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AN OVERVIEW OF DIFFERENT ANALYSIS ALGORITHM AND DATABASE FOR EARLY DETECTION OF DIABETIC RETINOPATHY

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Abstract: Diabetic Retinopathy (DR) is one of the major problems of diabetic patients. Typically there are no salient symptoms in early stage of diabetics until it is too late for effective treatment. It entail screening assessment of the retina with attention to a series of indicative features, i.e., blood vessels, optic disk and macula etc. Automatic screening test facilitate early detection of diabetic retinopathy through implementation of different analysis algorithm also these experimental test depends upon well formatted database. In this paper we have focused on different database that will help researchers to contribute in this context. Ophthalmologists can detect DR early since we are providing processed image.

Keywords: Diabetic Retinopathy; Retina; Blood Vessels; Algorithm; Database.

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INTRODUCTION

Early detection and diagnosis of retinal fundus images for diabetic patients are necessary steps for the Diabetic Retinopathy treatment to prevent vision loss in diabetic patients. Here we are focusing on different analysis algorithms & database available for research.

According to survey done for global prevalence of diabetes some numerical data is to be highlighted here so that we can understand about impact level for early detection of DR. Diabetics was the fourth most frequently managed chronic disease in general practice during year 2009, and the projections go as high as the second most frequent disease by the year 2030 [2].The global burden of diabetic patients is expected to rise from 171 million in 2000 to 366 million in 2030 [2]. In europe more than 52.8 million people are diagnosed with diabetes with the number expected to rise to 64 million by 2030.

Automatic screening is important as up to one third of people with diabetes may have progressive DR changes without symptoms will lid to vision loss [3], thus allowing the disease to progress and making treatment difficult. Systematic screening programs for diabetic eye disease have been developed in many countries.

To build a proper database for detection of DR, capture of retinal image by fundus camera has got massive importance with accurate and robust image processing and analysis algorithms for detection of abnormalities due to DR.

The main contribution of this work is to present an overview of algorithms for early detection of diabetic retinopathy in fundus photographs. In Section II typical symptoms of diabetic retinopathy are explained. In Section III an overview of image processing algorithms for early detection diabetic retinopathy is given. In Section IV currently available databases for image processing algorithms are discussed and finally in Section V we give a short conclusion.

Diabetic Retinopathy And It's Classification

DR can cause the loss of vision when it starts affecting your retina. Retinopathy a disease of the retina [3]. Explicitly retinopathy involving damage to the small blood vessels in the retina; results from chronically high blood glucose levels in people with poorly controlled diabetes. Diabetic retinopathy, the most common diabetic eye disease, occurs when blood vessels in the retina change. Sometimes these vessels swell and leak fluid or even close off completely. In other cases, abnormal new blood vessels grow on the surface of the retina [4].Classification of DR [24] is given below –

A. Classification

i. BDR-Background Diabetic Retinopathy

The earliest stage of diabetic retinopathy. With this condition, damaged blood vessels in the retina begin to leak extra fluid and small amounts of blood into the eye. Sometimes, deposits of cholesterol or other fats from the blood may leak into the retina.

ii. PDR- Proliferative Diabetic Retinopathy

Mainly occurs when many of the blood vessels in the retina close, preventing enough blood flow.

iii. SDR- Severe Diabetic Retinopathy

Continuous abnormal vessel growth & scare tissue, which lead to retinal detachment & hence loss of vision.

iv. Macular *Edema*

Diabetic macular edema may be asymptomatic at first. As the edema moves in to the fovea (the center of the macula) the patient will notice blurry central vision. The ability to read and recognize faces will be compromised.

