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Research Article

Effective Contrast Enhancement techniques for Fundus images

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Abstract: Diabetic Retinopathy is a medical condition associated with the eye suffered by a major population of diabetic patients. The progression of this micro-vascular condition of the eye is mainly targeted on small blood vessels of the retinal area. A major characteristic of this condition is the presence of exudates which is actually a fluid that may ooze out from affected regions, may it be a cut or any infected region. The situation when left untreated yields to blindness which is why early detection is the best take. Using image processing we can simplify the data analysis of the exudates images and ease the diagnosis in an efficient way. The fundus image we obtain for diagnosis will be in RGB model format. In order to distinguish the exudates, blood vessels, hemorrhage, optic disk and other features, it is essential to enhance the colour of the image. In this paper we will discuss the existing techniques that are present for this contrast adjustment and propose the most efficient method for the same. Following this, we will also look into the segmentation process which is used for OD and exudate extraction.

Keywords — Fundus, Exudates, Diabetic Retinopathy, Contrast Adjustment

1. Introduction

In the ever changing habitat of the human society, the lifestyle of an individual has rapidly caused a treat to the health of its own mankind. Diabetes is one of the most common medical conditions no one is less aware of. It has an adverse effect on the mankind. The fact that the stay of the disease makes it a home for associate illness is a caption of attention. An example of such a condition is Diabetic Retinopathy (DR). This is a condition wherein the small blood vessels, called the exudates tend to have a pus formation within them and lead to fluid oozing out of the area. Regular screening of the eye helps us capture the exudates and aid in early detection and diagnosis. Fundus imaging gives us an image of the exudates to study the condition further.

Fig. 1 shows an example of a DR affected eye image [1] and a healthy eye image capture [2]. A healthy eye will consist of blood vessels and optic disc only. Whereas a DR fundus image will bear many other features such as exudates, that may be hard or soft or a combination of both their presence, microneurysms, hemorrhage, and optic disk.

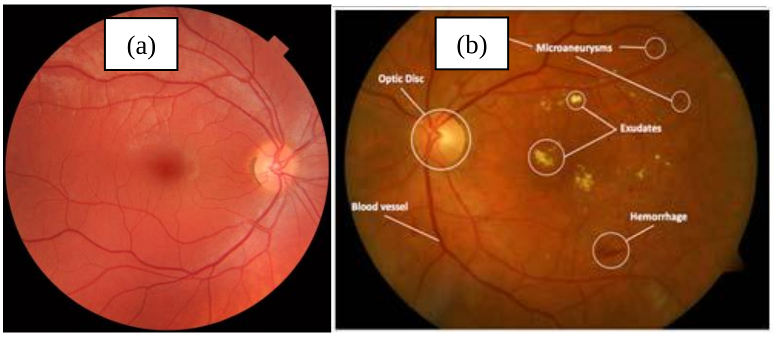


Fig. 1. (a) Normal Fundus Image of Eye (b) Unhealthy Eye affected by DR

Physical examination of every image is a meticulous work and the data accuracy will be on debate. Having an automated detection method for the analysis of the exudates during screening itself would be an effective approach in handling the circumstance. The pathological image obtained for exudates detection of the fundus would initially be in the RGB model. As in Fig. 1, it is evident that the exudates, like any other feature in the fundus image, has a similar colouration bearing same contrast level. If only we are able distinguish between the affected region from that of the normal features of the fundus, we will be able to detect the percentage of the DR condition for a patient. This brings us to an important concept known as Contrast Adjustment for the image. In this paper, we will discuss the different steps involved in the exudates extraction, known as the pre-processing and propose more effective enhancement methods for a good contrast fundus image.

Segmentation is the next topic of discussion which forms the base for our future work, where we will develop automated algorithm for exudates extraction. In this paper, we will have a briefing of the existing methodologies followed and implemented so far, their pros and cons, as well as have a glance of the proposed segmentation method too.

