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A NON-LINEAR TECHNIQUE FOR THE ENHANCEMENT OF EXTREMELY NON-UNIFORM LIGHTING IMAGES

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OLDUKÇA DÜZENSİZ AYDINLATILMALI GÖRÜNTÜLERİN ZENGİNLEŞTİRİLMESİ İÇİN DOĞRUSAL OLMAYAN BİR TEKNİK

ÖZET
Özellikle gece koşullarında ve düzensiz aydınlatılmış ortamlarda, zayıf ışık altındaki düşük yoğunluklu alanlar ve aşırı ışık altındaki yüksek yoğunluklu alanlar rahatlıkla görülemez. Oldukça zayıf aydınlatılmış ortamlardaki görüntülerin bilgilerini kurtarmak amacı ile bir çok görüntü zenginleştirme tekniği geliştirilmiştir. Bunlar arasında piksel karekteristiklerinin tümleşik komşuluk ilişkilerine dayalı ve ışık yoğunluğu-yansıtırlık modeline dayalı görüntü zenginleştirme teknikleri, düzensiz ve zayıf aydınlatmalı ortamlarda çekilen sayısal görüntülerin görsel kalitesini artırmakta iyi sonuçlar verir. Buna rağmen oldukça düzensiz aydınlatmalı ortamlarda elde edilen görüntülerde istenen sonucu veremezler. Bu makalede, oldukça düzensiz aydınlatmalı ortamlarda çekilen görüntülerin zenginleştirilmesi amacı ile Çok Pencereli Ters Sigmoid (Multiple Windowed Inverse Sigmoid - MWIS) adı verilen yeni bir doğrusal olmayan görüntü zenginleştirme tekniği önerilmiştir. Önerilen teknik ışık yoğunluğu-yansıtırlık özelliğini koruyarak parlak alanları sıkıştırma aynı zamanda karanlık alanları zenginleştirme yeteneğine sahiptir. Yapılan deneylerde, önerilen tekniğin oldukça düzensiz aydınlatmalı ortamlarda çekilen görüntülerde görsel olarak uygun sonuçlar verdiği gözlemlenmiştir. Ayrıca bu yeni tekniğin hava kuvvetleri faaliyetleri kapsamında elde edilen gece ve düzensiz aydınlatmalı görüntülerin görsel kalitesinin geliştirilmesinde yararlı olabileceği değerlendirilmiştir.

Anahtar Kelimeler: *Görüntü işleme, görüntü zenginleştirme, görüntü dönüşümü, kontrast zenginleştirme.*

ABSTRACT
At night scenes and under nonuniform lighting conditions, either the low intensity areas or the high intensity areas cannot be clearly seen. Various image processing techniques have been developed to recover the meaningful information under extremely low lighting conditions. Among these, the algorithms based on integrated neighborhood dependency of pixel characteristics and based on the illuminance reflectance model perform well for improving the visual quality of digital images captured under nonuniform and extremely low lighting conditions. But, they cannot perform well in extremely nonuniform lighting conditions. In this paper, a new nonlinear image enhancement algorithm, named Multiple Windowed Inverse Sigmoid (MWIS), is proposed for enhancing images captured in extremely non-uniform lighting environments. The proposed algorithm is capable of compressing bright regions and at the same time enhancing dark regions by preserving the main structure of the illuminance-reflectance modality. It is observed that the proposed algorithm yields visually optimal results on images captured under extreme lighting conditions. Also, it is envisaged that the new technique would be useful for improving the visibility of scenes of air force night time and nonuniform lighting activities.
Keywords: *Image processing, image enhancement, image transformation, contrast enhancement.*

1. INTRODUCTION

A human observer can clearly see individual objects both in the sunlight and shadowed areas, since the eye locally adapts while scanning the different regions of the scene. In human vision, first, the size of pupil adopts to accommodate different levels of radiance from different regions in a scene. When starting at a highly bright region in the scene, the pupil will shrink to compress the dynamic range. So, the eyes can deal with the dynamic range. Second, the major dynamic range compression process is taking place via the lateral processing at the retinal level. Finally, the early visual cortex is also found participating in some of the dynamic range processing [1].

When attempting to display the image on a display, either the low intensity areas, which are underexposed, or the high intensity areas, which are overexposed, cannot be seen. To handle this problem, various image processing techniques have been developed. Some of them are simple methods such as histogram equalization, gamma adjustment, logarithmic compression and levels/curves method. These techniques are usually based on global processing, so they have some limitations such as loosing of some features during processing, not enhancing of some features sufficiently. So, to obtain better performance, more advanced image enhancement techniques have been developed such as Adaptive Histogram Equalization (AHE) [2], Contrast-limiting AHE (CLAHE) [3] and Retinex [4-6].

Generally, these techniques enhance image contrast well. They are particularly good in improving images of scenes where there is a wide range of scene brightness, as for example when strong highlights and deep shadows appear in the same image in daylight. Although these techniques perform well in daylight, they cannot perform well in overexposed images under dark environment such as night driving, night landing and night security images.

