MULTIMODAL RETINAL VESSEL SEGMENTATION FOR DIABETIC RETINOPATHY CLASSIFICATION

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Abstract — Proliferative diabetic retinopathy is a rare condition likely to lead to severe visual impairment. It is characterized by the development of abnormal new retinal vessels. We describe a method for automatically detecting new vessels on the optic disc using retinal photography. In this work has focused on the evaluation of the multimodal approach for purposes of obtaining vessel segmentation. Multimodal approach used for obtaining slightly better vessel segmentation. In the first approach (referred to as the registered fundus vessel segmentation approach), vessels are first segmented on the fundus photograph directly (using a k-NN pixel classifier). In the second approach (referred to as the multimodal vessel segmentation approach), after fundus-to-SD-OCT registration, vessels are simultaneously segmented with a k-NN classifier using features from both modalities. Vessel-like candidate segments are first detected using a method based on watershed lines and ridge strength measurement. Fifteen feature parameters, associated with shape, position, orientation, brightness, contrast and line density are calculated for each candidate segment. Based on these features, each segment is categorized as normal or abnormal using a support vector machine (SVM).

Index Term --- multimodal vessel segmentation, spectral domain optical coherence tomography, SVM, fundus photography

I. INTRODUCTION

Diabetic retinopathy, the most common diabetic eye disease, occurs when blood vessels in the retina change. Proliferative diabetic retinopathy (PDR) mainly occurs when many of the blood vessels in the retina close, preventing enough blood flow. In an attempt to supply blood to the area where the original vessels closed, the retina responds by growing new blood vessels. This is called neovascularization. However, these new blood vessels are abnormal and do not supply the retina with proper blood flow. The new vessels are also often accompanied by scar tissue that may cause the retina to wrinkle or detach. In the RGB images, the green channel exhibits the best contrast between the vessels and background while the red and blue ones tend to be more noise. So we work on the gray image from green channel and the retinal blood vessels appear darker in the gray image, shown in. Normalization is performed to remove the gray-level deformation by subtracting an approximate background from the original gray image.

In our approach the first approach is referred to as registered fundus vessel segmentation approach vessels are first segmented on fundus photographs directly using a k-nearest-neighbor (K-NN) pixel classifier [8] and this vessel segmentation result is mapped to other fundus photography volume through registration. However, such an approach would not fully take advantage of the multimodal information. Thus, in the second approach, referred to as the multimodal vessel segmentation approach, after automated fundus-to-fundus registration, vessels are simultaneously segmented with a K-NN classifier using features from both modalities. From the multimodal vessel segmentation approach we classify the vessels with diabetic retinopathy or not. A support vector machine classifier is used to perform the classification of diabetic retinopathy.

II. METHODS

An overview of our registered-fundus and multimodal vessel segmentation approaches is presented in Fig. 1. In both approaches, we first segment the retinal vessels on original fundus photographs using a pixel-classification-base
A. Pre-Processing
Pre-Processing of retinal image is the first step in the automatic diagnosis of retinal diseases. The problem with retinal image is that the quality of the acquired images is usually not good. So, it is necessary to improve the quality of retinal image [3]. The purpose of pre-processing is to remove the noisy area from retinal image. This is required for the reliable extraction of features and abnormalities as feature extraction and abnormality detection algorithms give poor results in the presence of noisy background.

Steps for preprocessing
1. Divide the input retinal image into non-overlapping blocks.
2. Extract RGB components from the original color retinal image.
3. After gray-level conversion, use histogram equalization to enhance the contrast and to improve the quality of retinal image.
4. Use a large median filter to remove the noise from the image.

B. Vessel segmentation in original fundus photography
A supervised pixel-classification-based segmentation method is used to segment the vessels in the original fundus photographs [8]. A previously trained K-NN classifier is then applied and each pixel is assigned a soft label. This is then applied and each pixel is assigned a soft label. This results in a vesselness image, with the image intensity of each pixel representing the likelihood of belonging to a Vessel. While the training process requires expert delineations, after training process such classifiers enable a fully automated segmentation on previously unseen data. An example of an original fundus photograph and its vessel segmentation is shown in Fig. 2 the purpose of this step is to obtain vessel...
segmentation from fundus photographs alone (without the use of SD-OCT)

Fig 2. Fundus photography and its segmentation, (a) original color fundus photography, (b) segmented vessels

C. Image Registration

The fundus-to-fundus registration needs a reference image in the SDOCT modality. Thus we create an OCT projection image at the level of the NCO in the SD-OCT volume. More specifically, four intraretinal 3-D surfaces are simultaneously identified in the 3-D raw SD-OCT volumes using an optimal graph theoretic multilayer segmentation algorithm. Based on a segmented surface, we then flatten the raw SD-OCT volumes. The four segmented surfaces are also flattened by applying the same transformation. To register the segmented original fundus vessels to the vessel-oriented OCT projection image, we also segment the vessels on the vessel oriented fundus image using the OCT vessel segmentation approach.

