Automated detection of bright lesions from contrast normalized fundus images

Ashish Issac, Rishabh Madan, Malay Kishore Dutta
Department of Electronics and Communication Engineering, Amity University, Noida, India
Email: issac017@gmail.com, rishabhmadan17@gmail.com, malaykishoredutta@gmail.com

Carlos M. Travieso
Signal and Communications Department, IDeTIC
University of Las Pamas de Gran, Canaria, Spain
Email: carlos.travieso@ulpgc.es

***Abstract*— Exudates are one of the abnormalities present in the eye which can lead to vision loss. Fundus images may consist of artifacts which occur during image acquisition and hamper the accuracy of detection of exudates. There is a need to develop an image processing based techniques for automated and correct segmentation of exudates from fundus images. This paper demonstrates an automatic computer vision algorithm for efficient identification of the exudates from fundus images by strategic fusion of techniques i.e. contrast normalization, top-hat transformation and average filtering. The proposed technique correctly detects exudates from the fundus images and rejects the artifacts and reflections. The average computation time for exudates segmentation from fundus images is 11 seconds. The proposed method is computationally efficient and robust and can be used for real time applications.**

Keywords— Fundus Image; Exudates; Diabetic Retinopathy; Top-Hat Transform; Contrast adjustment; Average Filter

I. INTRODUCTION

Diabetic retinopathy is a one of those critical eye impairments that can lead to blindness or vision deprivation [1]. A person who is already affected by diabetes can suffer visual impairment or complete blindness, depending on the time of illness. An approximate of around 220 million people is affected by diabetes worldwide according to W.H.O. [2]. Hard Exudates are protein or lipid deposits, usually of yellow color, on the retinal surface from damaged blood vessels [3]. The presence of hard exudates is a clear sign of an unhealthy fundus. An efficient marking and detection system may help in early detection of DR and DME diseases.

In the recent years, a considerable amount of work has been done in the area of detection of exudates from the fundus images. Edge based detection of exudates has been proposed by Sanchez et al [4]. The use of non dilated fundus images for detection of hard exudates using mathematical morphological operation has been proposed by Sopharak et al [5]. Some morphological operations have been used by Gandhi et al [6] to identify exudates in fundus images. Curvelet wavelets have been proposed for optic disc and hard exudates segmentation from fundus images by Esmaeili et al [7]. A morphological approach has been proposed by Zhang et al [8] to identify possible candidates for exudates and rejecting the false ones using random forest algorithm. A strategic combination of intensity threshold and morphological operations has been proposed by Singh et al [9].

Although a lot of work has been done in recent years, still a need for more precise and competent algorithm for detection of exudates from fundus (retinal) images arises. The fundus images may have different artifacts and varied illumination which can be a major cause of false detections. So, a need for a method still pertain that can remove false candidate pixels and result in accurate segmentation of exudates.

A significant contribution of the paper is an automated image processing based technique which accurately segment out the exudates and rejects all artifacts making it unvarying to the quality of fundus images. The proposed method uses strategic computer vision based methods such as contrast normalization, top-hat transform and average filter and segments the exudates in an average time of 11 seconds. The computational strength of the proposed method makes it suitable for real time systems.

Another important contribution of the paper is the selection of adaptive threshold from statistical features of the images, making the algorithm unvarying to image quality. The use of these local features in deciding threshold will make the analysis for each image independent and results in proper segmentation of objects for images of varied illuminations and contrast.

The following paper is structured as: Section II discusses the proposed techniques and methods for exudates segmentation from fundus images. Section III discusses the experimental results. Section IV discusses the conclusion and future work of the proposed work.

II. PROPOSED METHODOLOGY

A healthy retinal image consists mainly of blood vessels, optic nerve head and macula. The optic nerve head is one of

This work was supported in part by the Grants from Department of Science and Technology, No. DST/TSG/ICT/2013/37”. Also the authors express their thankfulness to Dr. S.C. Gupta, Medical Director of Venu Eye research centre for his kind support.

978-1-5090-3251-8/16/$31.00 ©2016 IEEE

the vivid objects in a retinal image and is the region where all the blood vessels depart from the eye. The macula is the darkest region in the fundus image. However, an unhealthy eye may contain some lesions such as exudates, drusens, hemorrhages and microaneurysms. These abnormalities may prove fatal if not detected at an early stage and might even result in vision loss. Apart from these objects, the fundus images may also contain some artifacts which might occur during the acquisition process. Fig 1 shows a labeled fundus image [10] which contains all the aforementioned objects.

