Background Detection of Image using Approximation by Block and Opening by Reconstruction Transformation

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ABSTRACT

In this paper, change in the illumination condition of the background due to degraded lightning condition is analyzed and graded based on three methods using Weber's law. We present a comparison of the background using three methods. The first method consist of block by block approximation of the gray scale image, while the second method morphological transformations like morphological opening and closing are carried out which consist of the morphological erosion and dilation to detect the background in the images characterized by poor lighting. Opening by reconstruction is used to obtain the background. The objective of contrast operators are employed to avoid abrupt changes in the intensity within the image. Finally, the performance of all the three methods is compared on the basis of the histogram and their SNR curves plotted for all the three methods. The paper consists of three equations. The equations are based on the Weber's law. By applying these equations, the image background is determined and it is enhanced. And the input and the enhanced image are represented in the graphical form also.

General Terms
Digital image, Image processing, Signal to Noise ratio, Histogram.

Keywords
Contrast enhancement, Image enhancement, Morphological filters by reconstruction, Weber's law.

1. INTRODUCTION

The contrast enhancement problem in digital images can be approached from various methodologies; the key method is the mathematical morphology (MM). Morphology is biological term refers to study of form and structure, in imaging; mathematical morphology refers to a branch of nonlinear image processing and analysis that concentrates on the geometric structure within an image, it is mathematical in the sense that the analysis is based on set theory, topology, lattice, random functions, etc. Mathematical morphology is a branch of image processing that deals with the extraction of image components that are useful in representation and description of region shape, such as boundaries, skeletons and the convex hull. Mathematical morphology is well suited to the processing of elevation data because in morphology, any image is viewed as a topographic surface, the grey level of a pixel standing for its elevation. Hence, mathematical morphological operators are extremely useful and important in DEM analysis.

Mathematical morphology is considered as a powerful tool to extract information from images. Erosion and dilation are considered the primary morphological operations. Erosion shrinks or thins object in a binary image where as Dilation grows or thickens objects. The fundamental morphological operators are discussed in Matheron [3], Serra [4], Soille [5]. Morphological operators generally require two inputs; the input image *A*, which can be in binary or gray scale form, and the kernel *B*, which is used to determine the precise effect of the operator [6]. In spite of morphological contrast being largely studied, there are no methodologies, from the point of view MM, able to normalizing and at the same time enhance the contrast in images with poor lighting. But many methods such as use of non linear functions like log and power functions are used to enhance the dark regions of the image [12]; or employ a homomorphic filter to be manipulated in frequency domain [13]. Otherwise employ an analysis, based on global and local histogram equalization.

Homomorphic filtering is a generalized technique for signal and image processing, involving a nonlinear mapping to a different domain in which linear filter techniques are applied, followed by mapping back to the original domain. Homomorphic filter is sometimes used for image enhancement. It simultaneously normalizes the brightness across an image and increases contrast. Here homomorphic filtering is used to remove multiplicative noise. Illumination and reflectance are not separable, but their approximate locations in the frequency domain may be located. Since illumination and reflectance combine multiplicatively, the components are made additive by taking the logarithm of the image intensity, so that these multiplicative components of the image can be separated linearly in the frequency domain. Illumination variations can be thought of as a multiplicative noise, and can be reduced by filtering in the log domain.

To make the illumination of an image more even, the high-frequency components are increased and low-frequency components are decreased, because the high-frequency components are assumed to represent mostly the reflectance in the scene (the amount of light reflected off the object in the scene), whereas the low-frequency components are assumed to represent mostly the illumination in the scene. That is, high-pass filtering is used to suppress low frequencies and amplify high frequencies, in the log-intensity domain. This method is based on Fourier transform; the image can be enhancing based on value obtained from Fourier transform. But the input image needs some threshold intensity, if not the image will not be enhanced correctly. However the main disadvantage of this method is unnatural level of enhancement and neighbourhood pixel smoothness level is low.

Histogram equalization is a method in image processing of contrast adjustment using the image's histogram. This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values. The most important limitation of histogram equalization is that the global properties of the image cannot be properly applied in a local context, hence causing degradation in the detail preservation of the image, and also over whitening of the enhanced image.

