the accuracy of the applied algorithm. Therefore, a feature selection algorithm was applied to the data too.

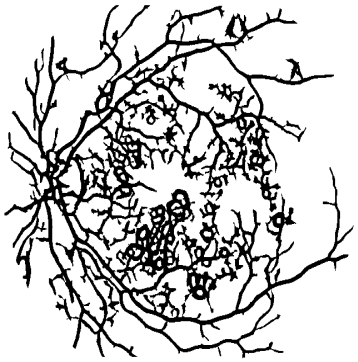
III. Vascular Tree Extraction

Vascular tree extraction is a very useful step for retinal images diagnosis and is considered as one of the most important anatomical structure in the RI [1-7] for DR diagnosis. The choice of VI hinges on its ability to map the whole the RI and it is translational and rotational invariant. In addition, it contains enough information for the localization of some anchor points and features.

In this work, we applied the algorithm presented in [10] for vascular tree extraction from RI. Fig. 1(a) and (b), show a retinal image and the segmented blood vessels from the background respectively.



(a)



(b)

Fig.1.Extraction of blood vessels, a) the actual retinal image b) the extracted blood vessels.

The applied algorithm involve three main steps, these are:

1) A match filter is applied to enhance the prominence of blood vessels.

2) A local entropy based thresholding scheme is used which takes into account the spatial distribution of gray levels and can well preserve the spatial structures in the binarized image.

3) A length filtering technique is used to remove misclassified pixels or insignificant small segments.

IV. Feature Extraction

The aim of feature extraction is to represent the properties of the RI in a compact way prior to classification stage. The set of features extracted play a vital role in achieving good classification results. In this work, two different types of features are extracted from each RI. These features are discussed herewith.

A. Statistical moments

In the context of image processing the central moments are defined in a similar way of the case one dimensional signals by replacing the probability density function with the intensity image *I(x,y)* such that [9]:

$$M_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}(x-\mu_x)^p(y-\mu_y)^q I(x,y)\,dx\,dy \quad (1)$$

where M_{pq} is the $(p-q)$ central moment of the 2-D image and μ is its mean value.

The normalized central moments are given by:

$$\eta_{pq} = \frac{M_{pq}}{M_{00}^{\beta}}$$

$$\beta = \frac{p+q}{2} + 1$$

and $p + q \geq 2$

Seven quantities which are invariant to translation, scale and rotation were derived from the central moments, these are:

$$\Lambda_1 = \eta_{20} + \eta_{02} \quad \text{.....(2)}$$

$$\Lambda_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \quad \text{.....(3)}$$

$$\Lambda_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \quad \text{.....(4)}$$

$$\Lambda_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \quad \text{.....(5)}$$

$$\Lambda_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{03} + \eta_{21}) \times [3(\eta_{30} + \eta_{12})^2 - (\eta_{03} + \eta_{21})^2] \quad \text{.....(6)}$$

$$\Lambda_6 = (\eta_{20} + \eta_{02})[(\eta_{12} + \eta_{30})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{21} + \eta_{03})(\eta_{12} + \eta_{30}) \quad \text{.....(7)}$$

$$\Lambda_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{03} + \eta_{21}) \times [3(\eta_{30} + \eta_{12})^2 - (\eta_{03} + \eta_{21})^2] \quad \text{.....(8)}$$

B. *Principal components*

The idea of PCA is to map the data into a new domain using the eigenvectors of the covariance matrix. PCA can be regarded as an optimal transform in the mean-squared-error (MSE) sense since it completely diagonalize the covariance matrix. The principal axes successively maximize the variance in the data with respect to themselves. The eigenvalues in the diagonal matrix directly specify the total amount of variance in the data associated with each principal component. These can be computed following a three step approach described herewith:

1) Form the data covariance matrix

$$C_X = E(X \otimes X) = \frac{1}{\sqrt{N-1}} X^T X \ldots\ldots \quad (9)$$

2) Perform an eigenvalue decomposition of C_X, which will return the eigenvectors and eigenvalues in the matrices V and Λ respectively.

$$C_X V = V\Lambda \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(10)$$

3) Project the data to the new space

$$Z = XV \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(11)$$

After which the projection of the data on the first two principal axes are taken as features

V. Retinal Images Classification

The applied classifier in this study is Sequential Minimal Optimization (SMO) algorithm, which is a SVM based algorithm. It normalizes all attributes. As SVM is sensitive to irrelevant attributes, proper feature selection can possibly further increase the accuracy of the applied algorithm. Therefore, a feature selection algorithm was applied to the data. The applied feature selection strategy is based on choosing subsets of features that are highly correlated with the desired class while having low inter-correlation with it. The method evaluates the worth of an attribute by measuring the gain ratio with respect to the desired class. All the classification evaluations in this work are based on 10-fold cross correlation.

The STARE (STructured Analysis of the Retina) database is used in this study. The database has been widely applied in the literature to test different vessel segmentation methodologies as well as classification algorithms. The advantage of this database is that it provides manual labelling and vessel segmentation for performance evaluation [9].

Aside the use of Accuracy for measuring the performance of the proposed methodology, a few other evaluation metrics is reported herewith in evaluating the system performance.

These metrics are Kappa Statistic, Precision and Recall. The kappa coefficient (*k*) is an evaluation criterion for classification problems [10]. In the *N* class problems the proper performance measure of the classifier is described by its confusion matrix [10]. If the *N* classes occur equally with probability of *1/N*, the relationship between kappa coefficient *k* and accuracy (*acc*) can be described as,

$$k = \frac{acc - 1/N}{1 - 1/N} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(12)$$

where *acc* is the classification accuracy. In our work, there exist an equal number of trials of each class. Therefore, we applied this simplified equation to evaluate the performance of classifiers.

Precision also known as Positive Predictive Value is defined as follow:

Precision= TP/(TP+FP)………………(13)

Recall also known as True Positive Rate is defined as follow:

Recall= TP/(TP+FN)………………...(14)

where TP means True Positive, FP stand for False Positive and FN is False Negative [1]. Both Precision and Recall are reported for each class separately. Class "a" belongs to healthy (RI) and class "b" belongs to non-healthy RI.

TABLE I: .Specification of classification results with SMO

Classification Accuracy		66.67%
Kappa statistic		0.3251
Precision	Class a	0.737
	Class b	0.634
Recall	Class a	0.483
	Class b	0.839

TABLE II: Specification of classification results with SMO After feature selection

Classification Accuracy		68.33 %
Kappa statistic		0.3567
Precision	Class a	0.813
	Class b	0.636
Recall	Class a	0.448
	Class b	0.903

V. Conclusion

This paper investigated the use of SMO classifier for RI diagnosis with different statistical features. Encouraging results have been achieved, however more investigation still need to be done on feature extraction. The challenge in this field is the difficulty of generalization of individual results due to the diversity of algorithms applied for image acquisition as well as the algorithms for compression and storage

Acknowledgment

This work was supported by the ministry of higher education (MOHE) of Malaysia under the Fundamental Research Grant Scheme FRGS (FRGS12-080-0229).

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