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Retinal Disease Screening Through Local Binary Patterns

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ABSTRACT: When sugar level (glucose) in the blood fails to regulate the insulin properly in human body, diabetic is occurred. The effect of diabetic on eye causes diabetic retinopathy. Diabetic Retinopathy is one of the complicated diabetes which can cause blindness. It is metabolic and the disordered patients perceive no symptoms until the disease is at late stage. So early detection and proper treatment has to be ensured. To serve this purpose, various automated systems have been designed. A key feature to recognize Diabetic Retinopathy is to detect Micro aneurysm in the fundus of the eye. This work investigates discrimination capabilities in the texture of fundus images to differentiate between pathological and healthy images. For this purpose, the performance of Local Binary Patterns (LBP) as a texture descriptor for retinal images has been explored. The goal is to distinguish between diabetic retinopathy (DR) and normal fundus images analyzing the texture of the retina background and avoiding a previous lesion segmentation stage. I propose pre-processing technique such as Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance the contrast of the input image and I use candidate extractors such as Circular Hough Transform to improve the red lesion detection. Finally the output image was classified as Normal and Diabetic retinopathy (DR). These results suggest that the method presented in this paper is a robust algorithm for describing retina texture and can be useful in a diagnosis aid system for retinal disease screening.

I. INTRODUCTION

Utilising computer-assisted diagnosis of retinal fundus images is becoming an alternative to manual inspection of the fundus by a specialist, known as direct ophthalmoscopy. Moreover, computer-assisted diagnosis of retinal fundus images was shown to be as reliable as direct ophthalmoscopy and requires less time to be processed and analysed. Various eye related pathologies that can result in blindness, such as macular degeneration and diabetic retinopathy are routinely diagnosed by utilising retinal fundus images [1]. One of the fundamental steps in diagnosing diabetic retinopathy is the extraction of retinal blood vessels from fundus images. Although several segmentation methods have been proposed, this segmentation remains challenging due to variations in retinal vasculature network and image quality. Currently, the main challenges in retinal vessel segmentation are the noise (often due to uneven illumination) and thin vessels. Furthermore, the majority of the proposed segmentation methods focus on optimising the preprocessing and vessel segmentation parameters separately for each dataset. Hence, these approaches can often achieve high accuracy for the optimised dataset, whereas if applied to other datasets the accuracy will be reduced. Although vessel segmentation methods usually contain pre-processing steps aimed at enhancing the appearance of vessels, some approaches skip the pre-processing steps and start with the segmentation step.

Nowadays, many segmentation methods rely on machine learning concepts combined with traditional segmentation techniques for enhancing the segmentation accuracy of their method by providing a statistical analysis of the data to support segmentation algorithms. These machine learning concepts can be broadly categorised into unsupervised and supervised approaches, based on the use of labelled training data. In a supervised approach, each pixel in the image is labelled and assigned to a class by a human operator, i.e., vessel and non-vessel. A series of feature vectors is generated from the data being processed (pixel-wise features in image segmentation problems) and a classifier is trained by using the labels assigned to the data. In an unsupervised approach, predefined feature vectors without any class labels are used where similar samples are gathered in distinct classes. This clustering is based on some assumptions about the structure of the input data, i.e., two classes of input data where the feature vectors of each class are similar to each other (vessel and not vessel). Based on the problem, this similarity metric can be complex or defined by a simple metric such as pixel intensities.

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II. LITERATURE SURVEY

Dataset

Publicly accessible digital retinal images for vessel extraction (DRIVE) [4], structured analysis of the retina (STARE) [37] and Child Heart and Health Study in England (CHASE_DB1) CHASE_DB1 [38] datasets used in this study are amongst the most popular datasets used for developing and testing the performance of various retinal segmentation methods. Datasets used also provide corresponding vessel segmentations manually done by different experts and are considered as the ground truth segmentation.

DRIVE dataset includes 40 colour fundus images that were equally divided into training and testing sets. For each image in the dataset, a FOV mask along with manual expert segmentation of the corresponding vessel tree (one expert for the training set and two experts for the testing set) were provided. A Canon CR5 non-mydriatic camera with a FOV of 45° and bit-depth of 8-bit was used to capture the images with a resolution of 768 × 584 pixels. Figure 3 illustrates an image from the test set with its respective manual vessel segmentation.

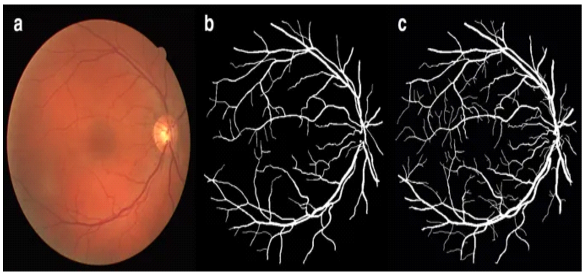

Fig. 3a An image from the DRIVE test set with its respective manual vessel segmentation the b first observer and c second observer

STARE dataset includes 20 colour fundus images with half of them containing signs of different pathologies. For each image in the dataset, manual segmentation of corresponding vessel tree done by two experts are provided. A canon TopCons TRV-50 fundus camera with FOV of 35° and bit-depth of 8-bit was used to capture the images with a resolution of 700 × 605 pixels. Figure 4 illustrates an image from this dataset with its respective manual vessel segmentation.