2. Methodology

The idea proposed is to develop a novel approach to identify the exudates in fundus images using automated techniques. An overview of the same is shown in Fig. 2. The functionality of each sequential step as shown in flowchart is as follows:

i. The fundus images are fed to the processor
ii. This processor houses an algorithm that can detect exudates
iii. The algorithm consists of the following steps:
a. Image Acquisition
b. Selecting suitable color model and contrast adjustment as part of the pre-processing
c. Performing segmentation to extract exudates
d. The texture & pixel characteristics of Optic Disc (OD) are similar to that of the exudates. Along with the exudates, OD is also extracted. Thus, OD removal must be carried out
e. Once exudates are retrieved, area of spread must be estimated
f. Perform Content Based Image Retrieval (CBIR) to prescribe medication

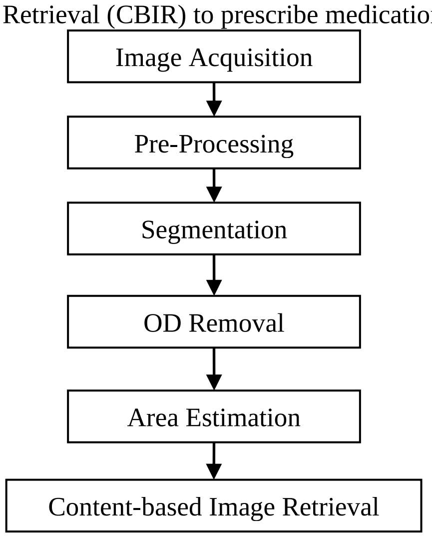


Fig. 2. Process Flow of Exudate Extraction

This paper mainly concentrates on the first section of the algorithm where, the fundus images are read, preprocessed and further segmented to obtain exudates and optic disk.

3. Pre-processing

To perform effective contrast adjustment for a fundus image, an acquired image goes through a series of processes, as shown in Fig. 3. One is the choice of the colour model. Since we have an RGB model, we have to filter the image to one of the true colours, i.e. red, green or blue. The other step is to choose an algorithm that would enhance the exudates features from the background information.

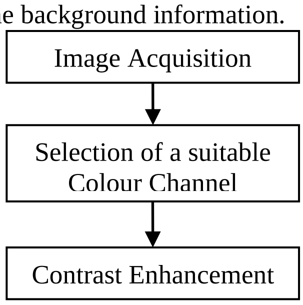


Fig. 3. Process Flow for Pre-Processing

3.1. Image Acquisition

Using pathological results of a DR image, we can perform various operations for exudates extraction. The basic requirement for our wok is a number of fundus images of varying infected levels of the infection. For this purpose, we use the database which is publically available - DiaRetDB0 and DiaRetDB1. We have used a combination of images from both the database set. The original images consist of true colours of the RGB model with each pixel bearing an 8-bit value.

For our analysis, we segregate images of the obtained database into 3 different categories of color visibility, i.e. light, medium and dark images, as shown in Fig. 4.

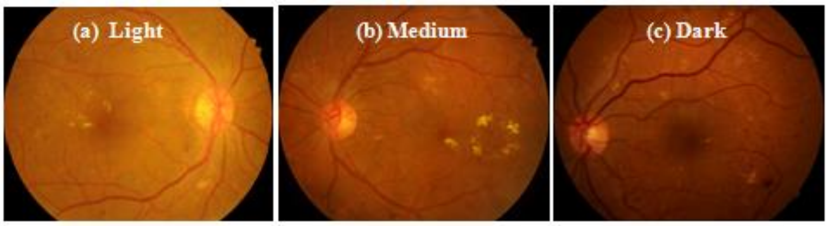
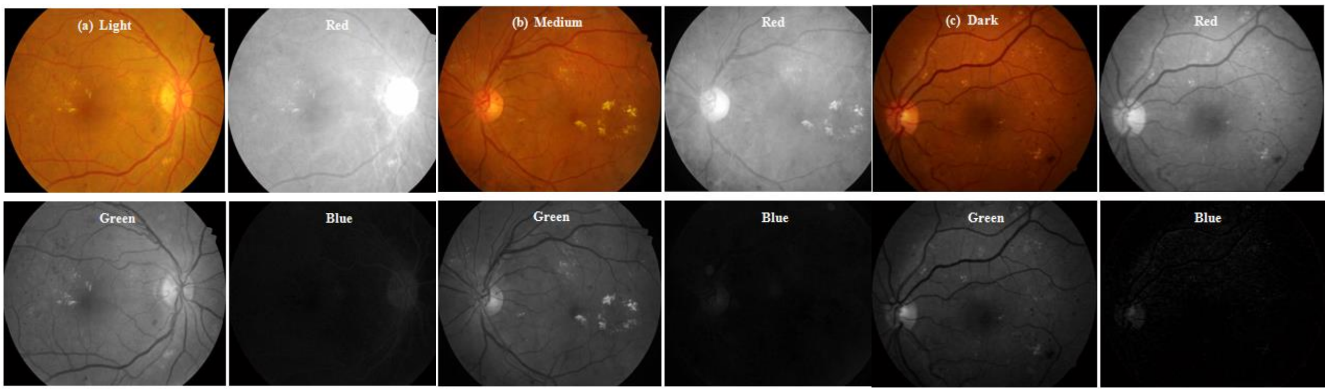


