

A New Method of Correcting Uneven Illumination Problem in Fundus Image

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Abstract

Recent advancements in signal and image processing have reduced the time of diagnoses, effort and pressure on the screeners by providing auto diagnostic tools for different diseases. The success rate of these tools greatly depend on the quality of acquired images. Bad image quality can significantly reduce the specificity and the sensitivity which in turn forces screeners back to their tedious job of manual diagnoses. In acquired fundus images, some areas appear to be brighter than the other, that is areas close to the center of the image are always well illuminated, hence appear very bright while areas far from the center are poorly illuminated hence appears to be very dark. Several techniques including the simple thresholding, Naka Rushton (NR) filtering technique and histogram equalization (HE) method have been suggested by various researchers to overcome this problem. However, each of these methods has limitations at their own and hence the need to develop a more robust technique that will provide better performance with greater flexibility. A new method of compensating uneven (irregular) illumination in fundus images termed global-local adaptive histogram equalization using partially-overlapped windows (GLAPOW) is proposed in this paper. The developed algorithm has been tested and the results obtained show superior performance when compared to other known techniques for uneven illumination correction.

Keywords:

Fundus Image, Overlap Technique, Adaptive Histogram Equalization, Median filtering, Windowing.

1. Introduction

Advancements in digital photography, Digital image processing and digital signal processing have opened up new dimensions in the area of medical diagnostic using images. Medical diagnostic are becoming easier by the application of techniques in the aforementioned fields. Lots of diseases are diagnosed nowadays from acquired digital images. A typical example is the diagnoses of diabetic retinopathy (DR) using fundus images. Present day diagnosis of DR involve acquiring retina images using specialized cameras; enhanced the acquired images if needed; Ophthalmologists or trained screeners then screen these images and search for different DR symptoms. Most of the acquired mages usually have severe problem of quality. In ensuring that screeners have

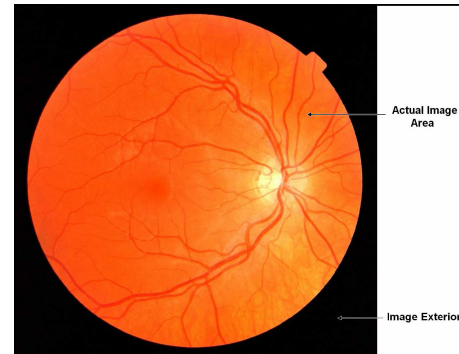


Fig. 1. A typical example of the partial area images, the retina fundus image [10].

good view of the whole, more than the needed number of images are sometimes taken. If there exists some image processing algorithm that can improve and consistently guaranteed good image quality specially the dark areas of the image and could retrieve all the corrupted detail of an image, there will be a drastic reduction in the image storage space requirement because only the sufficient number of images will be saved.

Furthermore, various algorithms have been developed for the automatic diagnoses of different diseases. The effectiveness of which greatly depends on the quality of the acquired input image. Thus, a need to have a good input image or better still a need to enhance the input image before further processing. The reasons for image enhancement after acquisition include; the presence of noise in the acquired images, motion, poor lighting and illumination problems. Uneven illumination is also a very common problem. If a good enhancement algorithm is used the effectiveness of the overall diagnostic system can be greatly improved.

In retina fundus images (FI's) in which the retina information is contained in a circular region within the acquired image template, the outside is noise which fills the whole rectangle outside the retina information. This is as shown in Fig. 1. The outer region is normally referred to as exterior of the image or exterior regions and the images of this type are normally referred to as partial area images. The presence of noise in the exterior region of the acquired image affects the results of obtained when subjecting such an image to illumination balancing algorithms.

In this paper, the solution to the problem of uneven illumination is been proposed. A new algorithm, named Global-Local Adaptive histogram equalization using

Partially-Overlapped Windows (GLAPOW) is been suggested. The algorithm is basically another variant of the adaptive histogram (AHE) used in [1]. During the first stage, the GLAPOW algorithm is applied in small, partially overlapped windows and then a weighted sum of the overlapping values is calculated to find the final values for all the pixels. The overlapped and non-overlapped blocked based AHE's can be considered as the special cases of the GLAPOW. Finally to address the problem of the partial area images which is mentioned earlier and to reduce the effect of exterior noise on the interior of the image some adjustments have been made in the algorithm.

The organization of the paper is as follows; Section. 2 discusses some of the work done in this area, in Section. 3 proposed technique is elaborated following experimental results in Section. 4 and Section. 5 concludes the paper.