III. SYSTEM ANALYSIS

3.1Existing System

The existing system in hospitals for leukocoria detection involves the manual calculation. The leukocoria was identified by manual observation. This system is highly prone to error because of the presence of noise accompanied in the image. Orientation of the images also varies and the eye may not contain a perfect circle for the cases when the picture is captured in angle with respect to the camera sensor. So there is much probability for wrong identification of noise as leukocoria and leukocoria as noise. It has two main drawbacks: large memory requirement and slowness. In order to find the plane parameters accurately, parameter space must be divided finely in all three directions, and an accumulator assigned to each block. Also it takes a long time to fill the accumulators when there are so many. The Fast Hough Transform gives considerable speed up and reduces memory requirement. Instead of dividing parameter space uniformly into blocks, the FHT homes in on the solution, ignoring areas in parameter space relatively devoid of votes. The relative speed advantage of the FHT increases for higher dimensional parameter spaces. Another weakness of the Hough Transform is that it often recognizes many similar lines instead of the one correct one. The algorithm only returns a line without a starting and ending point. For that different post processing algorithms have to be used.

3.2Proposed system

In order to overcome the drawbacks of the existing system and to provide an efficient system for leukocoria detection a new method has been suggested. Median filter based iteration a methodology is used to detecting the iris as region. This includes the use of watershed segmentation method which identifies the presence of leukocoria efficiently. The image processing involves denoising the input image to produce an image that is better suited for edge detection over relatively large regions with respect to the input size. This system also provides a well processing technique for removal of noise present in the image by use of median filters. In order to avoid costly skin-detection algorithms that could be used to remove (ignore) skin regions.

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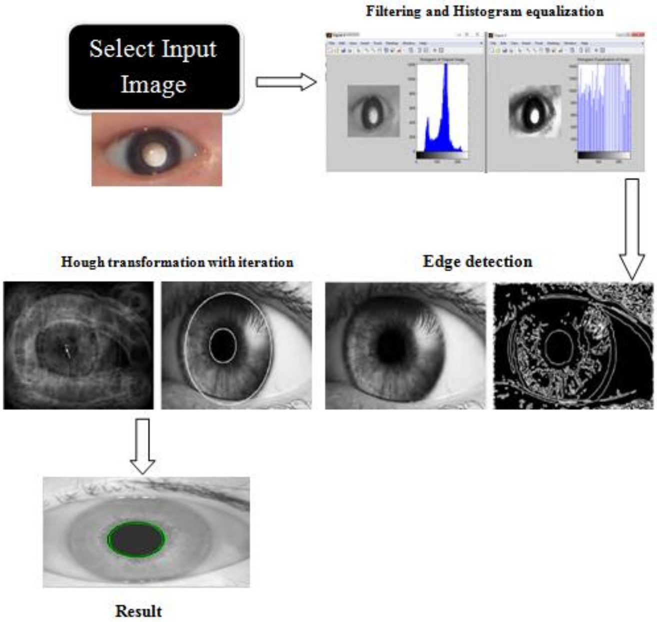
3.3Architecture



IV. SYSTEM IMPLEMENTATION

Pre-processing

The extracted green band from the original fundus image was first filtered by using a 3×3 median filter to reduce the image noise. As retina fundus images show high contrast around the edges of the image resulting in false positive vessels being detected around the edges of the image and the edges are smoothed by using the method proposed by [19]. Initial FOV mask was computed by thresholding the luminance channel on CIElab colour space [42] calculated from the original RGB fundus image. Then, the mask was dilated by one pixel iteratively where the value of the new pixel was calculated as the mean value of its 8-connected neighbouring pixels. This process was repeated 50 times to ensure that no false vessels will be detected near the FOV border.

Then, contrast limited adaptive histogram equalisation (CLAHE) algorithm [43] was used to enhance the contrast between vessels and background with the clip limit empirically set at 0.0023. CLAHE improves the local contrast by not over amplifying the noise present in relatively homogeneous regions and was used in many retina vessel segmentation methods. Next, the noise was suppressed by having the images opened morphologically by using a circular structuring element with a radius of 8 pixels. Finally, the image was further enhanced by using a combination of Top-hat and Bottom-hat morphological operations as illustrated in Fig. 6.