Fig. 4. Fundus images with varying brightness levels

3.2. Selection of Colour Channel

The actual image of the fundus is in the RGB model. Let us for an example consider three different images with varying brightness levels. Let us segregate the true colours i.e red, green and blue, and view them individually so as to know the best colour channel that would give us the best contrast. Every image, with different brightness concentration, is subjected to the true colour separation.



(a) Light contrast (b) Medium contrast (c) Dark contrast

Fig. 5. Fundus images with Red, Green and Blue channel models experimented on varying contrast dataset

From the above images, it is evident that using a green channel filter we can predominantly enhance the contrast of the exudates from that of the background information [3].

3.3. Contrast Enhancement

The next level in the pre-processing involves adjustment of the image intensity as obtained from the contrast channel filtering; in this case, it is the image post green channel. We subject the image to different algorithms wherein we find that the most significant is the Non-Linear Brightness Transformation.

3.3.1. Logarithmic Transform

Log transformation means replacing each pixel value with its logarithm value.

The log transformations can be defined by this formula,

$$s = c \log(r + 1) \tag{1}$$

where ‘s’ and ‘r’ are the pixel values of the output and the input image and ‘c’ is a constant [4].

The value 1 is added to each of the pixel value of the input image because if there is a pixel intensity of 0 in the image, then log (0) is equal to infinity. So 1 is added, to make the minimum value at least 1.

For lower amplitudes of input image the range of gray levels is expanded. For higher amplitudes of input image the range of gray levels is compressed.

3.3.2. Non-Linear Brightness Transformation

In this kind of image processing transform, each output pixel's value depends on the brightness of an image. This algorithm basically plays around with the brightness and contrast of the image. Here, the brighter regions become more bright, and the dark regions become more dark.

3.3.3. Histogram Equalization

Histogram equalization is a method to modify the intensity distribution of a histogram to obtain an adjusted contrast image. Histogram equalization is one of the forms of nonlinear contrast enhancement that is put mostly to use. An equalized histogram will have all pixel values redistributed so that each user defined / specific output gray scale will have an equal number of pixel approximately. The regions bearing the utmost population of brightness values in the histogram will experience and increased contrast. There will be automatic reduction of the contrast too in light or dark regions of the fundus image [5].