2. Related Work

Uneven illumination and poor contrast in digital images are common problems associated with digital image processing. These problems affect the accuracy and effectiveness of any proposed scheme. Real life application of this field include the development of automatic diagnoses of different diseases for medical usage, face recognition system for security identification purpose and video surveillance, all the aforementioned applications strongly depend on the image, video quality and illumination conditions. Some of the related work done by different researchers in solving these problems is discussed in sequel.

Histogram equalization also known as global histogram equalization (GHE) is considered to be a very simple and very efficient way of solving the problem of uneven illumination and contrast enhancement [2], [3]. GHE tries to make the density distribution of the image flat by stretching its dynamic range. In spite of all its advantages, it sometimes suffers from contrast losses in areas with low frequencies of occurrences which in turn makes GHE method impractical for most applications.

Adaptive histogram equalization (AHE) takes care of the local contrast from pixels of neighboring areas. There are lots of variants of AHE method. In general, AHE takes small blocks of the image and updates the central pixel using the histogram of the block as transfer function. The whole image is enhanced by sliding the block over the whole image. There are two major types of AHE, non-overlapped block AHE and overlapped block AHE. The overlapped AHE technique [2], [4] as the name suggests, uses overlapped blocks and gives better results compared to GHE and non-overlapped AHE. High processing power is the main concern associated with this technique which makes it impractical in the real time systems. Another problem is the over enhancement of noise in some image areas which needs noise filtering after enhancement. On the other hand non-overlapped AHE reduces the processing overhead since it uses non-overlapped blocks for histogram equalization. Poor performance compared to overlapped block AHE and the blocking artifacts are the main problems associated with this technique.

A non-linear filter called Naka-Rushton (NR) filter was used in [5] for balancing uneven illumination and getting high contrasts between the background and the foreground of the image. NR filter is based on the following Eq. (1)

$$Y(i, j) = \frac{I(i, j)}{I(i, j) + \mu_{win}} \quad (1)$$

where $Y(i, j)$ is the output pixel at the position (i, j) after filtering, $I(i, j)$ is the original image pixel and μ_{win} is the average of pixels in the chosen window. NR gives poor illumination balancing compare with AHE and sometimes results in the histogram concentration at a single intensity level making further processing of such image difficult.

An approach is proposed in [6] to solve illumination problem in face images. Here, first two enhanced images are created, one using block-based histogram equalization and second using simple histogram equalization. An illumination map is constructed by the pixel-wise difference of these two images. This difference image called illumination map is used to specify the category of the light source. Finally, an image with normal lighting conditions is reconstructed by using lighting model based on the corresponding light source category. A 2D face shape model is used to correct the uneven illumination for the face images. The method improved the results of the image recognition for the principal component analysis (PCA). The method need at least one training image which is not possible in some cases and being specific for face images, the method can not be used for other image classes including medical images.

Another technique used to solve uneven illumination problem is presented in [7] based on mask dodging (MD) principle. The MD technique is used to enhance photographs before printing. This technique is based on the supposition that image taken is an overlap of the original image with ideal conditions and the background image. This background image is considered to have uneven illumination and in turn is the source of all uneven illumination in the image. This model of the uneven illumination phenomenon is depicted in the Eq. (2)

$$I'(i, j) = I(i, j) + B(i, j) \quad (2)$$

where $I'(i, j)$ denotes image which is unevenly illuminated, $I(i, j)$ denotes same image in ideal conditions and $B(i, j)$ denotes background image. To balance the contrast, background image is generated first by low pass filtering the input image and then subtracting this background image from the original input image. One additional step is performed by stretching this subtracted image to compensate the other effects of this subtraction on the contract. This method works well with having some issues one of which is: the method is lacking in the ability to automatically choose the length of the Gaussian filter used to generate background image, giving optimal performance for every input image. Another illumination balancing technique is developed in [8]. This technique intends solving the uneven illumination problem in video presentation systems (VPS) images. The algorithm was first developed for text images and constitutes

the following steps; in the first called sampling gain estimation every line of pixels is divided into sections and in each section the background level is approximated by finding the average of M maximum valued background pixels. The background levels for each pixel are calculated by linearly interpolating these section levels, which in turn provides the light distribution for the whole image. Finally, using the background pixel level information the dark areas becomes bright and the bright areas remain almost the same by choosing different gain factors depending on the original value and the calculated background level for each pixel. This algorithm was then modified for the graphic images due to the fact that graphic images have continuous histogram over the whole range of pixel values which was not the case with the text images where histogram is more concentrated on either close to zero value or to the maximum value. The algorithm is supposed to work better as compared to other existing algorithms for both text and graphic images. But the problem of the partial images still needed to be solved in the algorithm.

