ISSN No. 0976-5697
Volume 5, No. 6, July-August 2014
International Journal of Advanced Research in Computer Science
RESEARCH PAPER
Available Online at www.ijarcs.info

Morphological Contrast Enhancement of Gray Scale and Color Images Based on Weber's Law

[1]Akshay Vartak , [2]Dr. Vijay Mankar
[1]Astt. Prof H.V.P.M.'s C.O.E.T, Amravati, MS, India
[2] Dy. Secretary, R.B.T.E., Pune 29. MS, India

Abstract:- Weber's law suggests a logarithmic relationship between perceptual stimuli and human perception. The Weber sampler is an adaptive, non uniform sampling mechanism that exploits Weber's law to sample the signal at a minimum rate without significant perceptual degradation. In this paper, We apply this fact to design contrast enhancement method for various images that improves local image contrast by controlling the local image gradient. We pose the contrast enhancement as an optimization problem that maximizes the average local contrast of an image strictly constrained by perceptual constraint derived from the Weber law.

In this paper, we introduce Morphological transformation and Block analysis is used to detect the background of various gray level and color images. These techniques are first implemented in gray scale and then extended to color images by individually enhancing the color components. Some morphological transformations are used to detect the background in color images characterized by poor contrast. Contrast operators are based on the logarithm function in a similar way to Weber's law. The use of the logarithm function avoids abrupt changes in lighting. The results of each technique are illustrated for various backgrounds, majority of them in poor lighting condition. The complete image processing is done using JAVA simulation model.

Keywords: Morphological transformation ,Weber's law, contrast enhancement, block analysis, opening by reconstruction.

I. INTRODUCTION

The sensitivity of the human eye to spatially varying contrast is a well-studied problem in the perception literature and has been studied at two levels: threshold and suprathreshold. Threshold contrast sensitivity studies the minimum contrast required for human detection of a pattern, while suprathreshold contrast studies the perceived contrast when it is above the minimum threshold level. These studies show that the contrast sensitivity of humans at suprathreshold levels follows the Weber law. Common techniques for global contrast enhancements, like global stretching and histogram equalization, do not always produce good results, especially for images with large spatial variation in contrast. To address this issue, a large number of local contrast enhancement methods have been proposed that use some form of image segmentation either in the spatial(multi scale) or frequency(multi resolution) domain followed by the application of different contrast enhancement operators on the segments[1][2].

Local contrast enhancement method driven by an objective function that is controlled by a single parameter derived from the suprathreshold contrast sensitivity of the eye. The perception of contrast is directly related to the local luminance difference, i.e., the local luminance gradient at any point in the image. Our goal then is to enhance these gradients. Methods dealing with gradient manipulation need to integrate the gradient field for image reconstruction.

In this work, two methodologies to compute the image background are proposed. Also, some operators to enhance and normalize the contrast in grey level images and color images with poor lighting are introduced. Contrast operators are based on the logarithm function in a similar way to Weber's law. The use of the logarithm function avoids abrupt changes in lighting. Also, two approximations to compute the background in the processed images are proposed. The first proposal consists in an analysis by blocks, whereas in the second proposal, the opening by reconstruction is used given its following properties: a) it passes through regional minima, and b) it merges components of the image without considerably modifying other structures. The proposals given in this paper are illustrated with several examples.

Finally, this paper is organized as follows. Section II, Weber's Law. Section III ,presents morphological Transformations. Section IV, gives experimental result. Finally, conclusions are presented in Section V.

II. WEBER'S LAW

Weber's law expresses a general relationship between a quantity or intensity of something and how much more needs to be added for us to be able to tell that something has been added. Experiments designed to find out such things are called discrimination threshold experiments, because the observer is asked to tell apart, or discriminate, two things that differ by only a slight increment. The discrimination threshold, then, is the smallest detectable increment above whatever the initial intensity was. This general relationship between the initial intensity of something and the smallest detectable increment is exactly what Weber noticed and formalized into Weber's Law. Weber's Law states that the ratio of the increment threshold to the background intensity is a constant. So when you are in a noisy environment you must shout to be heard while a whisper works in a quiet room. And when you measure increment thresholds on various intensity backgrounds, the thresholds increase in proportion to the background.

$$\frac{\Delta I}{I} = k$$

The fraction ΔI/I is known as the Weber fraction (aka Fechner fraction). If we rearrange the equation to ΔI=IK, you can see that Weber's Law predicts a linear relationship between the increment threshold and the background intensity. The discrimination threshold, or the threshold for detecting an increment in the quantity or intensity of something, changes depending on how much there is before we add the increment. Weber's law is a useful way to summarize the relation between the discrimination threshold ΔI and the base intensity I. In general, this relation holds true for many different physical dimensions. If we know that Weber's law holds for two dimensions, we can compare our sensitivity to changes along those dimensions by comparing the Weber fractions. The Weber fraction is often expressed as a percentage. A Weber fraction of 1% indicates a fairly high sensitivity to increments, while a Weber fraction of 15% is rather poor and indicates lower sensitivity to increments. When performing discrimination threshold experiments, the first analysis is often aimed at finding out whether or not Weber's law holds for that set of discriminations. If it does, we then want to find out what the Weber fraction is. Weber's law holds and we know what the Weber fraction is, we can predict what the discrimination threshold should be it's just the Weber fraction times the base intensity. Weber's Law states that the size of the just noticeable difference is a constant proportion of the original stimulus value. It is the minimum amount by which stimulus intensity must be changed in order to produce a noticeable variation in sensory experience[3]-[7].