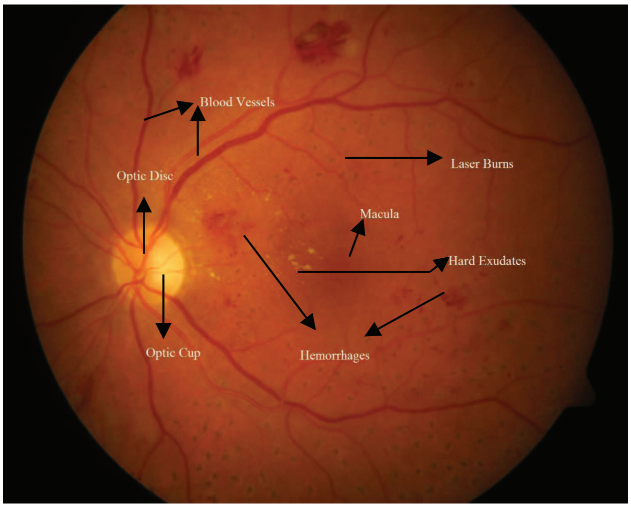

Fig.1 Fundus Image labeled with different retinal objects

The acquired retinal image is an RGB image having 3 channels, namely, red, green and blue. After analyzing many images, the green channel has been selected for exudates detection as the green channel has the highest contrast available and the boundary of exudates is distinguishable in green channel.

The proposed method involves identification of exudates by selecting the best candidate pixels of the following 3 methods:

1. Normalization using statistical features like mean and standard deviation
2. Top-Hat transformation
3. Averaging Filter

Fig. 2 demonstrates the process flow for detection of exudates from fundus images. The green channel is chosen in preference to the other two channels as it provides a good contrast of the objects from background. The green channel image is divided into small blocks and mean and standard deviation for every block is calculated. This is the local mean and standard deviation which is used alongwith the global mean and standard deviation to normalize the contrast of green channel. The green channel is also subjected to tophat transformation and average filter alongwith the contrast enhanced image and all 3 images are finally thresholded to obtain some possible candidates for exudates. The false pixels are rejected by applying logical operations to the candidate pixels and selecting only those pixels which are common in the results of all 3 techniques.

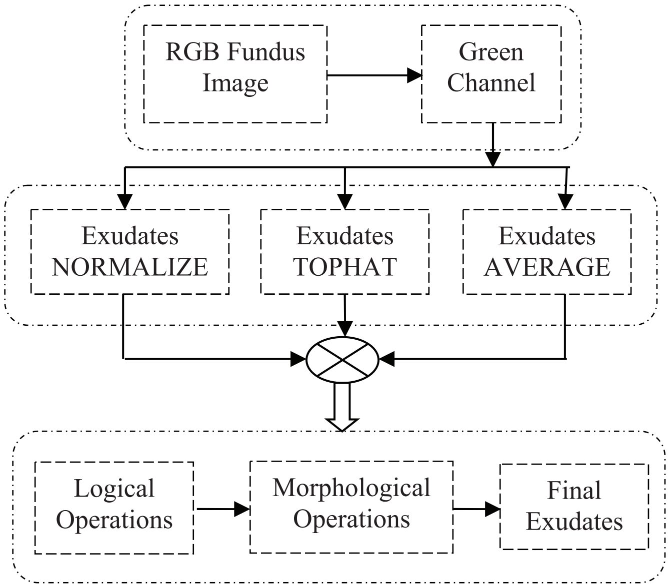

Fig. 2: Flowchart for exudates detection

A. *Contrast Normalization*

As already discussed, that the green channel has highest contrast as compared to the red and blue channel hence has been used for exudates detection. However, it has been observed that due to the acquisition process some artifacts may generate and can hamper the quality of the image. Such an image may lose contrast and also becomes blur. Detecting exudates from such fundus images becomes a seriously challenging task. The proposed work deals with such problems and uses contrast normalization technique as proposed by Foracchia et al [11].

