An Analytical Method for the Detection of Exudates in Retinal Images Using Invertible Orientation Scores

Surya Rajan, Taraprasad Das, R. Krishnakumar

Abstract—Diabetic retinopathy is an eye related complication of diabetes mellitus caused due to damage to the retinal blood vessels, resulting in micro-anneurysms, hemorrhages and exudates. DR is asymptomatic, necessitating the development of an automated screening system. Exudates appear in the later stages of diabetic retinopathy and their presence would classify the disease as moderate or severe. In developing countries, where access to training data is limited, there is a greater need for analytical methods than machine learning techniques. The proposed method uses the orientation scores of the retinal image to detect exudates. The 2D orientation score framework, proposed by Duits et al., inspired by the visual system of mammals, is a mapping which assigns the position and orientation angle of each pixel to a complex scalar and has been so far used to detect vasculature tree on the retina. This paper proposes the use of orientation scores to form an orientation enhanced image, from which a binary mask of exudates can be obtained by intensity thresholding. It achieves a sensitivity of 86.2% and a specificity of 85% on images of DIARETDB1 database.

Index Terms—Diabetic Retinopathy, Exudates, Orientation Scores, Cake Wavelets

I. INTRODUCTION

Diabetic retinopathy is increasingly becoming the common cause of blindness among the middle-aged population in India and the rest of the world. In a study conducted in [1], by 2050, there will be 244 million people (14.9% of the population) with diabetic retinopathy, compared with 42 million (4.5% of the population) in 1995. This indicates that retinal diseases would soon become the major cause of blindness in India. But, with limited number of specialist doctors, an automated screening system is essential to ensure an early diagnosis of the disease. The main symptoms of diabetic retinopathy are micro-anneurysms, exudates and hemorrhages. Micro-anneurysms occur due to weakening and bulging of blood vessel walls of the retina. They are typically round lesions of the size of only a few pixels. Hemorrhages form when the walls of a vessel ruptures. When the leakage from a vessel also contains lipids and proteins, it creates yellow spots on the retina known as exudates. They have well-defined edges, no consistent shape and their sizes vary widely. There are also lesions called cotton wool spots or soft exudates, which do not have sharp edges. An example of a retinal image containing exudates is given in Fig. 1.

Exudate detection in the retina is typically split into two steps: pre-processing of the images, and segmentation of the lesions. A noise mask was generated in [2] for pre-processing to exclude noisy regions and background subtraction was done in [3], [4], [5]. In-painting to remove dark structures and analysis using adaptive templates to remove bright structures were done in [6]. Contrast of the image was enhanced in [7] using a combination of complex shock filter and global histogram stretching. The segmentation of exudates may be achieved by machine learning techniques, or analytical methods. Machine learning techniques give good results, if one has a large training set. But, in a country like India, where access to images are limited, and different camera setups are used to capture retinal images, it is not practical to rely only on machine learning techniques for lesion detection. Therefore, there is a need to develop better analytical techniques. Morphological operations were carried out in [8] in order to generate candidate regions for exudates and optic disc, and then the OD was removed from the candidates to obtain the bright lesions. Morphological operations were used also in [9], [10], [11] to segment exudates. Several inverse segmentation methods were proposed in [12] such as region growing, region growing with background correction and adaptive region growing with background correction.

Many techniques have been used for a coarse extraction stage, including intensity thresholding [5], [13] and morphological techniques [6], [14], [15], [16]. In the latter case, the morphological operators were used to obtain a more accurate localization of exudates. The classification of candidates was done analyzing their edge strength in [5] by applying kirsch analysis and setting a threshold. In [17], a new approach using

Fig. 1. An image from DIARETDB1, with portions of exudates marked as shown
A complex shock filter is applied to the image to smooth out random fluctuations, and then the background is estimated and corrected. The complex shock filter smooths out the random noise fluctuations, without blurring the edges. To find the background image, an irregular grid is laid out, and the mean and standard deviation are found inside a window of size 125 pixels [7]. These values are interpolated and the Mahalanobis distance is calculated at each pixel. Those pixels with distance less than 1 are assumed to belong to the background [7]. The intensity is computed at each of the background pixels and interpolated to get the background intensity image. Illumination correction is performed, by subtracting this background from the original image. Contrast of the image is enhanced in two steps: edge enhancement and intensity separation. Edge enhancement is obtained by applying the complex shock filter to the illumination corrected image. For increasing the intensity separation between regions, a global contrast stretch is used and the intensities are saturated at extreme intensities. The R, G, B planes of the original image are then remapped by a post-processing step. The results are shown in Fig. 2. The output image has a Gaussian histogram in all three planes. The blue plane of the pre-processed image is used in further stages, since only pixels with high intensities are visible in the blue channel.