Weber's law states that, it is the ratio of the difference in maximum to minimum luminance value to the minimum luminance value and it is denoted by C.

$$C = \frac{L_{max} - L_{min}}{L_{min}} \qquad (1)$$

$$\text{If } L = L_{min} \quad \Delta L = L_{max} - L_{min}$$

can be rewritten as

$$C = \frac{\Delta L}{L}$$

This indicates $\Delta(\text{Log L})$ is proportional

to C; therefore,

Weber's law can be expressed as

$$C = k\log L + b \quad L > 0 \qquad (2)$$

Where, k and b are constants, b being the background.

III. MORPHOLOGICALTRANSFORMATIONS

There are two basic morphological operators erosion and dilation. These operators are usually applied in tandem. Opening and closing are two derived operations defined in terms of erosion and dilation. Erosion of a grey-level image F by another structuring element B, denoted $F \ominus B$, is defined as following:

$$F \ominus B\,(m, n) = \min\{F(m + s, n + 1) - B(s, t) \qquad (3)$$

Erosion is a "shrinking" operator in the values of $F \ominus B$ are always less than or equal to the values of F.

Dilation of a grey-level image F by another structuring element B, denoted $F \oplus B$, is defined as following:

$$F \oplus B(m,n) = \max\{F(m+s,n+t)+B(s,t)\} \qquad (4)$$

Dilation is a "expansion" operator in the values of $F \oplus B$ are always larger than or equal to the values of F.

By the erosion and dilation operators defined above, we can detect the edge of image F, denoted by $Ee(F)$, is defined as the difference set of the original image F and the erosion result of F.

This is also known as erosion residue edge detector:

$$E_e\,(F) = F - (F \ominus B) \qquad (5)$$

The edge of image F, denoted by $Ed(F)$, is defined as the difference set of the dilation result of F and the original image F.

This is also known as dilation residue edge detector:

$$E_d\,(F) = (F \oplus B) - F \qquad (6)$$

Opening of a data sequence by a structuring element is defined as erosion followed by dilation. Opening of a grey-level image F by another structuring element B, denoted $F \circ B$, is
defined as following:

$$F \circ B = (F \ominus B) \oplus B \qquad (7)$$

Opening of a data sequence can be interpreted as sliding the structuring element along the data sequence from beneath and the result is the highest points reached by any part of the structuring element[8]. Generally, opening can smooth the sketch of an image, and break narrow gaps. Closing of a data sequence by a structuring element is defined as dilation followed by erosion. Closing of a grey-level image F by another structuring element B, denoted $F \bullet B$, is defined as following:

$$F \bullet B = (F \oplus B) \ominus B \qquad (8)$$

Closing of a data sequence can be interpreted as sliding a "flipped-over" version of the structuring element along the data sequence from above and the result is the lowest points reached by any part of the structuring element. Generally, closing can fuse narrow breaks, fill up small holes, and as well as gaps in the sketch. The opening and closing operations can be used to construct top-hat transformation for enhancing the bright regions or dark regions. White top-hat transformation of image F, denoted as $WTH(F)$, is defined as the difference set of the original image F and the opening result of F that can be formulated as follow:

$$WTH\,(F) = F - (F \circ B) \qquad (9)$$

Black top-hat transformation of image F, denoted as $BTH(F)$, is defined as the difference set of the closing result of F and the original image F, that can be formulated as follow:

$$BTH\,(F) = (F \bullet B) - \text{F} \qquad (10)$$

Moreover, a simple neighborhood-based morphological contrast enhancement operation can be obtained by parallel computing the white and black top-hat of the image F. The white top-hat is then added to the original image F to enhance the bright objects, and the black top-hat is then subtracted from resulting image to enhance the dark objects. We denote the top-hat contrast enhancement operator by $\hat{e}TH$ and can be formulated as follow:

$$k^{TH} = F + WTH\,(F) - \text{BTH}\,(F) \qquad (11)$$

IV. EXPERIMENTAL RESULT

In this work, Morphological Transformation are used to detect background & Contrast Enhancement has been carried out by using Weber's Law. Two methodologies are used to detect background. First is Block analysis and second is Opening by reconstruction. Contrast operator are based on logarithm function similar to Weber's Law, because of logarithmic function avoids abrupt changes in lighting.

On the other hand, throughout the paper, we will use either size 1 or size (u) for the structuring element. Size 1 means a square of 3 x 3 pixels, while size(u) means a square of(2u+1) (2U+1) pixels. For example, if the structuring element is size 3, then the square will be 7 x 7 pixels, to render an analysis of 49 neighboring regions. For any size of the structuring element, the origin is located at its center.

A. Block Analysis:

The method consist in calculating average between smallest & largest regional minima has disadvantage that image background is not detected in local way as result contrast is not correctly enhanced in poor lighting so to compute image background by block analysis is introduced.

In this analysis, first of all an image will be read as input image and divided into several blocks and from each block ,the background will be determined and after applying the Weber's law , an enhanced image will be obtained [9]-[11].