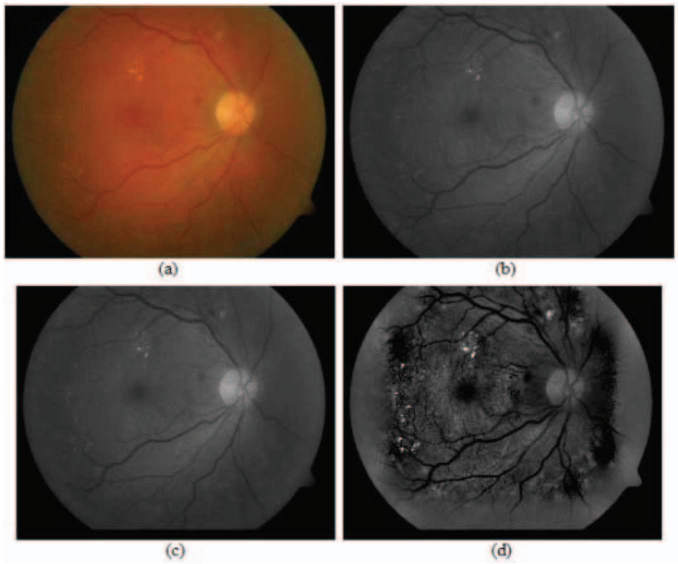

Fig. 3 Contrast Normalization: (a) Input Image under test (b) Green Channel Image (c) Resized Green Channel Image (d) Contrast Normalized Image

Fig. 3 presents the contrast normalization process. This image consists of some bright portion in the left bottom neighbourhood of the disc. The normalization process is carried on green channel of the fundus images. In this method, green channel is divided into small blocks and mean and standard deviation for each block is calculated. This mean and standard deviation is used to normalize the contrast of green channel. Fig. 3(d) shows the contrast normalized image in which only the lesions are enhanced while all the other bright regions, such as optic disc and left bottom region of optic disc, are suppressed. The complete process is explained in Algorithm 1 as follows:

Algorithm 1 : Exudates Segmentation using Contrast Normalization Method

Step 1: Divide green channel of fundus image into square blocks of size 150*150.

Step 2: Find local mean and standard deviation for each block and store them as images of size (rows/150, columns/150).

Step 3: Resize mean and standard deviation images to size of green channel using bi-cubic interpolation.

Step 4: Normalize the green channel using the resized mean and standard deviation images.

$$I = ((Ig - M_L) / (SD_L)) * SD_G + M_G \qquad (1)$$

Where, I = normalized image
Ig = Green channel
M_L = Local mean image obtained from blocks
SD_L = Standard deviation image obtained from blocks
SD_G = Global standard deviation of original green channel
M_G = Global mean of original green channel

Step 5: Threshold the normalized image to obtain exudates.

$$Th1 = 1.25*graythresh(I) + (mean(I) + 2*std(I)) \quad (2)$$

Where, Th1 = threshold to segment exudates
I = contrast normalized image
graythresh = Otsu's threshold
mean = mean of normalized image
std = standard deviation of normalized image

B. Top-Hat Transform

Top-hat transform is a mathematical morphology technique which is obtained by deducting the opened image from the original image. Mathematically, Top Hat Transform can be represented as:

$$TH(g) = g - (g \circ b) \qquad (3)$$

Where, TH = Output of Top-Hat Transformation
g = green channel of input image
b = structuring element
o = opening operation

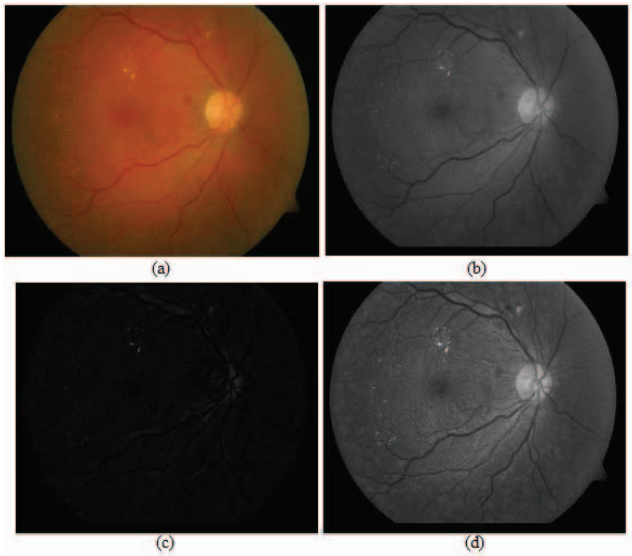

Fig. 4 Top-Hat Transformation: (a) Input Image (b) Green Channel Image (c) Top Hat Transformed Image (d) Green channel + Top Hat Transformed Image

