35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Adaptive Colour Transformation of Retinal Images for Stroke Prediction

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Abstract—**Identifying lesions in the retinal vasculature using Retinal imaging is most often done on the green channel. However, the effect of colour and single channel analysis on feature extraction has not yet been studied. In this paper an adaptive colour transformation has been investigated and validated on retinal images associated with 10-year stroke prediction, using principle component analysis (PCA). Histogram analysis indicated that while each colour channel image had a uni-modal distribution, the second component of the PCA had a bimodal distribution, and showed significantly improved separation between the retinal vasculature and the background. The experiments showed that using adaptive colour transformation, the sensitivity and specificity were both higher (AUC 0.73) compared with when single green channel was used (AUC 0.63) for the same database and image features.**

I. Introduction

Retinal vasculature, observed from non-invasive retinal imaging, has been shown to have a number of anatomic, physiological and embryological similarities in common with cerebral vasculature [1, 2]. The observable changes to retinal vasculature have been associated with various cardiovascular and metabolic diseases including stroke risk assessment [1, 2], and assessment of high blood pressure, diabetes, arteriosclerosis and other cardiovascular diseases [3]. Therefore, a number of automatic and semi-automatic retinal image analysis tools have been developed over the past 10 years [4] to improve the reliability and also make the procedure more robust and cost effective.

Stroke has been reported as the third most common cause of mortality in adults after ischemic heart disease and combined cancer [5], and predicted to become the most common cause of death [1, 6]. There is an urgent need for methods that can accurately assess the risk of stroke. Currently used risk assessment methods such as Framingham's equation are based on Meta data and suffer number of shortcomings such as poor specificity. Recent work by Kawasaki et al [7] and Zul [8] have attempted to use automatic retinal image analysis using fractal analysis for risk assessment of Stroke incidence which resulted into sensitivity and specificity of 72.52% and 69.67% respectively. There is an urgent need for improving these outcomes for reducing the incidence of stroke.

Automatic retinal image analysis requires the image quality to be good [9]. Presence of background and other noise, and light reflections can result in poor contrast and such images are unsuitable for automatic analysis. So far colour retinal image analysis has been conducted only on the red-free or the green channel only [10] as it is generally accepted that the green channel provides the best vessel to background contrast while the red and blue channels are in most cases, noisy and have low contrast (Fig. 1) [11]. However it has been shown that it is not always sufficient for texture analysis and feature extraction using a single channel in complex images [12, 13]. Marrugo et al [14] have developed principle component analysis (PCA) based colour space method to segment the optical disk in retinal images, and Sinthanayothin et al [15] proposed to have an adaptive colour channel for retinal image analysis. However, this has not been significantly tested in clinical settings.

In this paper, an adaptive colour transformation and feature extraction techniques has been used on the retinal images from the Blue Mountain Eye Study (BMES) database and tested for stroke prediction. In this study, thirty retinal images of participants who suffered stroke were analysed and compared with another thirty retinal images of matching control subjects. In this method PCA has been applied on RGB channels to find a new set of orthogonal axes based on the variance in the three colour channels. This method is comparable with the technique proposed in [16-18] for complex images. The significant contribution of this work is that it has shown the need for adaptive colour channel for different retinal images, and the significant improvement in stroke prediction.

II. Material

The Retinal images from a population-based study conducted in Blue Mountains, a suburban region west of Sydney, Australia, commonly referred to as Blue Mountain Eye Study (BMES), were analysed [19, 20]. The participant's age range was 60-89 years. All these images were obtained using a Zeiss FF3 fundus camera having 30 degree field of view. The photographs were taken after pupil dilation. The images were digitized using a Cannon FS2710 scanner with maximum resolution of 2720 dpi in 24-bit colour format. Among the total number of 1532 images available in our database, 104 images were of people who later suffered an episode of stroke. Eight of these images were discarded due to the poor quality. From these 96 images, 30 cases were selected and matched to corresponding 30 controls based on the age, gender and history of hypertension and diabetes. Stroke cases were defined as participants who did not have history of stroke at

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baseline (1992-94), but who developed incident stroke or died from stroke-related causes [21] over a 10 year time.

III. Methodology

PCA was performed on the RGB images to determine the most suitable colour vector that would provide the best features for further analysis. The image corresponding to this adaptively obtained colour vector was denoised using Gabor wavelet [11] and (GLCM) features were obtained [22]. Feature reduction was performed using Relief-F algorithm. Supervised classification was performed using support vector machine (SVM) on these feature set. For the purpose of comparison, the green channel image was analyzed exactly in the same way as the adaptive colour channel. The steps are described in detail below:

A. *Principal Component Analysis (PCA)*

PCA was used to transform the RGB axes to three new orthogonal principal axes. Consider an image; n×m×q, where n, m and q represent for the number of rows, columns and the RGB channels (q=3) respectively. The image matrix was reshaped to the new size of l×q where l=n×m. This matrix was then mapped into the PCA space. The output of this transformation formed a new set of image channels, also known as Eigenchannels [16]. The Eigenchannels were then reshaped back to size of the original image (n×m×q) as shown in Fig. 1. The values of the first Eigenchannel showed the maximum correlation of the data containing main structural features. The second one contained the texture features while the third Eigenchannel included uncorrelated noise. Inspection of the Eigenchannels and the corresponding histogram revealed that the second one had a bimodal histogram while the first and the third one had unimodal histograms (Fig. 2). Based on these results, the second Eigenchannel was found to be suitable for improved contrast and segmentation and was selected for further analysis.