In this paper, We address the problem of rendering images, which are captured extremely non-uniform lighting conditions. So, by taking inspiration from two existing image enhancement algorithms called AINDANE (Adaptive Integrated Neighborhood Dependent Approach for Nonlinear Enhancement of Color Images) [7] and IRME (An Illuminance-Reflectance Model For Nonlinear Enhancement Algorithm) [8], a new nonlinear image enhancement algorithm, named Multiple Windowed Inverse Sigmoid (MWIS), for the enhancement of the images captured in extremely non-uniform lighting conditions is proposed.

In the remainder of the paper, first, related work in image enhancement techniques is briefly reviewed. Then the details of the MWIS algorithm will be introduced. Finally, the image enhancement results are discussed and compared with those of citied techniques.

2. RELATED WORK

The retinex theory was thought as an idea by E. Land as a model of lightness and color perception of human vision system [4-6]. Land's theory is based on computing the product of the ratios between pixels value along a set of paths in the image and after that Land developed the concept of walk computation to a center/surround spatially opponent operation form. Land's theory accomplishes two of the utilities of a lightness-color constancy algorithm for machine vision [5-6]. These are; (i) dynamic range compression, (ii) color independence from the spectral distribution of the scene illuminant. According to [9], Land's theory does not accomplish the other utility i.e. color and lightness rendition.

MSRCR [9-12] is proposed by Z.Rahman et al. It is a retinex-based algorithm using logarithmic compression and spatial convolution to implement the idea of retinex. It aims to synthesizing local contrast enhancement, color constancy and lightness/color rendition for digital color image enhancement. In MSRCR, the chromatics of the original image are used to restore the color which stands in direct contrast to the color constancy objectives of the Retinex. It was found that the stronger the color restoration, the weaker the color constancy. An investigation about retinex [13] claimed that the color restoration function changes image chromatics in an unpredictable fashion. Thus, it would be nice to get the dynamic range compression and the contrast enhancement of the retinex while at the same time keeping the chromatics of the original image.

INDANE [14] is an algorithm to improve the visual quality of digital images captured under extremely low or uniform lightening conditions. It consists of two main parts: Luminance enhancement and contrast enhancement. Luminance enhancement is an intensity transformation with a nonlinear transfer function. This transfer function while compresses the dynamic range, at the same time enhances the dark valued pixel. Contrast enhancement tunes the intensity of each pixel based on its relative magnitude with respect to the neighboring pixels. After, luminance enhancement, the contrast of the luminance-enhanced image is degraded, so the contrast enhancement is applied. Rather than global contrast enhancement technique, a surrounding pixel (neighborhood)-dependent contrast enhancement technique is implemented. Because, the normal global contrast enhancement techniques simply increases the luminance for bright pictures, and decreases the luminance for dark pictures. So, the dynamic range can be significantly increased and the fine details do not bring out.

AINDANE [7] algorithm is adaptive version of INDANE algorithm. As INDANE, AINDANE algorithm consists of two main parts: Adaptive luminance enhancement and adaptive contrast enhancement. Adaptive luminance enhancement is an intensity transformation with a nonlinear, self-tuned by the histogram statistics of the input image. During intensity transformation, the luminance of the dark pixels is increased and the image is compressed dynamic range at the same time. Adaptive contrast enhancement, which is adaptively controlled by the global statistics of the image, tunes the intensity of each pixel based on its relative magnitude with respect to the neighboring pixels.

IRME [8] is an algorithm that is based on a physical description of the creation of radiance map of real world scene. It divides the object radiance into two parts: illumination and reflectance. We can describe illumination as the light intensity incident on object surface and reflectance as the light refection properties of the object surface. This separation provides a method to process images for the purpose of obtaining an improved visual perception of those scenes. In this algorithm, it is assumed that the illumination, *L(x,y),* is contained in the low frequency components of the image and the reflectance, *R(x,y),* is contained in the high frequency components of the image. In real world, the dynamic range of the illumination variation can be several orders larger than the dynamic range of the reflectance. Therefore, in this algorithm while the dynamic range of the illumination part of the image compresses, the dynamic range of the reflectance part of the image does not compresses.

3. MWIS ALGORITHM

MWIS is composed of three main parts: adaptive intensity enhancement, contrast enhancement and color restoration. The structure of MWIS is illustrated in Figure 1.

A. Adaptive Intensity Enhancement

First step of the adaptive intensity enhancement is to obtain the intensity image, *I(x,y)* , using NTSC color space. Intensity values of RGB image can be obtained as

$$I(x, y) = 0.2989 \times R + 0.587 \times G + 0.114 \times B \qquad (1)$$

where *R,G,B* are the red, green, blue components for color images in RGB space.