Fig 4 demonstrates the Top Hat transformation process. A disk shaped structuring element of size 50 has been used in the proposed work. After studying many images, it was observed that the exudates present in the images were not larger than 50 pixels. So, such a structuring element was chosen. Since, exudates are of bright intensity, hence, top hat transform is chosen as it selects all the pixels with high intensity of size less than 50. The resulting image from top-hat transformation is summed to green channel image and the output is thresholded using a certain threshold (Th2) to obtain the exudates. Fig 4(d) shows the highlighted exudates as compared to the original green channel. The complete process of exudates detection using top hat transformation is explained in Algorithm 2 as follows:

Algorithm 2: Exudates Detection using Top-Hat Transformation

Step 1: Create a disk shaped structuring element of size 50 pixels.

Step 2: Apply Top-Hat Transformation on green channel using the structuring element.

Step 3: Add the top-hat transformed image and green channel to highlight the exudates.

Step 4: Threshold the resultant image to obtain exudates.

$$Th2 = graythresh(TH) + (mean(TH) + std(TH)) \quad (4)$$

Where, Th2 = threshold to segment exudates
TH = Tophat + Green Channel image
graythresh = Otsu's threshold
mean = mean of resultant image
std = standard deviation of resultant image

C. Average Filter

The main idea behind averaging filter is to replace the pixels with the mean of neighbouring pixels. The mean is calculated as follows:

$$\bar{A} = \frac{1}{M*N} * \sum_{i=1}^{M}\sum_{j=1}^{N} A(i,j) \quad (5)$$

Where, $\bar{A}$ = mean of input image
A = green channel of input image
M*N = number of elements of which mean is calculated

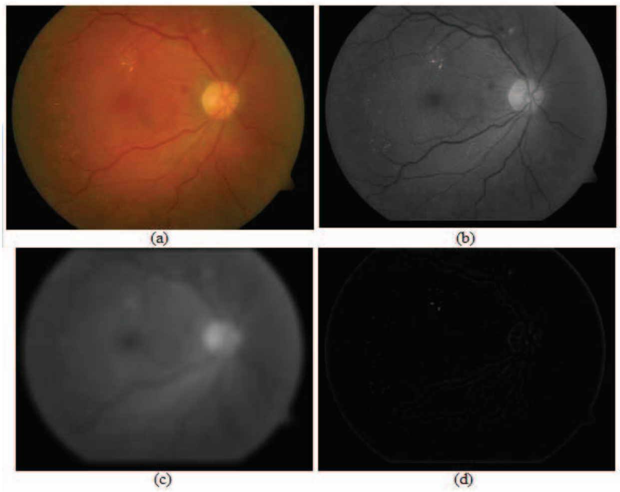

Fig. 5 Averaging Filter: (a) Input Image (b) Green Channel Image (c) Average Filtered Image (d) Green Channel – Average Filtered Image

Fig. 5 presents the averaging filter process. The green channel is filtered by an average filter of size 50*50. The selection criterion for size of average filter is already explained in previous section. The filtered image is smoothed and the pixels with higher intensities are suppressed while the pixels with lower intensities are raised to bring uniformity in the pixel intensities. When the average filtered image is deducted from original image, it results in the pixels with high intensity in the original image. The resultant image contains exudates candidates and is thresholded using certain threshold (Th3) to segment exudates from the image. Fig 5(d) shows the exudates detected from the averaging filter method. The process of exudates detection using averaging filter can be summarized as follows:

Algorithm 3: Exudates Detection using Averaging Filter

Step 1: Create an average filter of size 50*50.

Step 2: Filter the green channel using this averaging filter.

Step 3: Subtract the filtered image from the green channel to obtain pixels of high intensity.

Step 4: Threshold the subtracted image to obtain exudates.

$$Th3 = graythresh(H) + std(H) \quad (6)$$

Where, Th2 = threshold to segment exudates
H = Green Channel – Average Filtered image
graythresh = Otsu's threshold
std = standard deviation of resultant image