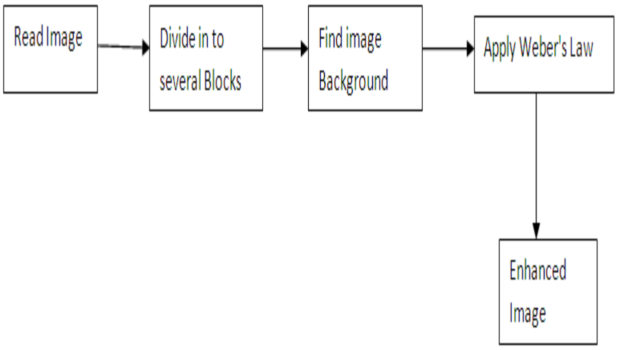


Figure.1. Block diagram of Background Detection by Block Analysis

Let f be the original image which is subdivided into number of blocks with each block is the sub-image of the original image. For each and every block n, the minimum intensity (mi) and maximum intensity (Mi) values are calculated.

For each analyzed block, maximum (M_i) and minimum (m_i) values are used to determine the background criteria T_i in the following way:

$$\tau_i = \frac{m_i + M_i}{2} \qquad \forall i = 1,2,.....n \qquad (12)$$

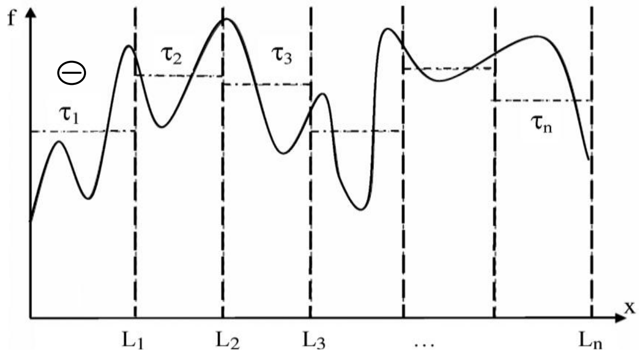


Figure 2. Background criteria obtained by block analysis.

In the 1-D case, as illustrated in Figure 2, the following expression is obtained:

Once T_i is calculated, this value is used to select the background parameter associated with the analyzed block. As follows, an expression to enhance the contrast is proposed:

$$\Gamma\tau_i(f) = \begin{cases} k_i \log(f+1) + M_i, & f \le \tau_i \\ k_i \log(f+1) + m_i, & \text{otherwise} \end{cases} \qquad (13)$$

Note that the background parameter depends on the T_i value. If f<= T_i(dark region), the background parameter takes the value of the maximum intensity(M_i) within the analyzed block, and the minimum intensity(m_i) value otherwise. Also, the unit was added to the logarithm function in above equation to avoid indetermination[12]. On the other hand, since grey level images are used in this work, the constant K_i in above equation is obtained as follows:

$$k_i = \frac{255 - m_i}{\log(256)} \qquad \forall_i = 1,2,....n \qquad (14)$$

$$m_i = \begin{cases} m_i, & f > \tau_i \\ M_i, & f \le \tau_i \end{cases} \qquad (15)$$

On the other hand, M_i and m_i values are used as background parameters to improve the contrast depending on the T_i value, due to the background is different for clear and dark regions. Now an image is formed by applying the equation number 6. Now consider a pixel in this image and the corresponding pixel in original image. Combine them using Weber's law which can be stated as follows. Thus, an enhanced image is formed[13][14].

The more is the number of blocks, the better will be quality of the enhanced image. In the enhanced images, it can be seen that the objects that are not clearly visible in the original image are revealed. As the size of the structuring element increases it is hard to preserve the image as blurring and contouring effects are severe. The results are best obtained by keeping the size of the structuring element as 1 (U=1).

B. Opening by reconstruction:

This method is similar to block analysis in many ways; apart from the fact that the manipulation is done on the image as a whole rather than partitioning it into blocks.

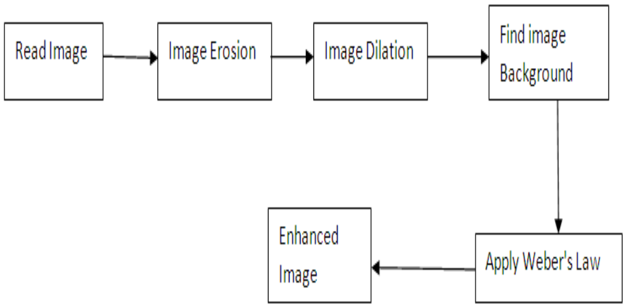


Figure.3. Block diagram of Background Detection by Erosion & Dilation

In a morphological operation, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors. By choosing the size and shape of the neighborhood, a morphological operation can be constructed that is sensitive to specific shapes in the input image. Dilation and erosion are two fundamental morphological operations. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries. The number of pixels added or removed from the objects in an image depends on the size and shape of the structuring element used to process the image. In the morphological dilation and erosion operations, the state of any given pixel in the output image is determined by applying a rule to the corresponding pixel and its neighbors in the input image[15] [16].

In erosion, every object pixel that is touching a background pixel is changed into a background pixel. Dilation adds pixels to the boundaries of objects in an image. In dilation, every background pixel that is touching an object pixel is changed into an object pixel. Note how the function applies the rule to the input pixel's neighborhood and uses the highest value of all the pixels in the neighborhood as the value of the corresponding pixel in the output image.