In this paper, comparison of three methodologies to enhance the image background is proposed. The three methods used in this paper are based on approximation to Weber's Law [1], [14]. The first Methodology consists of analysis of the image using block by block approximation. Whereas the second methodology consists of dividing the image into blocks and enhancing based on morphological operations. The last method uses opening by reconstruction.

Finally, this paper is organized as follows. In the next section, we outline each method of enhancement one by one. Section 3 details the experimental procedures used to compare the methods. The results of the experiment are presented in Section 4 and we conclude in Section 5.

2. METHODS

In this section we describe three methods to enhance images with poor lighting. Weber's law approximation was used with each method, by taking the luminance L as the grey level intensity of a function f (image). Thus we get contrast C of an object as:

$$C = k \log f + b \;; f > 0 \qquad (1)$$

Where, k and b are constants, b being the background of the image to be enhanced.

2.1 Block by Block Approximations

In block by block approximation method, the image is first converted into gray scale format. The obtained gray scale image is divided into number of blocks. Each block is a sub image of the original image. Each sub image (block) contains number of pixels that depends on block size. Calculate maximum M_x and minimum m_x pixel values for each block.

Threshold value T_x (background criteria) or average intensity for each block is given by:

$$T_x = \frac{Mx + x}{2} \qquad \forall\, x = 1,2,3,\ldots\ldots\ldots, \qquad (2)$$

Fig.1: represents one dimensional case, and its expression is shown below.

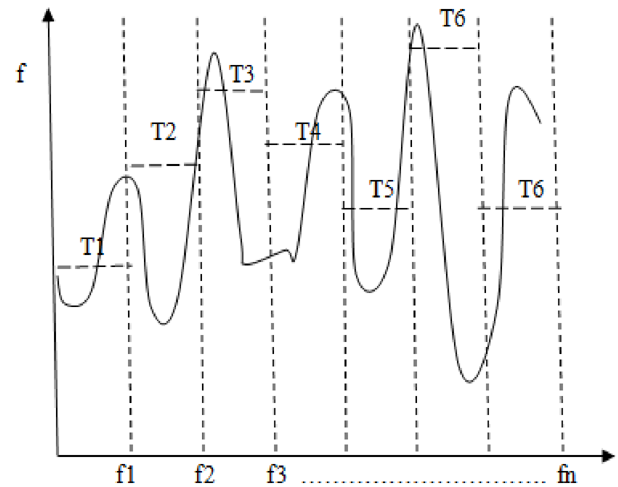

Fig 1: Threshold value obtained by block analysis.

$$T(x) = \begin{cases} T_1 & x \le f_1 \\ T_2 & f_1 < x \le f_2 \\ T_3 & f_2 < x \le f_3 \\ & \\ T_n & f_{n-1} < x \le f_n \end{cases} \qquad (3)$$

The value of Ti represents a border between dark ($f \le Tx$) and light ($f > Tx$) intensity levels. Once Tx is calculated, this value is used to select the background parameter associated with the analyzed block. Then the expression for contrast enhancement is given by:

$$CT_x(f) = \begin{cases} K_x \log(f) + M_x, & f \le T_x \\ K_x \log(f) + m_x, & \text{otherwise} \end{cases} \qquad (4)$$

From (4) it is clear that the background parameter depends on the T_x value. If $f < T_x$ (light region), the background parameter takes the value of the minimum intensity m_x within the analyzed block, and the maximum intensity value M_x otherwise. Since this paper uses only gray scale images, the constant k_x in (4) is obtained as follows:

$$K_x = \frac{\max it -}{\log(\max it + 1)} \qquad \forall\, x = 1,2,\ldots,$$

With

$$m_o = \begin{cases} m_x \;; & f > T_x \\ M_x \;; & f \le T_x \end{cases} \qquad (5)$$

Since gray scale value ranges from 0-255, we take *maxint* as 255 and *minint* as 0. Equation (4) modifies the intensity values depending on certain criterion. The criterion to enhance image in (4) is given by T_x. On the other hand, in this paper, Mi and mi values are used as background parameters to enhance the image depending on the T_x value, due to the background is different for clear and dark regions.