### B. Orientation Enhanced Image

The orientation scores of an image, calculated using the equation in section II, are a column of complex values at each pixel location. Fig. 3 shows the real and imaginary parts of the orientation score of a retinal image at \( \theta = 3\pi/8 \). The real part of the orientation score gives information regarding oriented structures, while the imaginary part contains edge information. An enhanced image can be formed using the real and the imaginary parts of the orientation scores, as explained below. The responses of the blue channel of the image to each of the cake filters, make up a conceptual stack of \( N_0 = 16 \) layers; each layer containing the pixels oriented in that particular direction. Exudates are either isotropic or moderately elongated structures. When isotropic, pixel information is uniformly smeared out over the different orientation layers. Therefore, at an exude pixel, every orientation gives a large response, though lower than the original pixel value. Information about moderately elongated exudate is available in one of the stacked layers. To form the enhanced image for exudate detection, the maximum intensity through the layers for each pixel is

![Image](image_url)
Fig. 3. Cake filters applied on a retinal image with N0=16. (a) Pre-processed image. Results at $\theta = 3\pi/8$ (b) Real part of the orientation score (c) Imaginary part of the orientation score

Fig. 4. Enhanced images in case of exudate detection, formed from (a) real part and (b) imaginary part of the orientation scores, (c) Final enhanced image, by adding (a) and (b)

extracted. It should be noted that blood vessels which are low intensity structures, give rise to negative orientation scores and are not confused with exudates, which are at the other end of the spectrum. The maximum intensity projection is done for real as well as imaginary parts of the orientation scores. An enhanced image is obtained by adding these two images, so that both the oriented structure information and the edge information are present in one image (Fig. 4).

IV. DETECTION AND ELIMINATION OF LANDMARKS

To ensure that other bright structures like optic disk and optic nerve striations on the retina do not get falsely detected as exudates, they are first detected and eliminated from the enhanced image.

A. Optic Disc

Optic disc is the brightest structure in a retinal image and therefore, it needs to be eliminated from the candidate image for accurate exudate detection. A mask of the optic disc is generated by the method laid out in [24]. The algorithm involves creating template orientation fields of the optic disc for the left and the right eye images and correlating them with a normalized orientation field of the input image to obtain a response map. Depending on whichever template generates the maximum response, the retina image is classified as belonging to the left or the right eye. Further processing is then performed on the response map, which has a local maximum at the center of the optic disc, to identify the correct location of the optic disc in the image. The exact boundary of the optic disc is found by using an area-conscious active contour model [24]. In order for the blood vessels lying in this region, not to introduce discontinuities along the boundary of the OD, they are removed by thresholding the region near the identified location at $\mu_c - \sigma_c$, where $\mu_c$ and $\sigma_c$ are the mean and standard deviation of all pixel values in it.

A sobel edge detection filter is applied to the vessel removed image and a corresponding gradient magnitude image is calculated. If the boundary of the optic disc is sufficiently strong and vessels have been successfully removed, an image is obtained with a relatively high value of gradient magnitude along the boundary of the optic disc and small gradients inside the OD region. A potential surface $P$ is obtained and the Derivative of Gaussian (DoG) filters is applied in X and Y directions on $P$, to calculate a smooth force field. The gradient vector flow (GVF) method in [25] is used to set up a vector field based on the image gradients, and a special outward force is added to the contracting contour to ensure that it does not collapse to a point in images where the boundary of the OD is weak or absent. This resistance force is calculated as:

$$F_{res} = \left(\frac{\text{area enclosed by the evolving contour}}{\text{area enclosed by the initial contour}}\right)^{-k} \hat{n} \quad (2)$$
VI. RESULTS AND DISCUSSIONS

The proposed algorithm was tested on the online database DIARETDB1, for the sake of evaluation. Receiver Operating Characteristics was used to determine the performance accuracy of the method. The ROC curve obtained is shown in Fig. 6 and the corresponding sensitivity, specificity and accuracy of performance are given in Table I. They show that the method performs better than other existing algorithms for exudate detection that do not use any type of machine learning for classification. The comparison was made against [8], [9], [10], [11] and not with the methods that use machine learning. A survey of literature gave only few analytical techniques, which were validated on DIARETDB1 and therefore a comparison was made against such methods only. From the images in Fig. 7, it can be observed that the proposed technique works well to detect lesions in images. Exudate detection shows good performance, irrespective of the size or shape of the lesion. If the retinal image is very bright and has a low contrast, a few false positives were detected, as shown in Fig. 7(e, f).

VII. CONCLUSION

A novel method to detect exudates on the retina was proposed. Recently, the field of machine learning has seen a rise in popularity, and hence most papers propose techniques that uses a trained model to classify lesions. Machine learning generally gives good results, but the outcome is heavily dependent on the data that is used to train the model. In a resource deficient country like India, access to datasets of retinal images are limited, and one has to depend on online datasets and ground truths for training models. But such a model fails to perform well on realworld images obtained from hospitals. Hence, it is not advisable to rely only on machine learning.

V. BINARY MASK OF EXUDATES

From the orientation enhanced image, after applying the masks, a binary mask of exudates can be obtained by simple intensity thresholding. The grayscale level 110 was found to be suitable for images having pixels within the range 0-255. This threshold value gave good performance for images from DIARETDB1. Multi-thresholding using Otsu method may also be used to generate the binary mask. The results of the proposed method are discussed in VI.

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techniques to develop automatic screening mechanisms for diabetic retinopathy.

The aim of this work is to develop an analytical method for the automatic segmentation of exudates on the retina. The method uses the orientation scores of the retinal image, from which, an enhanced image is generated using the orientation characteristics of exudates. After further processing, a binary image or mask of the lesion is obtained. The proposed method was found to perform better than other analytical methods on the DIARETDB1 dataset.

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