Let $I_{max}(x)$ and $I_{min}(x)$ be the maximum and minimum intensity values taken from one set of pixels contained in a window (B) of elemental size (3 X 3 elements), x belongs to D. Notice that the window corresponds to the structuring element .A new expression can be derived as shown:

$$\tau(x) = \frac{I_{\min}(x) + I_{\max}(x)}{2} \qquad (16)$$

Where $I_{max}(x)$ and $I_{min}(x)$ values correspond to the morphological dilation and erosion defined by the order-statistical filters. Thus, the above expression is expressed as

$$\tau(x) = \frac{\in_{\mu}(f)(x) + \delta_{\mu}(f)(x)}{2} \qquad (17)$$

Finally the proposed transformation is expressed as

$$\Gamma_{\tau(x)}(f) = \begin{cases} k_{\tau(x)} \log(f+1) + \delta_{\mu}(f)(x), & f \le \tau(x) \\ k_{\tau(x)} \log(f+1) + \in_{\mu}(f)(x), & \text{otherwise} \end{cases}$$

$$\text{and } k_{\tau(x)} = \frac{255 - \tau(x)}{\log(256)} \qquad (18)$$

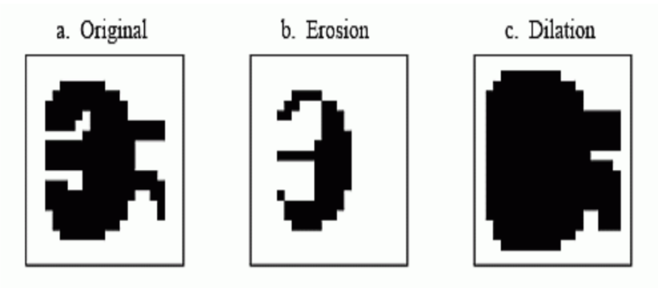


Figure. 4. a) Original Image b) Erosion c) Dilation

By employing Erosion-Dilation method we obtain a better local analysis of the image for detecting the background criteria T(x) than the previously used method of Blocks. This is because the structuring element UB permits the analysis of neighboring pixels at each point in the image. By increasing the size of the structuring element more pixels will be taken into account for finding the background criteria. It can be easily visualized that several characteristics that are not visible at first sight appear in the enhanced images. The trouble with this method is that morphological erosion or dilation when used with large size of U to reveal the background, undesired values maybe generated.

It is desirable to obtain a function that resembles the image background without dividing the original image into blocks, and without using the morphological erosion and dilation, since these morphological transformations generate new contours when the structuring element is increased. This situation is illustrated in Fig. 8. When morphological erosion or dilation are used with large sizes of to reveal the background, inappropriate values may be obtained. However, in MM, there is other class of transformations that allows the filtering of the image without generating new components; these transformations are called transformations by reconstruction. In our case, the opening by reconstruction is our choice because touches the regional minima and merges regional maxima[17][18]. This characteristic allows the modification of the altitude of regional maxima when the size of the structuring element increases. This effect can be used to detect the background criteria (T(x)) in (9), i.e.,

$$\tau(x) = \bar{\gamma}_{\mu B}(f)(x) \qquad (19)$$

Where opening by reconstruction is expressed as

$$\bar{\gamma}_{\mu B}(f)(x) = \lim_{n \to \infty} \delta_f^{\,n}(\varepsilon_{\mu B}(f))(x) \qquad (20)$$

It can be observed from the above equation that opening by reconstruction first erodes the input image and uses it as a marker. Here marker image is defined because this is the image which contains the starting or seed locations. For example, here the eroded image can be used as the marker. Then dilation of the eroded image i.e. marker is performed iteratively until stability is achieved.

Background parameter b (x) is calculated by eroding the above obtained background criterion T (x) which is described below:

$$b(x) = \varepsilon_1[\bar{\gamma}_{\mu}(f)](x) \qquad (21)$$

As it is already mentioned that morphological erosion will generate unnecessary information when the size of the structuring element is increased, in this study, the image background was calculated by choosing the size of the structuring element as unity.

Contrast enhancement is obtained by applying Weber's law as expressed below:

$$\xi_{\bar{\gamma}_{\mu}} = k(x) \log(f+1) + \varepsilon_1[\bar{\gamma}_{\mu}(f)] \qquad (22)$$

$$k(x) = \frac{\max\text{int} - \varepsilon_1[\bar{\gamma}_{\mu}(f)]}{\log(\max\text{int} + 1)} \qquad (23)$$

Where, maxint refers to maximum gray level intensity which is equal to 255. If the intensity of the background increases, the image becomes lighter because of the additive effect of the whiteness (i.e. maximum intensity) of the background. It is to be remembered that it is the objective of opening by reconstruction to preserve the shape of the image components that remain after erosion.

Once the contrast enhancement is implemented in gray scale it is possible to extend them for colour images. It is to be noted that the objective of image enhancement lies not only in enhancing the quality of the image but also in revealing the objects which are not visible in the original image. Firstly spatial domain techniques are considered, and then transform domain. All the above implemented methods in gray scale can be also extended to color images by following a standard procedure.

a. The logical descriptions are given below:

a) Preprocess to get data from image (i.e. color data retrieve of image)
b) Pixelgrabber retrieve image data in 1 D array.
c) R G B component are now separated
d) Converts RGB into Black & White . This data is linear data (1 D data)
e) For image processing ,converts it into 2D
f) For each pixel , gets (Known) min & max value of surrounding pixel.