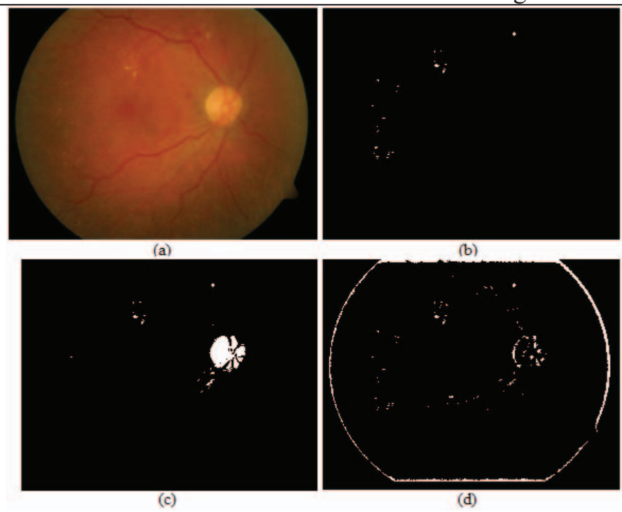

Fig. 6 Exudates after thresholding: (a) Input Image (b) Exudates from Contrast normalization method (c) Exudates from top hat transformation method (d) Exudates from averaging filter method

Fig. 6 presents the exudates segmented from each of the above discussed methods after performing threshold. Fig 6(b) shows the thresholded image from contrast normalization method and it contains exudates and some other regions but no reflections or artifacts while Fig 6(c) and Fig. 6(d) are the threshold image from top hat transformation and averaging filter results in some of the artifacts. A logical OR operation is performed between the output of top hat and average filter output to combine the results from both methods. The combined image is logically AND with the output from contrast normalization method to remove all the artifacts. Some noise which is generated is removed by performing area based thresholding in which isolated regions with area less than 15 pixels are removed. The final image obtained after logical and morphological operations contain only exudates and final detected exudates can be seen in Fig 7(b).

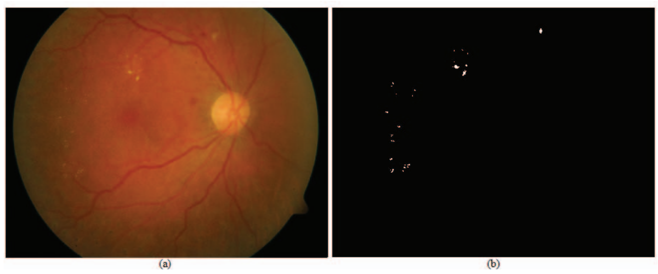

Fig. 7 Detected Exudates: (a) Input Image (b) Final Segmented Exudates

III. Experimental Results

The proposed methodology has been tested on 89 images from DIARETDB1 database [10]. The database consists of normal and unhealthy images. The unhealthy images contain bright and red lesions. The database consisted of 47 images with hard exudates. The annotated exudates are available and the results are compared and checked with the annotated ground truths.

Fig 8 shows the segmentation results for some of the samples from the DIARETDB1 database. Fig 8(a) is the RGB input fundus image which is subjected to the proposed method. Fig 8(b) shows the final segmented exudates which are obtained by applying some logical operations to the results from all the three methods. Fig 8(c) shows the annotated exudates which are already available with the database. The proposed algorithm has been tested on all images from the database and has shown good segmentation results. Also, there were no exudates detected from normal images. The database consists of images with varied illumination and the segmentation results proved to be satisfactory when tested on all images from the database.

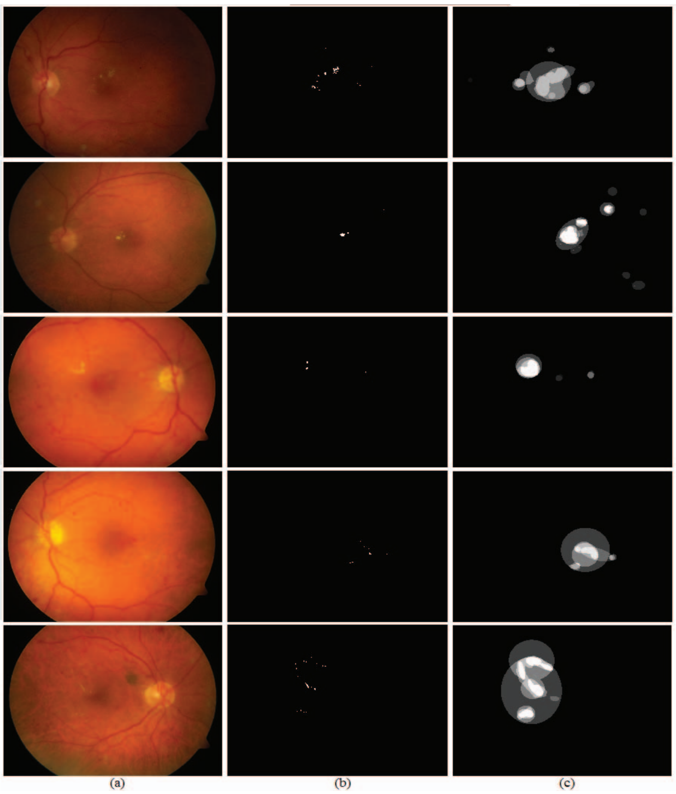

Fig. 8 Results: (a) Input Image (b) Exudates detected from proposed work (c) Ground truth for exudates