3. Proposed Method

The proposed algorithm is described in parts. In sub section 3.1 the general form of GLAPOW is presented and some adjustments are made in sub section 3.2 part to make the algorithm more suitable for FI's.

3.1 Global-Local Adaptive Histogram Equalization using Partially-Overlapped Windows

The GLAPOW is based on the technique used in [1] for AHE. The main objective of this method is to define a point transformation within a local fairly large window with the assumption that the intensity value within it is a stoical representation of local distribution of intensity value of the whole image. The local window is assumed to be unaffected by the gradual variation of intensity between the image centers and edges. The point transformation distribution is localized around the mean intensity of the window and it covers the entire intensity range of the image. Consider a running window W of $N \times N$ pixels centered at the pixel $x(i, j)$, the window is filtered to produced another window Q of the same size as that of W . The transfer function used for this purpose is given in Eq. (3).

$$Q(i, j) = 255 \cdot \frac{\{\Phi(x(i, j)) - \Phi(x_{\min})\}}{\{\Phi(x_{\max}) - \Phi(x_{\min})\}} \quad (3)$$

where $x(i, j)$ is the original pixel value at the position (i, j) , x_{\min} and x_{\max} are the minimum and maximum intensity levels respectively in the whole image, μ_w and σ_w are mean and standard deviation respectively of the chosen window and $\Phi(\cdot)$ can be found using Eq. (4).

$$\Phi(x) = \frac{1}{\left\{1 - \exp\left(\frac{\mu_w - x}{\sigma_w}\right)\right\}} \quad (4)$$

This window is then moved to the next position by step size s and the whole process is repeated till the whole image is

processed. Since the overlapping windows were used, this resulted in multiple values for output pixels at the overlapping positions. The unique output values for all the pixels were calculated by weighted sum of these different values for the same pixels as given in Eq. (5).

$$y(i, j) = \sum_{n=1}^N k_n * x(n) \quad (5)$$

where N is the total number of overlapping windows at position (i, j) , $x(n)$ is the value calculated for pixel $x(i, j)$ in n th window and k_n is the corresponding weight for this value. These weights were calculated according to the position of the considered pixel within the window. If the considered pixel lies in the center of the window, the value calculated for this pixel using this window will have the largest weight and the value calculated for the same pixel using another window where the same pixel lies at the edge of that window, the weighting factor will be the smallest. Any suitable distribution can be used to assign the weights to the different locations within a window. Since the calculation of weights depends on window size, sliding step size and the distribution used for this purpose which makes this weight assignment process complicated. To reduce the complexity and computational load we choose the uniform distribution for this weight assignment. This can be done by choosing equal weights (i.e. $k_n = 1/N$) for all values, making it equivalent to that of calculating the mean of the values calculated for a given pixel in different windows and Eq. (6) can be used instead of Eq. (5) to calculate the output.

$$y(i, j) = \frac{1}{N} \sum_{n=1}^N x(n) \quad (6)$$

This averaging process reduces the over-enhancement of the background pixels caused by the use of small window size, since each pixel value is a result of multiple overlapping windows. This increases the area of the image which affects the resulting value of a single pixel. This is in opposition to most of the AHE algorithms which use a single window for any pixel where it lies in the center of the window.

3.2 Adjustments for Fundus Images

As discussed earlier, only some regions in FI's contain useful information while remaining part called exterior regions only contains noise. When GLAPOW or any other local contrast enhancement algorithm is applied to this type of image, some noise is introduced because of this exterior of the image since. This is because some window contains some of the image area and some part of the image exterior then μ_w and σ_w will be affected by the exterior since these values are calculated for all the window pixels and this in turn affects the output of the algorithm ending up with noise introduced near to the image edges.

To overcome this problem and to minimize this effect, a mask representing the image interior was created and then the values μ_w and σ_w were calculated for every window according to the following criteria.

- 1) If $W \in$ image interior only.

Both μ_w and σ_w are calculated for the whole window pixels.

- 2) If $W \in$ image exterior only.

Both μ_w and σ_w are set to zero and this window is not enhanced.

- 3) If $W \in$ both image interior and exterior.