Meanv= (maxv+minv)/2.0

g) For each pixel , value mv is greater or min
h) If max K=(255-maxv) , If less K=(255-minv)

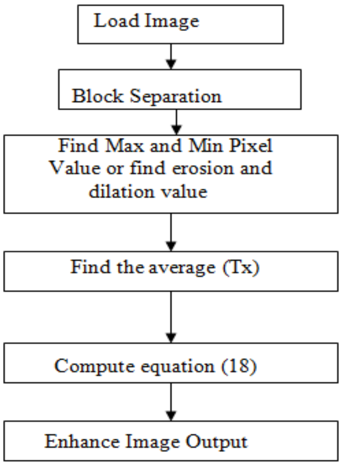


Figure. 4. The architecture of the proposed system

This proposed work can detect the image background also can enhance the contrast in color images with poor lighting. For background detection two methodologies are used. One is image background detection by blocks. Secondly morphological transformations such as opening by reconstruction are used. Morphological contrast enhancement transformations based on Weber's law, which normalize the color image intensities and avoid sudden changes in illumination. Mean filtering is a common image enhancement technique for removing salt and pepper noise. Because this filtering is less sensitive than linear techniques to extreme changes in pixel values, it can remove salt and pepper noise without significantly reducing the sharpness of an image. In this topic, use the contra-Harmonic Mean Filter block to remove salt and pepper noise from an intensity image. This research work will be reducing the time complexity of color image enhancement. Finally calculate the simulation time for each working sector and then compare to existing work. In this way, even though the reported algorithms to compensate changes in lighting are varied, some are more adequate than others. The proposed method for enhancing the various poor lighting images have been implemented using JAVA tool. The result of each method are analysed by using statistical parameter. The detailed descriptions are given below.

b. Proposed segmentation algorithm:

a) Preprocess to get data from image (i.e. color data retrieve of image)
b) Pixelgrabber retrieves image data in 1 D array.
c) R G B component are now separated
d) Converts RGB into Black & White . This data is linear data (1 D data)
e) For image processing ,converts it into 2D
f) For each pixel, gets (Known) min & max value of surrounding pixel.

Meanv= (maxv+minv)/2.0

g) For each pixel, value mv is greater or min
h) f max K= (255-maxv) , If less K=(255-minv)

APPENDIX A

Properties fulfilled by the morphological dilation erosion, and opening by reconstruction [18]

1) $\delta_\mu(f)(x)$, is an extensive transformation i.e. f(x) $\leq \delta(f)(x)$.

2) $\delta_\mu(f)(x)$, is an inextensive transformation i.e. f(x) $\geq \delta(f)(x)$.

3) $\delta_\mu(f)(x)$, and $\varepsilon_\mu(f)(x)$ areincreasing transformations, i.e. given f(x) and g(x) with g(x) □ f(x), then and .

4) Property of the opening by reconstruction $\bar{\gamma}_\mu(f)(x)$

Given $□_1$> 0, □□> 0, with $□_1$<□□ then (19)

Properties of the Operator in (13).

1) It is a nonincreasing transformation. Let f(x) and g(x) be two functions, with g(x) □ f(x). We suppose that the number of blocks n is given and finite, and let i be the ith block. Then

$$m_i(g) \leq m_i(f)$$
$$M_i(g) \leq M_i(f) \qquad (20)$$

So

$$\tau_i(g) = \frac{m_i(g)+M_i(g)}{2} \leq \frac{m_i(f)+M_i(f)}{2} = \tau_i(f) \qquad (21)$$

On the other hand

$$m_i^*(g) \leq m_i^*(f)$$
$$-m_i^*(g) \geq m_i^*(f)$$
$$255 - m_i^*(g) \geq 255 - m_i^*(f)$$

Consequently

$$k_i(g) = \frac{255-m_i^*(g)}{\log(256)} \geq \frac{255-m_i^*(f)}{\log(256)} = k_i(f) \qquad (22)$$

Also, since g □ f, then

g + 1□ f+1

log (g + 1) □ log (f+1)

however, the increasing property for (22) is not satisfied.

2)It is not an idempotent transformation. In fact

$$\Gamma_{\tau i}(\Gamma_{\tau i}(f)) \neq \Gamma_{\tau i}(f)$$

3)It is an extensive transformation. In fact

$$f(x) \leq \Gamma_{\tau 1}(f)(x)$$

Property of the Operation in (15):

1)Multibackground. For all $□_1$> 0, □□> 0,

and $□_1$<□□, □ $\bar{\gamma}_{\mu 1}(f) \geq \bar{\gamma}_{\mu 2}(f)$,

then $\varepsilon_1[\bar{\gamma}_{\mu 1}(f)](x) \geq \varepsilon_1[\bar{\gamma}_{\mu 2}(f)](x)$.

This property may be intuitively derived from (19).

V. CONCLUSION

This paper presents the method to detect the image background and to enhance the contrast in grey scale and color images with poor lighting. First, a methodology was introduced to compute an approximation to the background using blocks analysis. This proposal was subsequently extended using mathematical morphology operators. However, a difficulty was detected when the morphological erosion and dilation were employed, therefore, a new methodology to detect the image background was propounded, that is based on the use of morphological connected transformations.