2.2 Morphological Block by Block Approximation

Morphological block by block approximation is another form of previous method. Like block by block approximation, the image is first converted into gray scale format. The obtained gray scale image is divided into number of blocks. Each block is a sub image of the original image. Each sub image (block) contains number of pixels that depends on block size. Instead of Calculating M_i and m_i, here we perform and calculate erosion $\xi_\mu(f)$ and dilation $\delta_\mu(f)$ value for each blocks. So here the average value depends on erosion and dilation.

Threshold value T_x (background criteria) or average intensity for each block is given by:

$$T(x) = \frac{\xi\mu\,(f) + \delta\mu\,(f)}{2} \quad (6)$$

Then the expression for contrast enhancement is given by:

$$CT_x\,(f) = \begin{cases} K_x \log(\,f\,) + \delta_\mu(f), & f \leq T_x \\ K_x \log(\,f\,) + \xi_\mu(f) & \text{, otherwise} \end{cases} \quad (7)$$

And

$$K_x = \frac{255-}{\log(256)} \quad (8)$$

With

$$m_o = \begin{cases} \xi_\mu(f) & ; \; f > T_x \\ \delta\mu(f), & ; \; f \leq T_x \end{cases} \quad (9)$$

The performance of (4) and (7) with different block sizes are shown at the comparison and result section.

2.3. Background Approximation using Opening by Reconstruction

Reconstruction is a morphological transformation involving two images and a structuring element (instead of a single image and structuring element). One image, the marker, is the starting point for the transformation. The other image, the mask, constrains the transformation. The structuring element used defines connectivity. Reconstruction transformation is a useful concept introduced by mathematical morphology for removing the undesirable regions in an image without considerably affecting the remaining structure of the image. In morphological opening, erosion typically removes small objects, and the subsequent dilation tends to restore the shape of the objects that remain. However, the accuracy of this restoration depends on the similarity between the shapes and the structuring element. The method discussed in this section, opening by reconstruction, restores the original shapes of the objects that remain after erosion.

In opening by reconstruction method, the entire image is eroded and diluted number of times that depends on structuring element size μ. Then that value will be subtracted

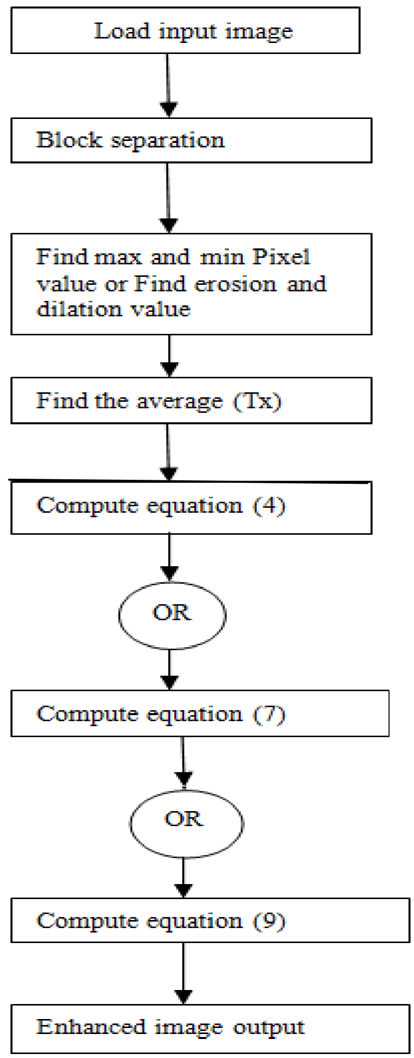

Fig 2: The architecture of the proposed systems

from the original image. The entire image is diluted many times, and that result will be eroded finally, thus we get the threshold or background value:

$$T(x) = \xi_I[\,\delta_\mu(F)]\,(x) \quad (10)$$

Thus the expression for contrast enhancement that is derived from (1) is given by:

$$C_{\delta\mu}(f) = k(x)\log(f) + T(x) \quad (11)$$

And

$$k(x) = \frac{255 - T(x)}{g\ 256} \quad (12)$$

If the threshold image increases, the image tends to become lighter due to the additive effect of the image background. The performance of (8) and (10) with different structuring element size are shown at the comparison and result section. The architecture of the proposed systems is shown in fig.2.