The proposed algorithm is computationally lightweight and clocks an average of 11 seconds for final exudates detection from the fundus images. The algorithm is invariant to illumination of images and selection of strategic threshold makes it independent of the nature of images. The algorithm is able to reject the reflections even though they have the same intensity, and color as that of exudates.

IV. Conclusions

The proposed algorithm accurately segments the exudates from fundus images of varying illuminations and images that contain artifacts and reflections. The strategic combination of the image processing operations efficiently suppresses the artifacts and accurately distinguishes them from the exudates. The algorithm is computationally efficient and can be used in the development of a screening tool for Diabetic Retinopathy or Diabetic Macular Edema where exudates are useful in determination of the disease. The encouraging results from the algorithm make it suitable for real time applications.

References

[1] T. Walter, J. C. Klein, P. Massin, A. Erginay, "A Contribution of Image Processing to the Diagnosis of Diabetic Retinopathy—Detection of Exudates in Color Fundus Images of the Human Retina", IEEE Transactions On Medical Imaging, Vol. 21, No. 10, October 2002,pp. 1236-1243.

[2] World Health Organization (WHO) 2011. http://www.who.int/mediacentre/factsheets/fs312/en/

[3] R. J. Winder, P. J. Morrow, I. N. McRitchie, J. R. Bailie, P. M. Hart, "Algorithms for digital image processing in diabetic retinopathy," *Computerized Medical Imaging and Graphics*, vol. 33, no. 8,2009,pp 608 – 622.

[4] C. I. Sánchez, R. Hornero, M. I. López, J. Poza, "Retinal Image Analysis to Detect and Quantify Lesions Associated with Diabetic Retinopathy", Proceedings of the 26th Annual International Conference of the IEEE EMBS San Francisco, CA, USA,September 2004,pp. 1624-1627.

[5] A. Sopharak, B. Uyyanonvara, S. Barmanb, T. H. Williamson, "Automatic detection of diabetic retinopathy exudates from non-dilated retinal images using mathematical morphology methods", Computerized Medical Imaging and Graphics 32 (2008) 720–727.

[6] M. Gandhi, R. Dhanasekaran, "Diagnosis of Diabetic Retinopathy Using Morphological Process and SVM Classifier", International conference on Communication and Signal Processing, April 2013, pp. 873-877

[7] M. Esmaeili, H. Rabbani, A.M. Dehnavi & A. Dehghani, "Automatic detection of exudates and optic disk in retinal images using curvelet transform" IET image processing, 2012, pp. 1005-1013.

[8] X. Zhang, G. Thibault, E. Decencière, B. Marcotegui, B. Laÿ, R. Danno, G. Cazuguel, G. Quellec, M. Lamard, P. Massin, A. Chabouis, Z. Victor, A. Erginay, "Exudate detection in color retinal images for mass screening of diabetic retinopathy", Medical Image Analysis , 2014, pp. 1026-1043.

[9] A. Singh, N. Sengar, M. K. Dutta, K. Riha, J. Minar, "Automatic Exudates Detection in Fundus Images using Intensity Threshold and Morphology", 7th International Congress on Ultra Modern Telecommunications and Control Systems 2015, Chez Republic, IEEE, pp 331-334.

[10] T. Kauppi, V. Kalesnykiene, J. K. Kamarainen, L. Lensu, I. Sorri, A. Raninen, R. Voutilainen, H. Uusitalo, H. Kälviäinen, J. Pietilä, *DIARETDB1 diabetic retinopathy database and evaluation protocol*, In Proc of the 11th Conf. on Medical Image Understanding and Analysis (Aberystwyth, Wales, 2007).

[11] M. Foracchia, E. Grisan, A. Ruggeri, "Luminosity and contrast normalization in retinal images", Medical Image Analysis, Volume 9, Issue 3, June 2005, Pages 179-190.