Also, morphological contrast enhancement transformations were introduced. Such operators are based on Weber's law notion. These contrast transformations are characterized by the normalization of grey level intensities, avoiding abrupt changes in illumination. The performances of the proposals provided in this work were illustrated by means of several examples throughout the paper. Also, the operators performance employed in this paper were compared with others given in the literature. Finally contrast enhancement transformations studied in this paper is that they can only be used satisfactorily in images with poor lighting.

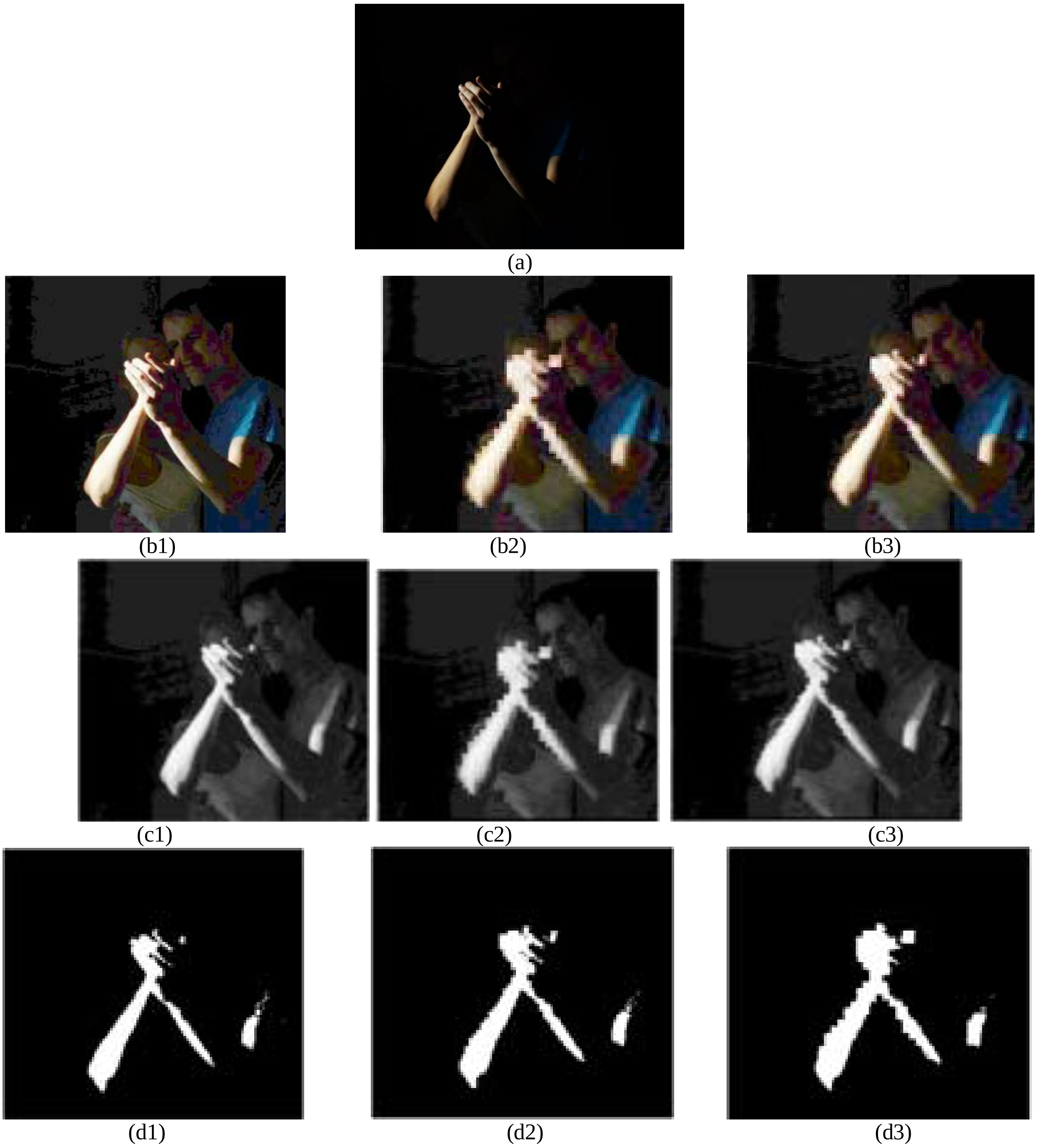
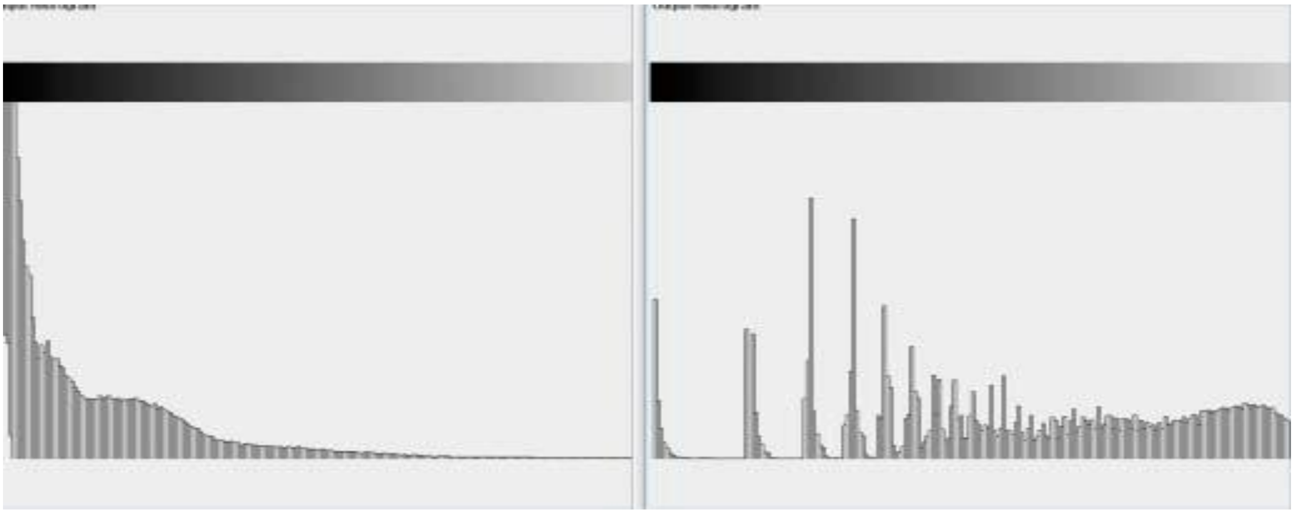