3. COMPARISON OF THE METHODS

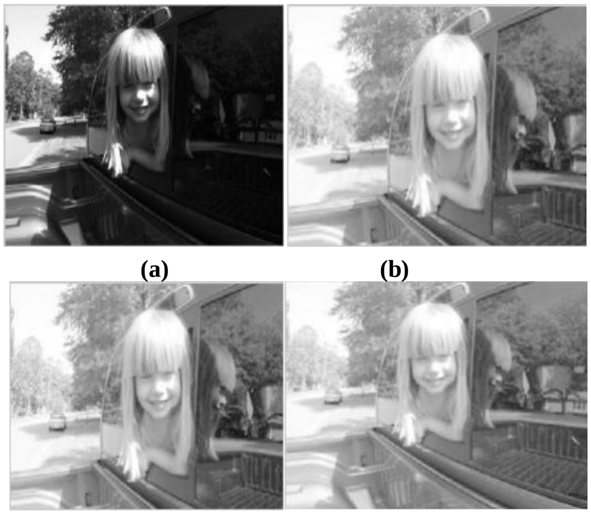

Fig 3: Example of background detection of image with poor lighting using proposed systems. (a) Original image (b), (c) and (d) enhanced image obtained from the application of block by block (equation 4) approximation, morphological block by block (equation 7) approximation and approximation using opening by reconstruction.

The three methodologies used to enhance the image in poor lighting conditions were compared on the basis of the same image given as input to the three algorithms.

With block approximation it was found that as the number of blocks increased, the computation time decreased. But the quality and clarity of the image decreased. This method causes over illumination of the image. Same is the case for morphological block by block approximation. We get a better output if the block size is small, but the computation time will increase. It is also indicated by the SNR curves obtained for different block size. As the number of blocks increases, the SNR decreases with increase in the number of pixel in each block.

Here we need a function that will neither divide the image into blocks nor will it use only erosion or dilation. Because using any one of the morphological operation will generate new contour line when structuring element size is increases. Hence we go for the third method which uses opening by reconstruction.

For the third method as the size of the structuring element increases, the quality of the image decreases. Also this method proves that it is useful for the images that have the shape same as the structuring element, if not the image quality keeps on deteriorating. It is also indicated by the SNR curves obtained for different structuring element size. From the graph itself it is clear that, as the μ size increases the signal level will decrease.

4. EXPERIMENTAL RESULTS

Here we present a summary of the experimental results carried out on the images using the three methods. In block by block approximation, as the no of blocks increases the SNR

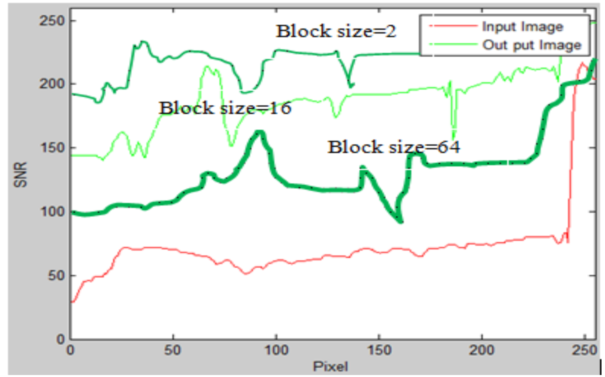

Fig 4: SNR curves (block by block approximation) for different block sizes.

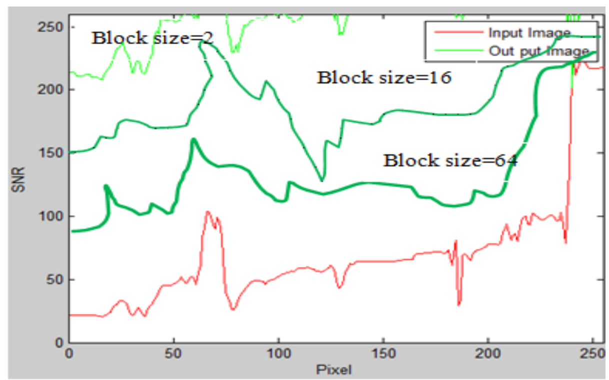

Fig 5: SNR curves (Morphological block by block approximation) for different block sizes.