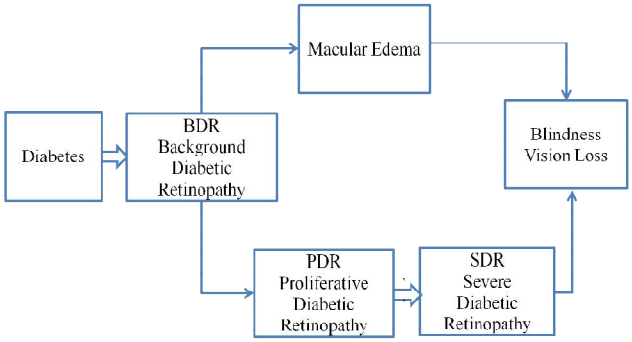

Fig 1 Classification of diabetic retinopathy

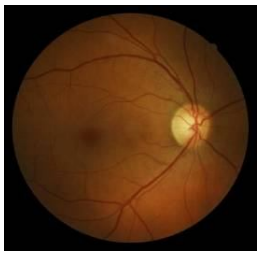

Fig 2 Healthy eye

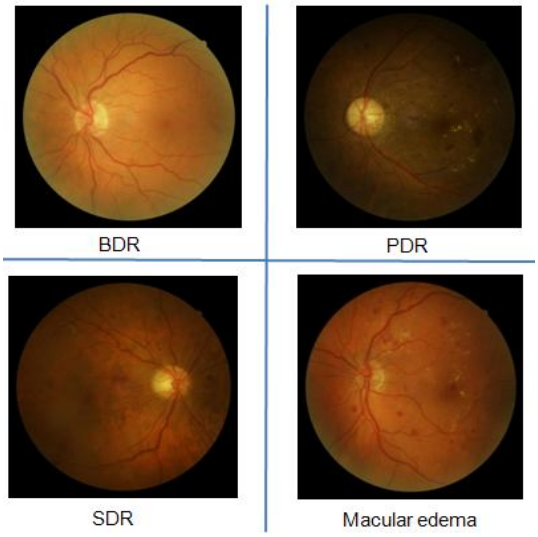

Fig 3 Unhealthy eye patterns

IMAGE PROCESSING ALGORITHM

An overview of image processing algorithm known to us are focused here also we have divided execution steps as

B. Image Preprocseeing

Patient movement, poor lumination can cause a significant proportion of images to be of such poor quality as to interfere with analysis. In approximately 10% of the retinal images, artifacts are significant enough to impede *human grading.* Preprocessing of such images can ensure adequate level of success in the automated abnormality detection. In the retinal images there can be variations caused by the factors including differences in cameras, illumination, acquisition angle and retinal pigmentation. First step in the preprocessing is to attenuate such image variations by normalizing the colour of the original retinal image against a reference image. Few of the retinal images acquired using standard clinical protocols often exhibit low contrast. Also, retinal images typically have a higher contrast in the centre of the image with reduced contrast moving outward from the centre. For such images, a local contrast enhancement method is applied as a second preprocessing step. Finally it is required to create a fundus mask for each image to facilitate segmentation of lesions and anatomical structures in later stages. All this steps are explained below in detail.

i. Colour Normalization

This step is includes in image preprocessing because intra & inter retinal colour image variation observes in different patients. Also we can include difference on retinal image contributed by skin pigmentation, aging of the patient and iris colour. Colour normalization provides image invariance w.r.t background pigmentation. As per [1], colour normalization is executed using histogram matching.

In the adaptive algorithms each pixel is modified based on the pixels that are in a region surrounding that pixel. This region is called contextual region. The adaptive histogram equalization is computationally intense, locally adaptive, and usually produces superior images and for this reason we are implementing this step to increase the speed of the basic non-adaptive method. If we have an image of n x n pixels, with k intensity levels and the size of contextual region is m x m, then time required is calculated as

$$\text{Computation Time} = o(n^2(m+k)) \qquad (1)$$

A standard retinal image is used as a reference for histogram specification technique in agreement with the expert ophthalmologist. This method is applied to normalize the values of only those images in the database that varies in colour with reference to the standard image. The histogram specification technique is independently applied to each individual RGB channel to match the shapes of three specific histograms of the reference image. Figure 4 show the reference retinal image and its RGB histogram. To demonstrate the colour normalization effect, a different colour retinal image and its RGB histograms are shown in Figure 5. The image normalized version and the relevant RGB histogram can be seen in Figure 6. It can be seen that normalization process modifies the colour distributions of the considered image to match the reference image's distribution. This can be seen from comparison of the normalized image histograms with the reference image's histograms. In [6] authors proposed a multilevel histogram equalization method as a preprocessing step in the detection of drusen. The approach is based on the sequential application of histogram equalization to progressively smaller non-overlapping neighbour hoods.

CLAHE operates on small regions in the image, called *tiles*, rather than the entire image. Each tile's contrast is enhanced, so that the histogram of the output region approximately matches the histogram specified by the 'Distribution' parameter. The neighbouring tiles are then combined using bilinear interpolation to eliminate artificially induced boundaries. The contrast, especially in homogeneous areas, can be limited to avoid amplifying any noise that might be present in the image [23]. Refer Fig 4, 5, 6 for colour normalization using histogram matching technique.