Figure. 5 Image background using the opening by reconstruction with different sizes (a) original image; (b1), (b2), (b3) background images obtained after applying equation (15) with structuring element sizes 10, 30,

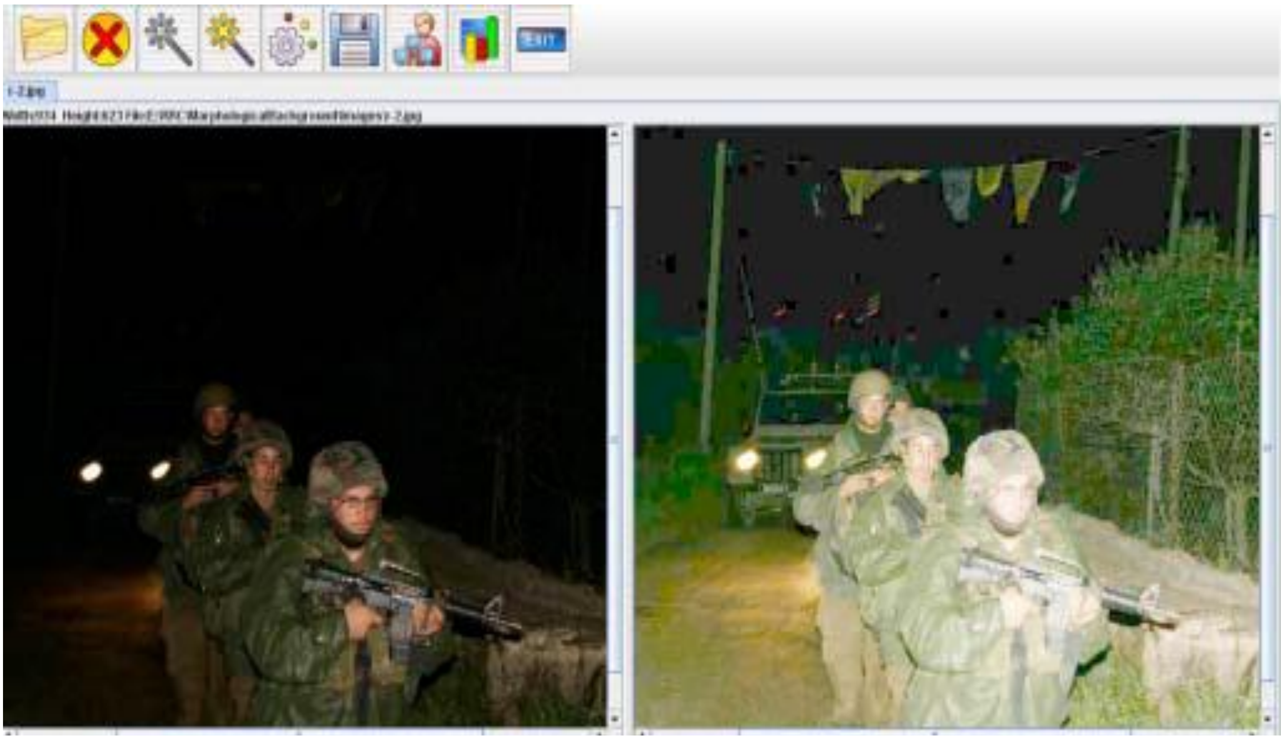
50; (c1), (c2), (c3), (d1), (d2), (d3) enhanced images obtained 10, 30, 50

(a1) (a2)

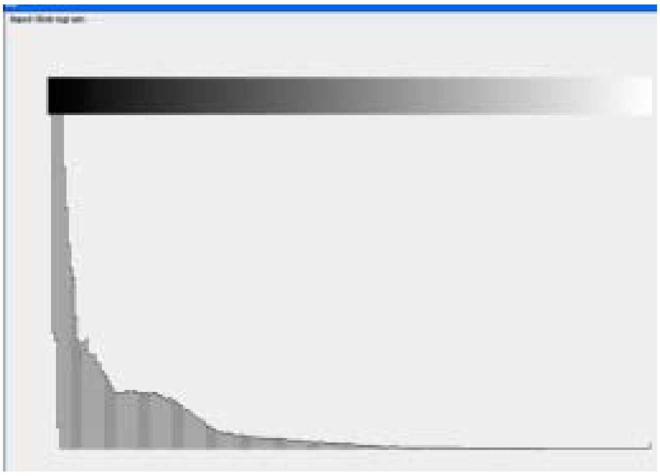


(b1) (b2)