The values are calculated as follows:

a) if $P_i \leq 0.6 * P_w$, μ_w and σ_w are calculated only for the window pixels which are part of image interior.

b) if $P_i > 0.6 * P_w$, μ_w and σ_w are calculated for the whole window pixels, where P_i is the number of window pixels which belong to the interior of the image and P_w is the total number of pixels in a window.

The two major parameters that affect the quality and computational time of GLAPOW are window size and sliding step size. The use of small windows gives high image quality with increased possibility of over-enhancement of the background information while large windows decrease the over-enhancement possibilities of the background information but with lesser image quality. If window size is equal to the image size, then GLAPOW will be equivalent to GHE. Step size on the other hand controls the blocking effects in the enhanced image and the computational time. Large step size will introduce blocking effects with small computational time while small steps reduce the blocking effects at the cost of increased computational time. For the smallest step size (=1) the algorithm is similar to AHE. In this way GHE and AHE can be considered as the special cases of the GLAPOW algorithm. The algorithm can be customized with the help of above mentioned two parameters to fulfill any type of requirements. For example if high speed with a considerable amount of enhancement is required, medium and large step sizes can be used and for the better enhancement and slow processing needs small step sizes can be used. The GLAPOW was used in the later scenario in [9] where better enhancement quality was emphasized, compromising on the increased computational load.

4. Experimental Results

The proposed algorithm was tested on a small database of 25 FI's of the size 1320x1032 each. The output image obtained by the application of GLAPOW proven to perform better than any of GHE, AHE and Naka Rushton filtering algorithms for enhancement and illumination correction. Two examples are presented here in the Fig. 2 and Fig. 3. In Fig. 2(a) is the input FI and it can be seen clearly that most of the area is very dark and vein network can not be seen clearly, especially the small veins. Fig. 2(b) is the enhanced image using GHE, Fig. 2(c) using AHE, Fig. 2(d) using Naka Rushton filtering and finally Fig. 2(e) is the image created by applying GLAPOW algorithm. Fig. 3 is organized similarly. It can be seen clearly from Fig. 2 and Fig. 3 that GLAPOW performs best among the compared algorithms for enhancement in solving the uneven illumination problem. The contrast enhancement between the background and the

objects (veins and exudates in this case) is the clear gain for GLAPOW.

In a separate evaluation, the resulting output images were made available to 10 different observers, 3 of which are professionals in this field, 9 out of the 10 observers remarked that the image with best clarity is that obtained using GLAPOW.

Conclusion

In this paper, another variant method which involves partial overlap of adaptive histogram equalization data, have been presented. The method is a better compromise between the overlapped and non-overlapped versions of adaptive histogram equalization. The presented method also allow for adaptation for usage in various application by varying the value of the window size and step size. Window size controls the local contrast enhancement between objects and the background and the step size controls blocking effect caused by partial overlapping of windows. The transfer function used in the proposed method uses some of the whole image features to calculate the new histogram for a window in the image which in turn gives rise to the reduction of the over enhancement phenomenon caused by using small number of pixels for histogram equalization. Furthermore the adjustments made for partial area images (e.g. fundus images) are valuable and can be used to avoid the errors introduced by the exterior part of the image and an overall good contrast can be achieved in any type of image.

The application areas of the proposed algorithm include computer aided designs, face detection and the automatic diagnoses systems based on digital images.