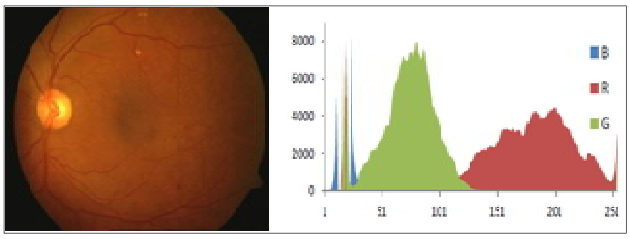

Fig 4 Reference RGB image & histogram

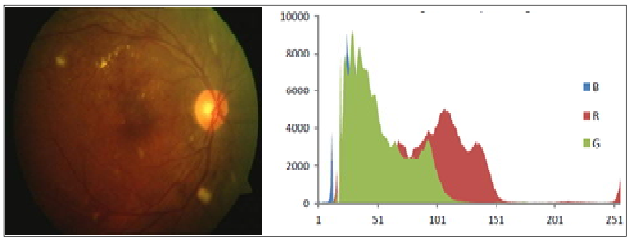

Fig 5 Input RGB image & histogram

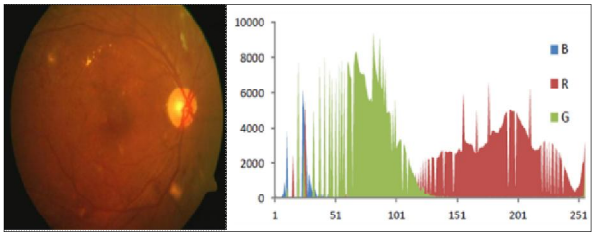

Fig 6 Colour normalized RGB image & histogram

ii .Contrast Enhancement

This step is applied in a preprocessing after colour normalization. By using contrast enhancement we can change the visual characteristic that can help to distinguish an object from background. It can be seen that retinal image contrast is decreased as the distance of a pixel from the centre of the image increases [6].

Here first RGB component of original image is transformed to HSI stands for Hue, Saturation & intensity. Among all HSI component, *Hue* represents dominant colour as perceived by an observer. *Saturation* refers to relative purity or the amount of white light mixed with hue. *Intensity* reflects the brightness. So such representation of an image provides better result of image processing algorithm [9].

$$I = \frac{1}{3}(R + G + B) \quad (2)$$

$$S = 1 - \frac{3}{(R + G + B)}[\min(R, G, B)] \quad (3)$$

$$H = \cos^{-1}\{\frac{0.5[(R - G) + (R - B)]}{\sqrt{(R - G)^2 + (R - B)(G - B)}}\} \quad (4)$$

C. Localization and segmentation of the optic disk

The optic disk (OD) centre and margin are typically requisite landmarks in establishing a frame of reference for classifying retinal and optic nerve pathology. Reliable and efficient OD localization and segmentation are important tasks in automatic eye disease screening.

Optic disk localization consist mainly of finding the approximate centre of the optic disk or placing the disk within a specific region such as a circle or square. In either way, many distractors like blood vessel edges or large exudate lesions complicate the process of optic disk localization. In early papers the optic disk was localized by identifying the largest cluster of bright pixels [8].

Advancement for OD localization is done in [7] by using a new, fast, and fully automatic OD localization and segmentation algorithm developed for retinal disease screening First, OD location candidates are identified using template matching. The template is designed to adapt to different image resolutions. Then, vessel characteristics (patterns) on the OD are used to determine OD location. Initialized by the detected OD centre and estimated OD radius, a fast, hybrid level-set model, which combines region and local gradient information, is applied to the segmentation of the disk boundary. Morphological filtering is used to remove blood vessels and bright regions other than the OD that affect segmentation in the peripapillary region.

D. Segmentation of the retinal vasculature

Basically main objective of image segmentation is to extract various features of the image in order to analyze it [9]. The segmentation of the retinal vasculature is very important because retinal vasculature contains many useful information about the patients health. Accurate segmentation of the retinal blood vessels is often an essential prerequisite step in the

identification of the retinal anatomy and pathology. Segmentation of blood vessels is important for image registration or spatial alignment of images.

Matched filtering for the detection of the vasculature convolves a 2D kernel with the retinal image. In [8] authors proposed a two-dimensional linear kernel with a Gaussian profile for segmentation of the vasculature. The profile of the filter is designed to match that of a blood vessel, which typically has a Gaussian or a Gaussian derivative profile. The kernels are typically rotated in 30–45 degree increments to fit into vessels of different orientations. The highest response filter is selected for each pixel and is typically threshold to provide a vessel image. Further post processing is then applied to identify vessel segments. Matched filtering performs well when used in conjunction with additional processing techniques but there are some problems. Convolution kernels may be quite large and need to be applied in several orientations which can be very computationally expensive. Kernel responds optimally to vessels that have the same standard deviation of the underlying Gaussian function specified by the kernel. Retinal background and low contrast of smaller vessels increase the number of false responses around bright objects. Several authors have proposed refinements and extensions which address many of these problems [10]. In [11] many authors experimented with vessel tracking algorithms. Vessel tracking algorithms segment a vessel between two points. A vessel tracking algorithm typically steps along the vessel. The centre of the longitudinal cross section of vessel is determined with various properties of the vessel including average width. The main advantage of vessel tracking methods is that they provide highly accurate vessel widths, and can provide information about individual vessels that is usually unavailable using other methods. Unfortunately, they require the starting point and sometimes vessel tracking techniques may be confused by vessel crossings and bifurcations.