D. Feature extraction

After performing the above mentioned preprocessing steps, the new eye image is obtained. Since the retinal image is of shape circle, features related to circle are taken.
1. Area of on pixels: It is the area of the white pixels with value 1 on the black and white image.
2. Mean: The mean is the arithmetic average of a set of values. Here in the eye image, it is obtained by adding all of the pixel values together, then dividing by the number of original values.
3. Standard Deviation: The Standard deviation for an image is found by squaring each pixel Values of all the individual samples, and then calculating average for the number of samples, the standard deviation measures the spread of data about the mean value. It is approximately equal to the average deviation from the mean value. The Sample standard deviation, denoted by s and defined as follows

$$s = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \bar{x})^2}{n-1}}$$  (1)

Where, $x_i$ is the value of the mean, $N$ is the sample size, $X_i$ represents each data value from $i=1$ to $N$.

E. k-NN classification

After separately extracting the pixel features from the vessel-oriented OCT projection and registered fundus images, the feature spaces of the two modalities are combined. In other words, for each sample in the multimodal image space, the multimodal feature vectors include the features from both modalities and each feature vector is normalized to zero mean and unit variance. In a training set (as described in Section III), each pixel is labeled “vessel” or “non-vessel” for use within a k-NN classifier.

F. Support vector machine (SVM):

The standard SVM is a binary classifier which has found widespread use in pattern recognition Problems such as image and audio recognition, handwriting recognition, medicine, science, finance and so on. The support vector machine or SVM framework is currently the most popular approach for “off-theshelf” supervised learning [4]. There are three properties that make SVMs attractive:
1. SVMs construct a maximum margin separator—a decision boundary with the largest possible distance to example points. This helps them generalize well.
2. SVMs create a linear separating hyperplane, but they have the ability to embed the data into a higher dimensional space, using the so-called kernel trick. Often, data those are not linearly separable in the original input space are easily separable in the higher dimensional space. The high-dimensional linear separator is actually nonlinear in the original space. This means the hypothesis space is greatly expanded over methods that use strictly linear representations.
3. SVMs are a nonparametric method—they retain training examples and potentially need to store them all. Thus SVMs combine the advantages of nonparametric and parametric models: they have the flexibility to represent complex functions, but they are resistant to over fitting. The input points are mapped to a high dimensional feature space, where a separating hyper-plane can be found. The algorithm is chosen in such a way as to maximize the distance from the closest patterns, a quantity which is called the margin. SVMs are learning systems designed to automatically trade-off accuracy and complexity by minimizing an upper bound on the generalization error. In a variety of classification problems, SVMs have shown a performance which can reduce training and testing errors, thereby obtaining higher recognition accuracy. SVMs can be applied to very high dimensional data without changing their formulation.

III. EXPERIMENTAL METHODS

During the experimentation, fifteen image pairs are randomly chosen as the training set and the remaining 19 pairs are used as the test set. Each stereo color fundus photograph has 768×1019 pixels. The vessel-oriented images, and the cropped color fundus registered images have a size of 200×200 pixels.

Expert-defined manual tracing with each pixel labeled as “vessel” or “non-vessel” are obtained based on the vessel oriented OCT projection and cropped fundus registered images using a viewer that enables the registered images to be examined on top of one another simultaneously, resulting in 200×200×15=600000 training samples for the training set of 15 images and 200×200=40000 test sample for each test image. In particular, the performance of each vessel segmentation approach is evaluated based on the AUC of the ROC curves. The AUC between the ROC curves between each pair of approaches are compared using the non parametric approach proposed by Delong et al. [10], which is based on the theory of generalized U statistics. The pROC package [11] for R is used to perform this test and p values less than 0.05 are considered significant.

IV. RESULTS

The Proposed method was implemented in Mat lab. Based on the feature extracted, the SVM is trained for normal and abnormal images. Finally, image is classified as exudates or nonexudates using SVM. In the region outside the NCO, the multimodal approach performs significantly better than the registered-fundus approach and in the region inside the NCO; it presents a similar performance to the registered-fundus approach. Overall, the multimodal approach performs significantly better than the registered fundus approach.

V. DISCUSSION AND CONCLUSIONS

In our proposed system the registered-fundus approach in general provides accurate vessel segmentation due to the high vessel contrast on fundus photographs overall the proposed method exhibits a low computational complexity and a good performance we plan to use the measurements of vessel width and tortuosity vessels for a more complete validation of the proposed method, as well as to apply this method to other types of vascular images, preliminary results were obtained in retinal fluoroangiograms and coronary, where as the neovascularization analysis in corneal photography needs a modification because there is not an unique starting point like OD. Therefore automatic and accurate methods are very useful for the analysis of retinal images at regular intervals, to evaluate the progression and therapy efficiency.

In conclusion, we present a novel registered-fundus and a novel multimodal vessel segmentation approach to obtain better vessels. Overall, the two present fundus-related approaches perform better than two closest previous OCT-based vessel segmentation approaches. The multimodal approach performs better than all the three unimodal vessel segmentation approaches of the registered fundus and the two OCT-based approaches quantitatively and qualitatively.
REFERENCES