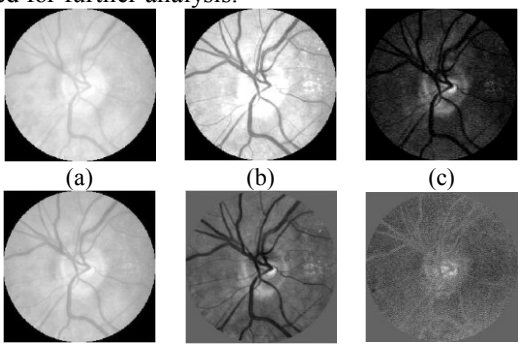

Figure 1: Original Image and the PCA Eigenchannels. a) R channel b) G channel c) B channel d) 1st Eigenchannel e) 2nd Eigenchannel f) 3rd Eigen channel

B. *Multi-Scale wavelet decomposition*

The image obtained after PCA was filtered using the pyramidal multiresolution Gabor wavelet filter bank described by Oscar Nestares et al [23] with six levels and eight orientations. Unlike other pyramidal methods (i.e. Gaussian [24] and Laplacian [25]), there is no loss of information in the decomposition process in wavelet transform [26]. The reason for selection of six levels has been investigated in the result section (section IV) in terms of providing better accuracy, sensitivity, specificity and AUC. The original image and the outputs at each level were convolved with even and odd symmetric Gabor wavelets at eight orientations resulting to even-odd images at each orientation. The particular spatial frequency and orientation responses were obtained by finding the Euclidean distance of the even-odd images at each level.

C. *Gray level co-occurrence matrices (GLCM)*

Gray level co-occurrence matrix (GLCM), proposed by Haralick et al. [22] in 1973 describe the texture of the image. It has been found to be suitable for texture retrieval and feature extraction and has been demonstrated by Doyle et al [27] to grade prostate cancer.

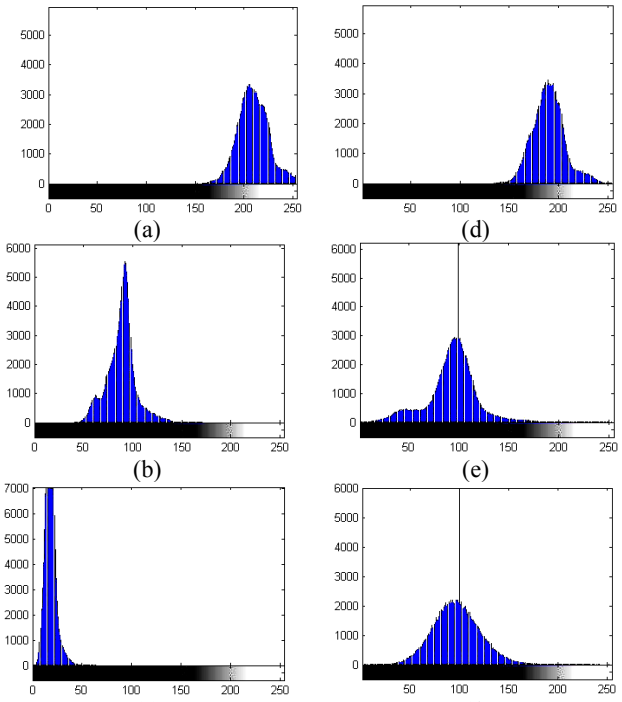

Figure 2: Histograms of original Image and the PCA Eigenchannels. a) R channel b) G channel c) B channel d) 1st Eigenchannel e) 2nd Eigenchannel f) 3rd Eigen channel

The four common GLCM features of contrast, correlation, homogeneity, and energy were used in this study [28, 29]; These are based on the assumption that the texture information can be adequately derived by calculating the frequency of the occurrence of a pixel with gray-level value of "*i*" horizontally adjacent to a pixel with the value "*j*". Using the notation and referencing format used in [22]:

$$\text{Contrast:} \quad \sum_i \sum_j |i-j|^2 \, p(i,j) \qquad (1)$$

$$\text{Correlation:} \quad \sum_i \sum_j \frac{(ij)P(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{2}$$

$$\text{Homogeneity:} \quad \sum_i \sum_j \frac{p(i,j)}{1+|i-j|} \tag{3}$$

$$\text{Energy:} \quad \sum_i \sum_j p(i,j)^2 \tag{4}$$

where $p(i,j)$ is the $(i,j)^{th}$ element in the GLCM matrix and μ_x, μ_y, σ_x and σ_y are the means and standard deviations of $p_x(i) = \sum_j p(i,j)$ and $p_y(j) = \sum_i p(i,j)$ respectively.