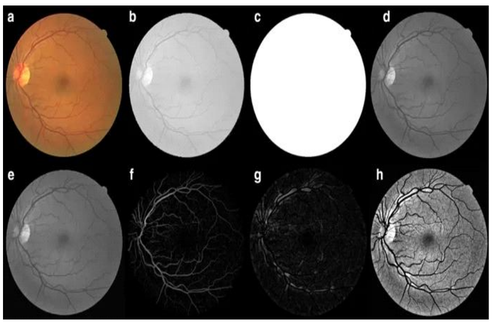


Fig. 6 A sample image from the DRIVE dataset with different preprocessing steps illustrated. a Color fundus image, b CIElab color space luminance channel, c FOV mask, d RGB color space green channel, e image after median and morphological filtering, f morphological Top-hat, g morphological Bottom-hat and h image after morphological filtering

Gabor Filtering

For enhancing the small vessels inside the image, a Gabor wavelet-based filter was used. For 2D images (spatial Gabor filter), convolution was used for applying Gabor's filters where varying kernels were defined as Gaussian kernels

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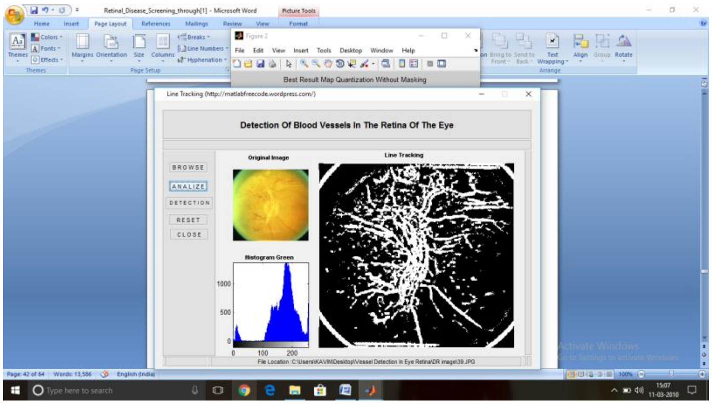
modulated by a sinusoid [44]. By using a Cartesian basis as the centre, these kernels were defined based on an abscissa with orientation θ. Gaussian and sinusoid components of the Gabor's filter $K\theta,\sigma,\gamma,\lambda,\varphi K\theta,\sigma,\gamma,\lambda,\varphi$ can be independently customised:



Results and Discussion

In this study, similar to the majority of other studies, the proposed method was compared to the ground truth segmentations provided by the first observer (mentioned as the first expert in some publications) in CHASE_DB1 and STARE datasets and the test set of the DRIVE dataset. Since CHASE_DB1 and STARE datasets do not provide the FOV masks and to make the proposed method compatible with other datasets, FOV mask in this study was automatically generated and no FOV masks supplied in datasets were used in this study. All experiments were done by using MATLAB 2013a on an HP ProBook (2.3 GHz Intel Core i5 Processor, 4 GB RAM).

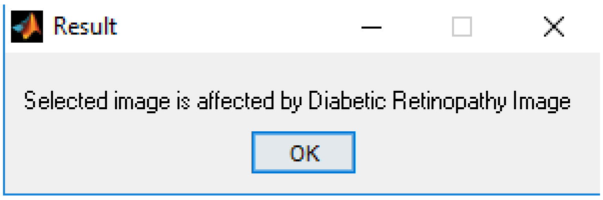
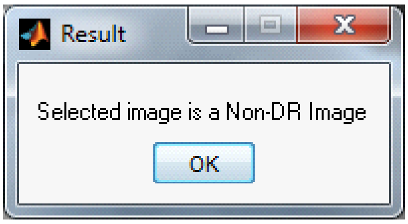


Table 1 demonstrates the performance of the proposed method as compared to the most recent segmentation methods for STARE and DRIVE datasets, while Table 2 shows a comparison of the proposed method and other state-of-the-art segmentation techniques in the CHASE_DB1 dataset. Please note that character "-" in tables indicated that the performance metric was not implemented by the authors in their respective papers. While it is possible to increase the segmentation accuracy of the proposed method by selecting preprocessing and filtering parameters for each dataset separately, the goal of the study is to propose a method that could be used on a variety of datasets and images.



Although the proposed method is considered as an unsupervised segmentation, the results achieved are comparable to supervised segmentation methods while the processing time and computation requirements are notably lower, making the proposed method applicable for use in batch processing on large screenings. As mentioned, supervised segmentation methods require the computation of large pixel-wise feature vectors coupled with difficulties in training an efficient classifier, making them computationally demanding and time-consuming in batch applications.

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V. CONCLUSIONS & FUTURE ENHANCEMENT

Vessel segmentation can be considered as one of the main steps in retinal automated analysis tools. In advanced retinal image analysis, the segmented vasculature tree can be used to calculate the vessel diameter and tortuosity, discriminating veins and arteries along with measuring the arteriovenous ratio. In this study, a retinal vessel segmentation algorithm based on fuzzy c-means clustering and level set method was proposed. Utilising morphological processes, the CLAHE and matched filtering techniques, the images were enhanced before the fuzzy clustering of vessel pixels. Finally, the vessels were segmented by a level set approach. The proposed segmentation method was validated on publicly accessible data sets by using common validation metrics in retinal vessel segmentation where the results on DRIVE (Sensitivity = 0.761, Specificity = 0.981), STARE (Sensitivity = 0.782, Specificity = 0.965) and CHASE_DB1 (Sensitivity = 0.738, Specificity = 0.968) were shown to be comparable to other methods from the literature. In future to handle noisy and pathological images and produce good segmentation, especially in thinner vessels while being computationally efficient.

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