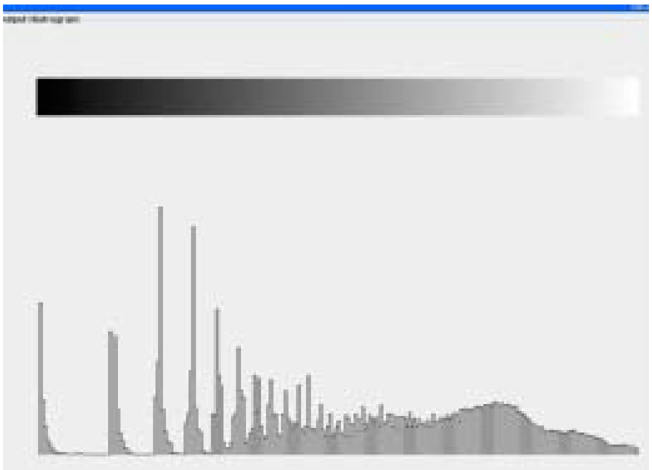
Figure. 6 (a1) Original Gray scale image, (b1) Histogram of Original Image (a2) Enhanced Gray Scale image, (b2) Histogram of enhanced image



(a1) (a2)



(b1)



(b2)

Figure. 7 (a1) Original Color image, (b1) Histogram of Original Image (a2) Enhanced Color image, (b2) Histogram of enhanced image

VI. REFERENCES

[1]. Onkar Dabeer,Subhasis Chaudhuri , “ Analysis of An Adaptive Sampler Based on Weber’s Law",IEEE Transactions on Signal Processing (Impact Factor: 2.81). 05/2011.

[2]. Nagarajan Raju,“A Comparison of Contrast Enhancement Techniques in Poor Illuminated Gray Level and Color Images ”, International Journal of Computer Applications (0975 – 8887)Volume 25– No.2, July 2011

[3]. A.Majumder and S. Irani, “Perception-based contrast enhancement of images,” ACM Trans. Appl. Percpt., 4(3): (2007).

[4]. S. and R. Manavalan , “Analysis of Background Detection and Contrast Enhancement of MRI Images,” International Journal of Computer Applications (0975 – 8887) Volume 36–No.12, December 2011.

[5]. K.Sreedhar and B.Panlal “Enhancement of Images using Morphological Transformation,” International Journal of Computer Science & Information Technology (IJCSIT) Vol 4, No 1, Feb 2012 .

[6]. JianhongShen “Weber’s Law and Weberized TV Restoration,” School of Mathematics University of Minnesota Minneapolis, MN 55455, USA.ÀÛÜ

[7]. A.I. BEENA and B. ARTHI , “Contrast enhancement in gray-scale images using background approximation by blocks and morphological operations,” Oriental Journal of Computer Science& Technology Vol. 3(1), 69-73 (2010).

[8]. Ying-Tung Hsiao, **“**A Contour based Image Segmentation Algorithm using Morphological Edge Detection **,”** in IEEE International Conference on (Volume:3) , 2005 .

[9]. Angélica R. Jiménez-Sánchez, Jorge D.Mendiola-Santibañez, “Morphological Background Detection and enhancement of Images with Poor Lighting,” IEEE Trans. Image Process. 18(3), pp. 613-623 (2009) .

[10]. Soille, P., “Morphological image analysis: principles and applications,” Springer Verlag, Berlin (2003).

[11]. Xinbo Gao,Image, “Quality Assessment Based on Multiscale Geometric Analysis , ” IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 18, NO. 7, JULY 2009.

[12]. Tinu Alexander John , “ Background Detection of Image using Approximation by Block and Opening by Reconstruction Transformation , ” International Conference on Emerging Technology Trends (ICETT) 2011.

[13]. Z. Liu, C. Zhang, and Z. Zhang, “Learning-based perceptual image quality improvement for video conferencing,” presented at the IEEE Int. Conf. Multimedia and Expo (ICME), Beijing, China, Jul. 2007.

[14]. J. Serra and P. Salembier, “Connected operators and pyramids,” presented at the SPIE. Image Algebra and Mathematical Morphology, San Diego, CA, Jul. 1993.

[15]. A. Toet, “Multiscale contrast enhancement with applications to image fusion,” Opt. Eng., vol. 31, no. 5, 1992.

[16]. S. Mukhopadhyay and B. Chanda, “A multiscale morphological approach to local contrast enhancement,” Signal Process. vol. 80, no. 4, pp. 685–696, 2000.

[17]. Erik R. Urbach and Michael H. F. Wilkinson “Efficient 2-D Grayscale Morphological Transformations With Arbitrary Flat Structuring Elements,” IEEE TRANSACTIONS ON Image Processing, VOL. 17, NO. 1, January 2008,

[18]. I. R. Terol-Villalobos, “A multiscale contrast approach on Morphological connected contrast Mappings,” Opt. Eng., vol. 43, no. 7, pp. 1577–1595, 2009.