3.3.4. Adaptive Histogram Equalization

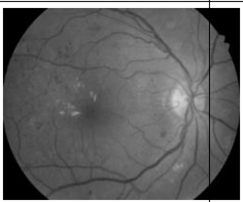
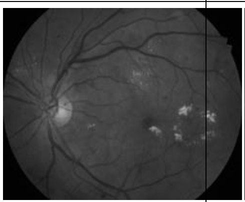
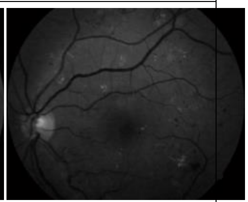
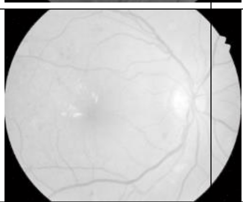
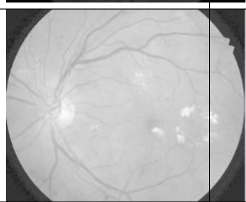
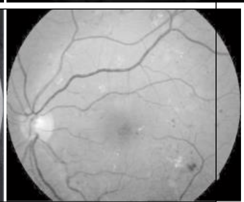
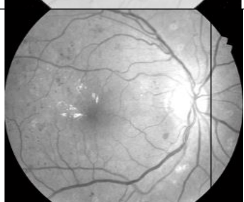
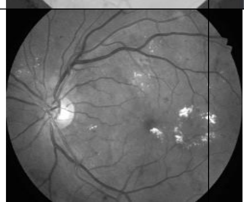
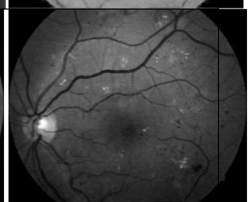
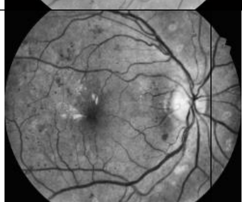
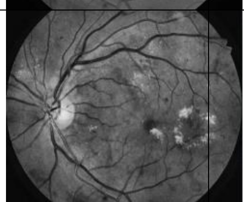
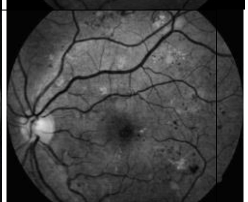
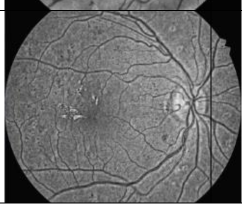
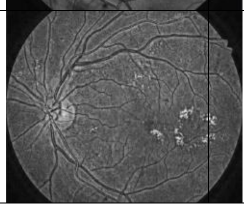
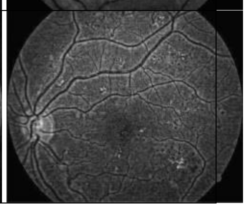
It differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. It is therefore suitable for improving the local contrast and enhancing the definitions of edges in each region of an image [5].

3.3.5. Contrast Adaptive Histogram Equalization

Contrast Limited AHE (CLAHE) differs from adaptive histogram equalization in its contrast limiting. In the case of CLAHE, the contrast limiting procedure is applied to each neighborhood from which a transformation function is derived. CLAHE was developed to prevent the over amplification of noise that adaptive histogram equalization can give rise to [6].

Table 1 shows a comparison of all the images of the various transformation methods performed for the three different brightness modes.

Table 1. A comparative table of different transformation methods on different colour contrast images

Type of Transformation	**Original Colour Contrast of Image**		
	Light	**Medium**	**Dark**
Original Image			
Logarithmic Transformation			
Non-Linear Brightness Transformation			
Adaptive Histogram Equalization			
Contrast Adaptive Histogram Equalization			

4. Segmentation

Segmentation is a process wherein the fundus image is partitioned into specific portions in order to isolate the affected areas of the eye, such as, blood vessels, optic disc, hemorrhage, and exudates. As per the proposed algorithm, segmentation is performed to extract optic disk and exudates.

Previously we have observed that the NLBT has the best transformation image where the exudates, blood vessels, etc. are clearly visible. The proceeding step involves segmentation.

Before we look at a brief of the two methods, let us have an overview of the importance of Threshold of an image. We know that each fundus image is composed of a collection of a number of pixels. Every pixel will have a unique value corresponding to the brightness of that particular image grid. In segmentation, we chose a way to isolate the exudates alone by using the appropriate pixel value.

4.1. Existing Methodologies

There are a few existing algorithms by which can perform segmentation. Few of them are as follows:

4.1.1. Watershed Algorithm

This method is proposed using the morphological information of the fundus image. The idea of this algorithm is to consider the entire fundus image as a mountain consisting of hills and valleys, and flood the entire model by punching a hole at the base of the valley. As a rescue solution, a dam is built. The flooding will lead to a model where aerial view will provide only the dam boundaries, which is nothing but the watershed divided lines [7].