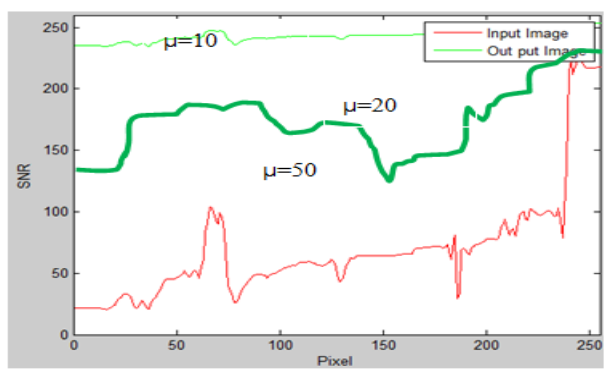

Fig 6: SNR curves (approximation using opening by reconstruction) for different structural element size.

by block approximation to morphological block by block decreases. Also the SNR is improves as we move from block approximation. Also as the no of pixel increases the morphological approximation outperforms the block by block approximation. Opening by reconstruction is a simple method among the three methods used. Here the image is not divided into sub images. Hence the data base needed to store the image is less compared to the other methods discussed in 2.1 and 2.2. For opening by reconstruction high value of SNR is obtained.

Fig 4: and Fig 5: shows SNR curve of block by block approximation and Morphological block by block approximation for different block sizes. Though the increase in SNR level decreases the block size and results in better output, but it also causes increase in the computation time. Fig 7: shows the enhanced image and its corresponding histogram for different block sizes. From the histogram itself it is clear that the output quality is more as block size decreases, i.e.; histogram is more uniformly distributed.

Fig 6: shows the SNR curve of opening by reconstruction for different μ sizes. As the μ size decreases the quality of enhancement is more. Fig 8: shows enhanced image and its corresponding histogram for different μ sizes.