The Gabor wavelet transform has some impressive mathematical and biological properties. We have learned that the wavelet transform could perform multi-resolution & multi-orientation time-frequency analysis. It consists of a group of Gabor filters at different frequencies and directions. Gabor wavelets were produced by a Gabor kernel that is a product of an elliptical Gaussian and a complex plane wave [13].

It has been observed that wavelet transforms are not capable of reconstructing curved images perfectly; hence we switch over concept, called Contourlet Transform, proposed by Do and Vetterli [12].

Image Databases

Images of retina captured using fundus camera are used for processing purpose so that we able to diagnose the retinal diseases. In medical terms fundus is termed as bottom or baseline of

anything. Fundus image consist retina, optic disc, macula & posterior pole.Image databases are very important because all image processing algorithms developed have to be tested and verified. An overview of all publicly available retinal image databases known to us is given in this section.

A. DRIVE (Digital Retinal Images for Vessel Extraction) Database

The database consists of 40 colour fundus photographs & their ground truth images. Each image is JPEG compressed. All images in DRIVE database are digitized using a Cannon CR5 non-mydriatic 3CCD camera with a 45 degree field of view (FOV). Each image is captured using 24-bits per pixel at the image size of 768×584. These images were labeled by hand, to produce ground truth vessel segmentation. Below figure shows a sample of the input image from this database [14].

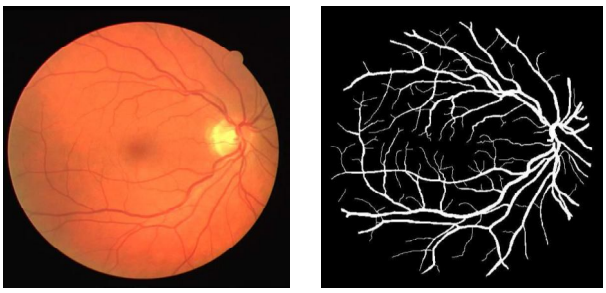

Fig 7 Retinal images from DRIVE database (left), hand labeled ground truth vessel segmentation

B. STARE (Structured Analysis of Retina) Database

Here there are twenty retinal fundus slides and their ground truth images. The images are digitized slides captured by a Top Con TRV-50 fundus camera with 35 degree FOV. Each slide was digitized to produce a 605 x 700 pixel image with 24-bits per pixel (RGB image). All the twenty images were carefully labeled by hand to produce ground truth vessel segmentation by an expert. Below figure shows a sample of the input image from this database [15].

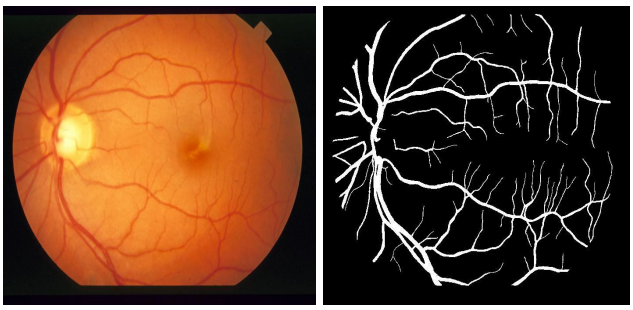

Fig 8 Retinal images from STARE database (left), hand labeled ground truth vessel segmentation

C. ARIA online Database

This database was created in 2006, in a research collaboration between St. Paul's Eye Unit, Royal Liverpool University Hospital Trust, Liverpool, UK and the Department of Ophthalmology, Clinical Sciences, University of Liverpool, Liverpool, UK .The trace of blood vessels, the optic disc and fovea location was marked by two image analysis experts as the reference standard. The images were captured at a resolution of 768×576 pixels in RGB color with 8-bits per color plane with a Zeiss FF450+ fundus camera at a 50 degree FOV and stored as uncompressed TIFF files [16].