The whole image is divided into small non-overlapping segments. Here, there is a possibility over segmentation. To solve this, an enhanced version of this algorithm was re-modeled to highlight only the watershed marks. This way, the reconstructed grey image conveyed better information of the actual image [8].

4.1.2. Saliency Method

This method determines a threshold value in order to perform the last step of the segmentation. Unique colors in the original fundus images are captured so as to highlight the exudates bearing a greater pixel weight [9].

4.1.3. Using Histogram of Contrast Adjustment Image

Exudate and background pixel intensities are bifurcated into two data sets, wherein, the pixel value of each grid changes to 1 or 0 depending on the average of the two datasets [8].

4.1.4. SWFCM Clustering algorithm

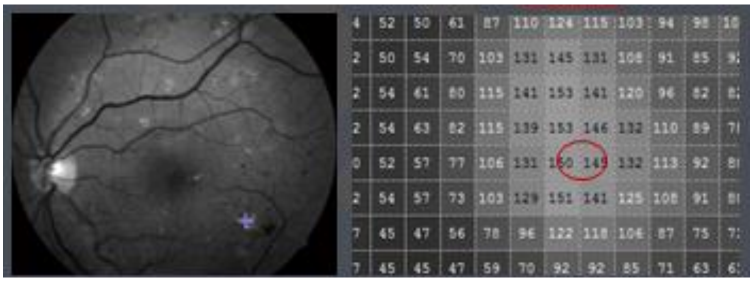
Spatially Weighted Fuzzy c-means clustering method is used which is a more speedy process compared to the existing FCM. Considering the grey image of histogram, the equation of FCM is extended by weighing the neighboring pixels also [8].

4.2. Manual Segmentation

Method

The method that is proposed in this paper is to set the threshold value of the fundus image in a robust and efficient way, such that all the bright areas of the fundus become white, while the rest become dark. Considering all the images in the dataset, the average all the minima intensities of the exudates is considered to be the threshold. Upon application of this threshold, a binary image is finally obtained that highlights the exudates and the optic disk [12]. Furthermore, the obtained optic disk must be eliminated so that only exudates can be further analyzed [13].

(a)

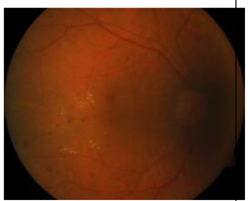
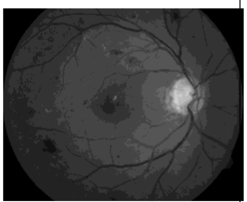
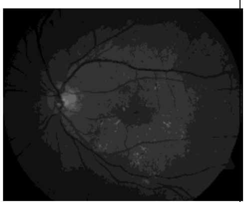
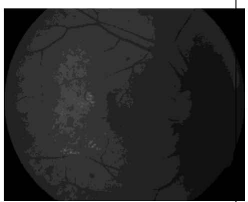
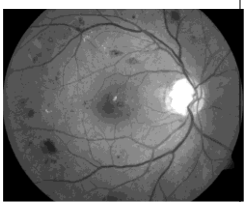
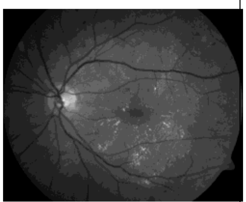
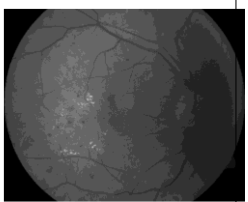


(b)

Fig. 6. (a) shows an RGB DR image after the green channel filter and NLBT (b) shows the pixel grid of a particular area of the exudates pointing out how to spot the minimum pixel value manually

Table 2 shows an image comparison consisting of all the pre-processing steps performed so far.