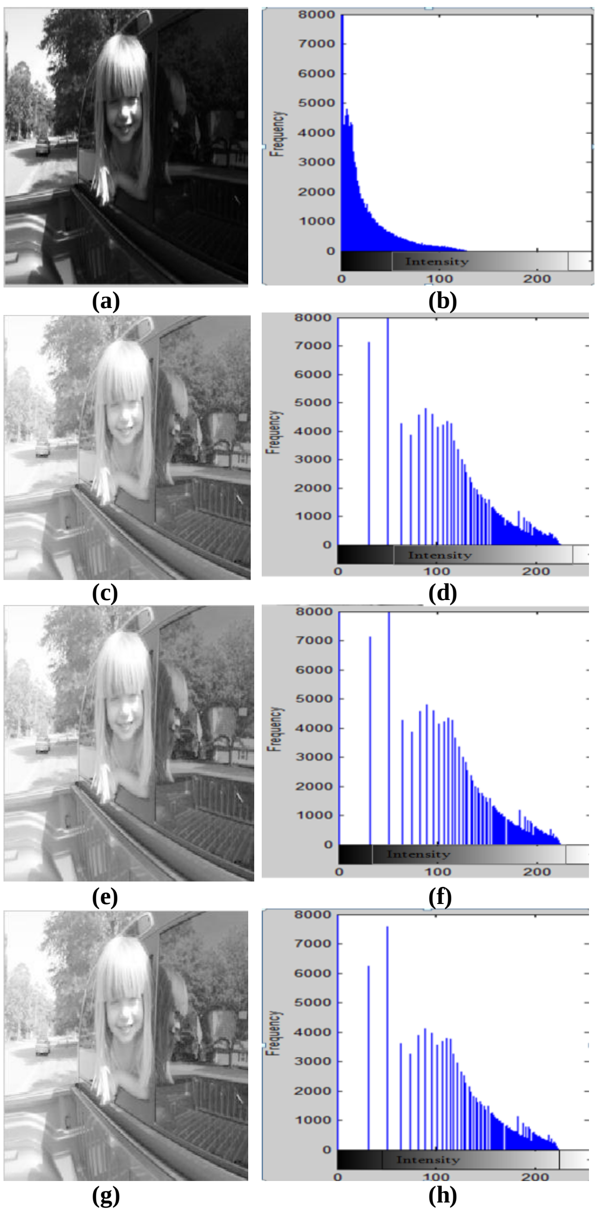

Fig 7: Block by block approximation. (a) Original image, (b) histogram of the image. (c), (e) and (g) enhanced images with Block size= 2, 16, 64 and (d), (f), (h) represents its corresponding histogram.

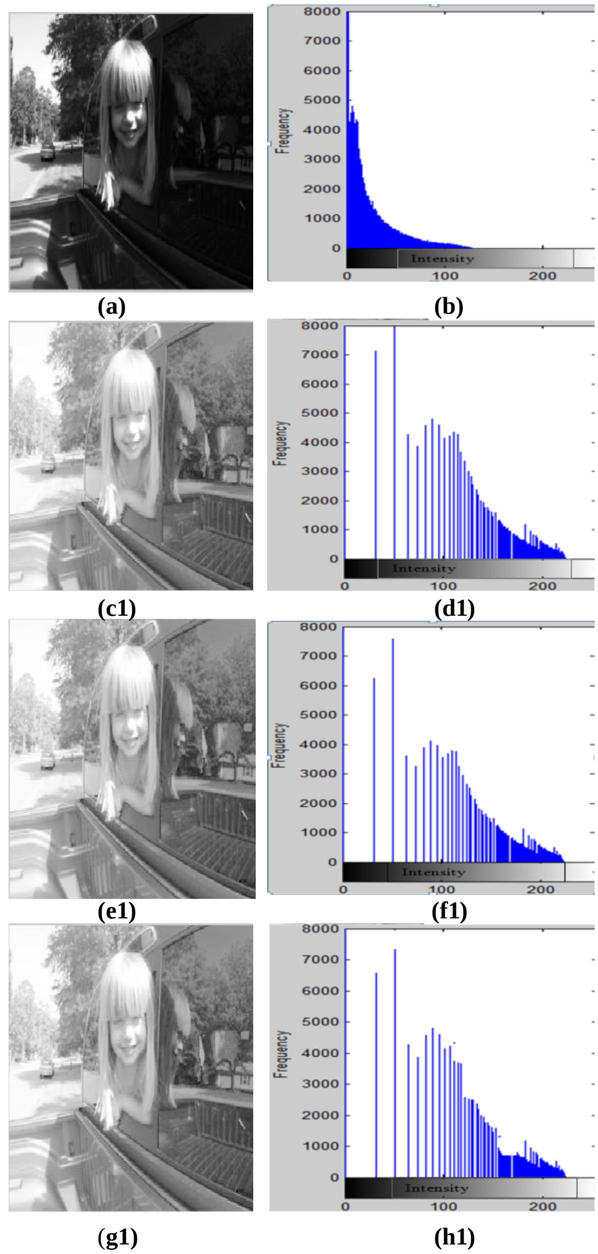

Fig 8: Background approximation using opening by reconstruction. (a) Original image, (b) histogram of the image. (c1), (e1) and (g1) enhanced images with μ= 10, 20, 50 and (d1), (f1), (h1) represents its corresponding histogram.

5. CONCLUSION

This paper presents a study on performance of the three methods employed to enhance the contrast in grey level images with poor illumination. Firstly, a method was incorporated to obtain and approximation to the background using blocks by block approximation of an image which is gray scale. This proposal was then thoroughly extended to using mathematical Morphology operators using block approximation. Also it was extended to opening using reconstruction to

Obtain Morphological connections. All the three methods are based on Weber's law notion. The performances of these methods are illustrated using various examples in the paper. This methodologies can be used only for poor contrast images. The methods may be extended for abrupt changes in illumination.

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