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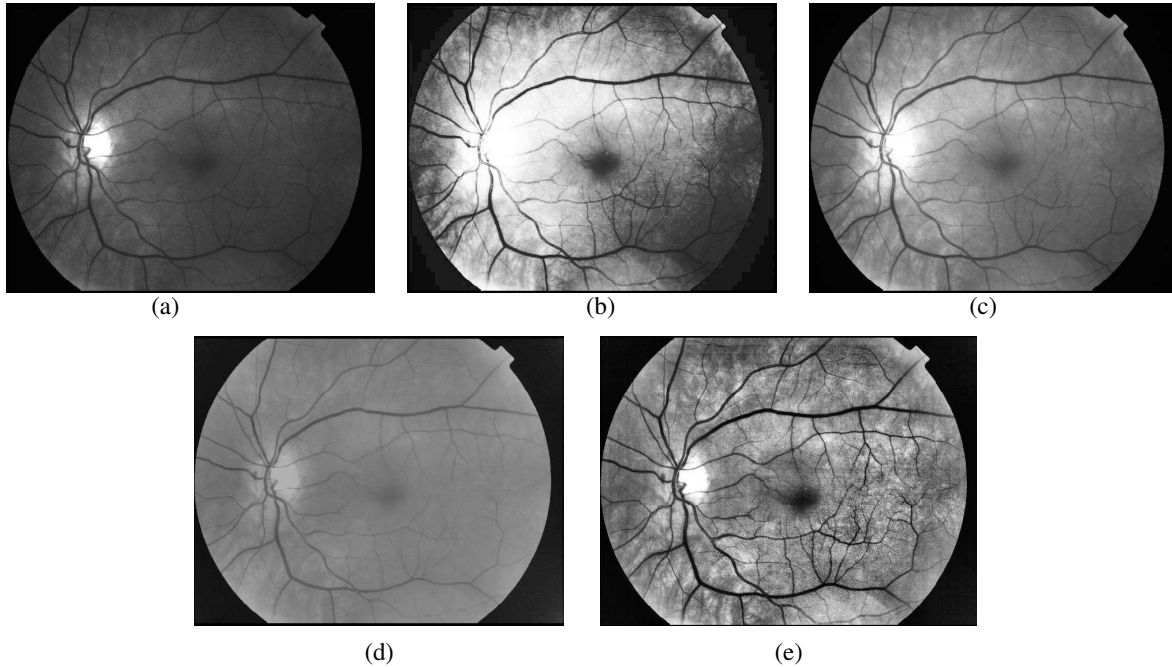


Fig. 2. Comparison among different algorithms (a) input fundus image (b) enhanced image using GHE (c) enhanced image using AHE (d) enhanced image using Naka Rushton Filter and (e) enhanced image using GLAPOW.

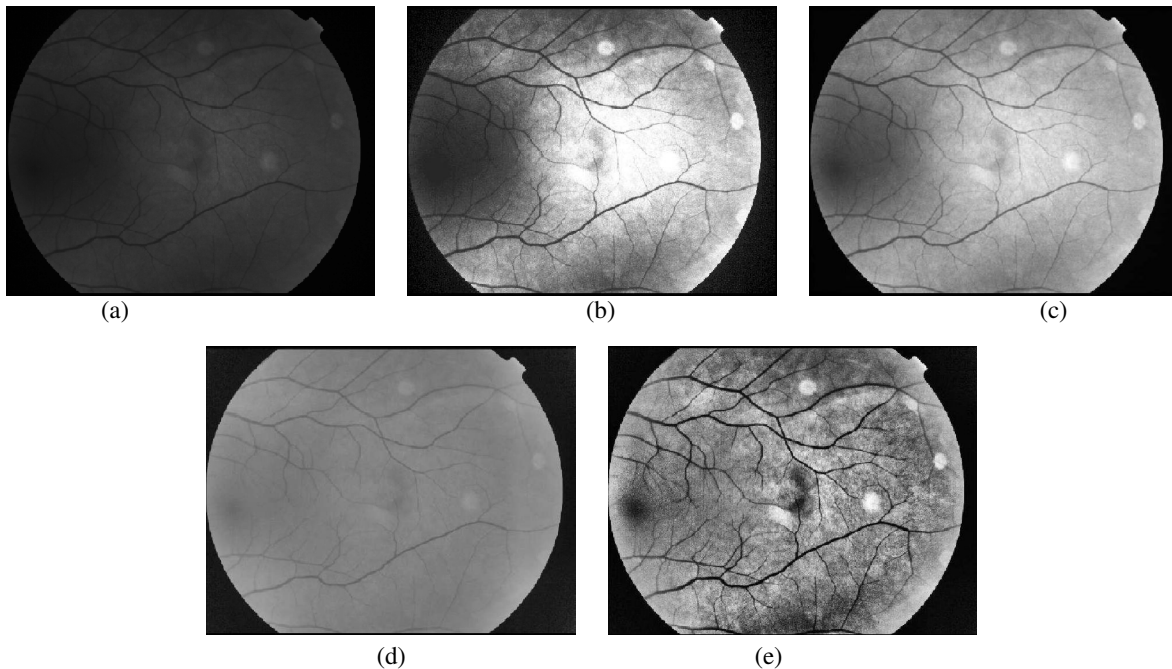


Fig. 3. Comparison among different algorithms (a) input fundus image (b) enhanced image using GHE (c) enhanced image using AHE (d) enhanced image using Naka Rushton Filter and (e) enhanced image using GLAPOW.