D. *Feature Reduction*

The use of the six scales over eight orientation angles for the four GLCM measures, results in 192 (6×8×4) features for each image. A key issue prior to any machine learning and feature classification is to estimate the quality of attributes and find strong dependencies to other attributes [25]. Supervised learning and classification of high dimensional data can lead to over-trained system which will affect the classification performance [30]. High dimensional data also increases the computational complexity. It is important to identify the most suitable feature set that will provide the best separation between the different classes; the stroke cases and the controls.

In this research, an extension of Relief algorithm, Relief-F [25], was used for feature selection and dimensionality reduction. This technique is suitable when the dimensionality is high and is also suitable for noisy datasets [26] which is the case in population based studies. The importance of each feature is defined in terms of a set of weights. The initialisation of weights is random and an iterative process determines the weights for each feature to maximise the distance between the two classes. Relief-F analysis on the data showed that three of the 192 features, the 63rd, 158th and 142nd features were recognized as most suitable and used for further analysis.

E. *Classification of clinical cases*

The features selected using Relief-F were classified using V Support Vector Machine (V-SVM) [31] into two classes; control and stroke patients. V-SVM has soft-margins and allows for classifying data where there is an overlap. The regularization parameters (V) determines the trade-off between the complexity of a support vector machine and the number of non-separable points and this was set to 0.1 based on the leave one out error minimisation.

F. *Validation and performance Estimation*

In order to validate the classification performance, hold-out validation, ten-fold cross-validation and receiver operating characteristics (ROC) were used as the most common techniques. To compare the results with other works in literature, the three validations methods were performed. Hold-out validation was tested with the data randomly split into 70% training and 30% testing samples and repeated 10 times. Ten-fold cross validation was performed to cross-validate the results and remove any ambiguity due to the data selection during the hold-out validation. Ten-fold validation was done using two measures; 'Leave one out' and "10 times, 10 fold" approach. Receiver Operating Characteristic (ROC) analysis was performed to find the area under the curve (AUC) for each of the above validation methods. ROC is a measure of predictive ability and reliability of the system. The analysis was conducted for the adaptive colour image proposed by this research and also for the green channel for comparison purpose.

IV. Results

Table 1 illustrates the three cross validation performance namely 'Hold-Out', 10 times-10 fold repeated analysis and 'Leave-one-out Validations' for both PCA and green colour spaces. According to this table, the sensitivity, specificity and AUC of adaptive colour selection, was consistently better (0.73) than the green channel; for all validation techniques. The accuracy was defined as the proportion of true results to the whole population study. Table 2 provides a comparison between the cross validation results for three different decomposition levels (four, five and six).The number of orientations was kept at 8 for all the levels.

TABLE 1: CROSS-VALIDATION EVALUATION (PCA SPACE VS GREEN CHANNEL)

Validation	Method	Hold-Out	10 Times 10 Fold	Leave One Out
Accuracy	**PCA**	**0.738**	**0.733**	**0.733**
	Green	0.670	0.627	0.567
Sensitivity	**PCA**	**0.766**	**0.733**	**0.733**
	Green	0.659	0.744	0.678
Specificity	**PCA**	**0.711**	**0.733**	**0.733**
	Green	0.681	0.500	0.457
AUC	**PCA**	**0.738**	**0.733**	**0.733**
	Green	0.736	0.684	0.630

TABLE 2: CROSS-VALIDATION EVALUATION OF CLASSIFICATION RESULTS FOR DIFFERENT WAVELET SCALES (10-TIMEs-10 FOLD VALIDATION)

	Accuracy	Sensitivity	Specificity	AUC
Gabor Level 4	0.616	0.633	0.600	0.616
Gabor Level 5	0.433	0.241	0.612	0.429
Gabor Level 6	**0.733**	**0.733**	**0.733**	**0.733**

V. Discussion and Conclusion

This paper reports an adaptive technique to select the colour channel of the eye-fundus images. The proposed technique has been tested using 10-year stroke data to predict the incident of stroke events. The technique determines suitable colour channel for the highest contrast by performing PCA on the RGB channels. GLCM was used as measure of the image texture and four features of contrast, correlation, homogeneity and energy were generated at each wavelet scales. Feature reduction was performed using ReliefF on the 192 GLCM features and the three most suitable features

from this set were identified for each image. These features were then classified using V-SVM supervised classifier.

This study has shown that when adaptive colour channel is used, the classification results are better (0.733) than when sole green channel is used (0.63). The results obtained from green channel had AUC of 0.63, which was similar to the work by Kawasaki et al [7]. However, the results of adaptive colour space showed a significant improvement, with the AUC being 0.73. This would make the system more attractive for clinical deployment. The results were validated using hold-out, 10-times 10-fold and leave one out validation techniques. Accuracy, sensitivity, specificity and ROC were measured for these validation techniques and all of them showed a significant improvement when adaptive colour channel was used. With the improved accuracy, specificity, and sensitivity; eye fundus imaging may now be more applicable for clinical applications.

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