Table 2. A comparative table of the proposed algorithm

Type of Transformation	Original Colour Contrast of Image		
	Light (Image No. 16)	Medium (Image No. 2)	Dark (Image No. 8)
Original Image in RGB Model			
Green Channel Model			
Non-Linear Brightness Transformation			
Manual Segmentation			

5. Conclusion

In our paper, we have discussed on two different aspects as part of the extraction of optic disk and exudates for an effective data analysis of the DR affected fundus images. For an optimum colour code of the RGB model of the obtained image, we can conclude that the G-image gives the best colour filter out of all the true colours. Compared to other methods discussed previously, NLBT works the best. Also, when segmentation comes into picture, in the proposed methodology, the threshold value of the cumulative dataset of every pixel value in the grid of an exudates image is calculated manually and applied. Though this works for most of the images in the dataset, it must also be noticed that this technique did not work for few images. Hence as future work, other algorithms must be explored that assures nearly 100% of accuracy for the segmentation technique.

References

1. Ravitej Singh Rekhi, Ashish Issac, Malay Kishore Dutta, Carlos M. Travieso, “Automated classification of exudates from digital fundus images”, 2017 IEEE.
2. https://en.wikipedia.org/wiki/Fundus_photography
3. Vasanthi Satyananda, K V Narayanaswamy, Karibasappa, “ Hard Exudate Extraction from Fundus Images using Watershed Transform”, Indonesian Journal of Electrical Engineering and Informatics (IJEEI) Vol. 7, No. 3, Sep 2019, pp. 449~462v.
4. Er. Nancy1 , Er. Sumandeep Kaur, “Comparative Analysis and Implementation of Image Enhancement Techniques Using MATLAB”, IJCSMC, Vol. 2, Issue. 4, April 2013, pg.138 – 145.
5. Mr. Salem Saleh Al-amri1,Dr.N.V.Kalyankar2,Dr.S.D.Khamitkar, “Linear and Non-linear Contrast Enhancement Image”, IJCSNS International Journal of Computer Science and Network Security, VOL.10 No.2, February 2010
6. Ali M. Reza, “Realization of the Contrast Limited Adaptive Histogram Equalization (CLAHE) for Real-Time Image Enhancement”, Journal of VLSI Signal Processing 38, 35–44, 2004.
7. B. Han, "Watershed Segmentation Algorithm Based on Morphological Gradient Reconstruction," 2015 2nd International Conference on Information Science and Control Engineering, Shanghai, 2015, pp. 533-536.
8. Vasanthi Satyananda, K V Narayanaswamy, Karibasappa, “Exudate Extraction from Fundus Images”, 2019 IEEE.
9. N Nur1 and H Tjandrasa, “Exudate Segmentation in Retinal Images of Diabetic Retinopathy Using Saliency Method Based on Region”, MISEIC 2018 IOP Conf. Series: Journal of Physics: Conf. Series 1108 (2018) 012110.
10. Jen Hong Tan, Hamido Fujita, Sobha Sivaprasad , Sulatha V. Bhandary, A. Krishna Rao, Kuang Chua Chua, U. Rajendra Acharya, “Automated segmentation of exudates, haemorrhages, microaneurysms using single convolutional neural network”, 2017 Elsevier Information Sciences 420 (2017) 66–76 .
11. THE INFLUENCE OF ARTIFICIAL INTELLIGENCE WITH THE INTERNET OF THINGS & MACHINE LEARNING IN THIS GROWING WORLD, Prof. Vrushali Dhanokar, Prof. Priyanka Fulsoundar, International Journal Of Advance Research In Science And Engineering http://www.ijarse.com IJARSE, Volume No. 10, Issue No. 01, January 2021 ISSN-2319-8354(E).
12. Aishwarya.K.Dixit and Dr.Parimala Prabhakar “Hard exudate detection using Linear Brightness method”, 2019 4th International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT-2019).
13. S. R. Rupanagudi et al., "Optic Disk Extraction and Hard Exudate Identification in Fundus Images using Computer Vision and Machine Learning," 2021 IEEE 11th Annual Computing and Communication Workshop and Conference (CCWC), 2021, pp. 0655-0661, doi: 10.1109/CCWC51732.2021.9376018.
14. Angadi, Shweta & Bhat, Varsha & R, Pushpalatha & Rupanagudi, Sudhir. (2020), “Exudates Detection in Fundus Image using Image Processing and Linear Regression Algorithm”, 5. 13.