D. Image Ret

The Image Ret database was made publicly available in 2008 and is subdivided into two sub-databases, DIARETDB0 and DIARETDB1. DIARETDB0 contains 130 retinal images of which 20 are normal and 110 contain various signs of diabetic retinopathy. DIARETDB1 contains 89 images out of which 5 images represent healthy retinas while the other 84 have some diabetic retinopathy signs. The images were acquired with a 50 degree FOV using a fundus camera at a size of 1500×1152 pixels in PNG format. The images were annotated by four experts for the presence of micro aneurysms, haemorrhages, and hard and soft exudates [17].

E. Messidor

The Messidor-project database, with 1200 retinal images, is the largest database currently available on the Internet and is provided by the Messidor program partners [18]. The images were acquired by 3 ophthalmologic departments using a color video 3CCD camera on a Topcon TRC NW6 non-mydriatic camera with a 45 degree FOV. The images were captured using 8 bits per colour plane at 1440×960, 2240×1488, or 2304×1536 pixels. 800 images were acquired with pupil dilation and 400 without dilation. The reference standard provided contains the grading for diabetic retinopathy and the risk of macular edema in each image.

F. Review

The Retinal Vessel Image set for Estimation of Widths (REVIEW) [19] was made available online in 2008 by the Department of Computing and Informatics at the University of Lincoln, Lincoln, UK. The dataset contains 16 mydriatic images with 193 annotated vessel segments consisting of 5066 profile points manually marked by three independent experts.

G. ROC micro aneurysm set

The Retinopathy Online Challenge micro aneurysm dataset is part of a multi-year online competition of micro aneurysm detection that was arranged by the University of Iowa in 2009.

[20]The set of data used for the competition consisted of 50 training images with available reference standard and 50 test images where the reference standard was withheld by the organizers. The images were captured using a Topcon NW100, a Topcon NW200 or a Canon CR5-45NM non-mydriatic camera at 45 degree FOV and were JPEG compressed in the camera. There are three different image sizes present in the database; 768×576, 1058×1061 and 1389×1383 pixels.

H. HEI-MED

The Hamilton Eye Institute Macular Edema Dataset (HEI-MED) is a collection of 169 fundus images to train and test image processing algorithms for the detection of exudates and diabetic macular edema [21].The dataset is composed of 169 JPEG images compressed at highest quality. Each image of the dataset was manually segmented by Dr. Edward Chaum (an expert ophthalmologist from HEI). He identified all the exudation areas and other bright lesions such as cotton wool spots, clearly visible fluid occurring on the fundus.

I. DRiDB

Diabetic Retinopathy Image Database is a new database developed in cooperation between Faculty of Electrical Engineering and Computing, University of Zagreb and Clinical Hospital Centre “Sestre Milosrdnice” from Zagreb. The images were captured at a resolution of 720×576 pixels in RGB color with 8-bits per color plane with a Zeiss VISUCAM 200 fundus camera at a 45 degree FOV and stored as uncompressed BMP files. A set of ground truth images accompanies every color fundus image from the database. For each image from the database five experts independently marked diabetic retinopathy findings (micro aneurysms, haemorrhages, hard exudates, soft exudates). The experts were asked to mark the blood vessels, optic disc and macula alongside marked diabetic retinopathy findings and finally experts performed annotation of neo vascularisations.

Benchmarking Parameters

In medical diagnosis, the medical input data is usually classified into two classes, where the disease is either present or absent. The classification accuracy of the diagnosis is assessed using the sensitivity and specificity measures. Following the practices in the medical research, the fundus images related to the diabetic retinopathy are evaluated by using sensitivity and specificity per image basis. Sensitivity is the percentage of abnormal fundus classified as abnormal, and specificity is the percentage of normal fundus classified as normal by the screening. By using equation 5 & 6 we can have formula for accuracy calculation. The higher the sensitivity and specificity values, the better the diagnosis. Sensitivity and specificity can be computed as

$$Sensitivity = \frac{TP}{TP + FN} \quad (5)$$

$$Specificity = \frac{TN}{TN + FP} \quad (6)$$

$$Accuracy = \frac{(TP + TN)}{TP + FN + TN + FP} \quad (7)$$

Here TP denotes true positive, FP denotes false positive, FN is false positive & TN is true negative. True Positive refers to the correctly identified vessel pixels, True Negative refers to the wrongly identified vessel pixels, False Positive refers to the correctly identified background pixels and False Negative refers to the wrongly identified background pixels.

CONCLUDING REMARKS

To develop an automatic retinal image processing system, the first important thing is to obtain an effective database. To realize this and also for facilitating comparison with the existing methods, nine sets of retinal databases with their specifications are focused. Main aim is to incorporate types of available databases for researchers.

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