First assumption to estimate the illumination is that an image may be characterized by two components [15]: (1) the amount of source illumination incident on the scene being viewed. (2) the amount of illumination reflected by the objects in the scene. These are called the illumination and reflectance components and denoted by *L(x,y)* and *R(x,y),* respectively. The two functions combine as a product to form an image:

$$I(x, y) = R(x, y).L(x, y) \qquad (2)$$

In such a combination, it is possible to control independently the illumination and the reflectance components. Thus, it is possible to modify the dynamic range of the illumination without any modification in the details.

Second assumption is the illumination included in the low frequency components of the image and the reflectance illustrates the high frequency components of the image. The reflectance is generally varies much faster than illumination in most region of the image except sudden change of illumination.

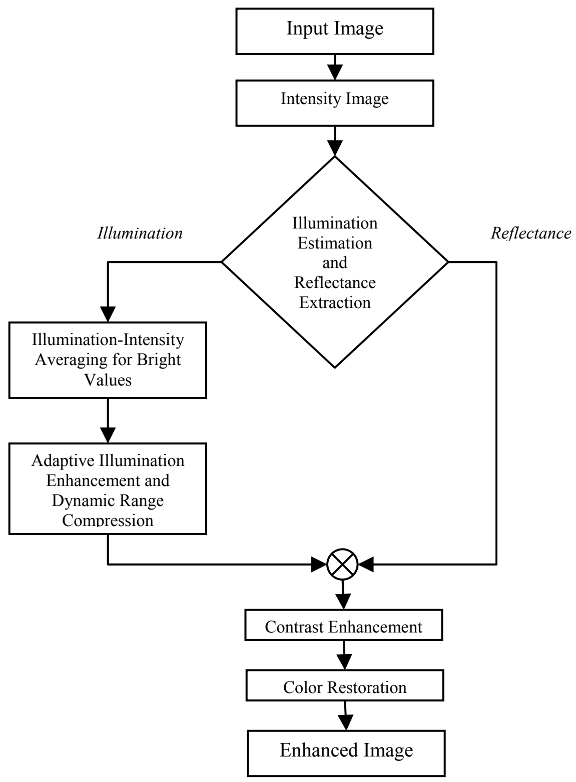


Figure 1. Structure of MWIS algorithm.

The estimation of the illumination from a given image is known to be a mathematically ill-posed problem. In order to handle this problem, an additional assumption is required. This assumption is that spatially smooth parts of the intensity, *I*, originated from the illumination image, whereas edges in the intensity are due to the reflectance in the image. In the algorithm, as the estimation of the illumination, the Gaussian low-pass filtered result of the intensity image is used. In spatial domain, this process is a 2D discrete convolution with a Gaussian kernel which can be expressed as

$$L(x, y) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I(m, n) F(m + x, n + y) \qquad (3)$$

where F is the 2D Gaussian function with size M×N and can be defined as

$$F(x,y) = K \exp\left(-\frac{(x+y)^2}{c^2} \right) \quad (4)$$

where K is determined by $\sum_x \sum_y F(x,y) = 1$

and c is the size of the neighborhood and $c = 5$ is used in this algorithm.

The estimated illumination, which is obtained in previous section is based on the fact that the illumination changes quite smoothly in the parts of the image illuminated from the same luminous source, but however, it can also present abrupt variation when the scene is illuminated by different light sources in the case of background lights. To reduce the influence of neighbor areas whose luminance produces a high contrast, which would lead to artifacts, a weighted averaging method is preferred for bright pixels. So, the illumination estimation: for less than 80% of the highest gray scale value (i.e. 255 for 8-bit image) is the illumination which is obtained in Equation (3) and for the other gray scale values, it is a weighted averaging of illumination and intensity values, which decreases the contribution of the illumination linearly as the value of the gray scale increases. This averaging can be mathematically expressed as for 8-bit image.

$$L'(x,y) = \frac{I(x,y) - 204}{51} I(x,y) + \left(1 - \frac{I(x,y) - 204}{51} \right) L(x,y) \quad (5)$$

After obtaining new illumination estimation, the reflectance estimation can be obtained by Equation (2).Before treating by enhancement process the new illumination values $L'(x,y)$ is normalized to the range [0 10] using Equation (6)

$$L''(x,y) = \frac{L'(x,y)}{25.5} \quad (6)$$

for 8-bit depth images.

Then normalized illumination values are treated by an enhancement and compression process to improve the illumination values of low-illumination (dark) pixels, and meanwhile to reduce the illumination values of high-illumination (bright) pixels using a specifically designed nonlinear multiple windowed inverse sigmoid (MWIS) transfer function. This process also normalizes the illumination values to the range [0 1] at the same time. This transfer function can be defined as

$$L''_{enh} = \frac{1}{1+e^{(-\alpha \times L'')}} + \frac{1}{1+e^{(-\beta \times (L''-10))}} - 0.5 \quad (7)$$

where α is a parameter to adjust the curve for dark pixels and β is a parameter to adjust the curve for bright pixels. This transfer function is the sum of two inverse sigmoid functions and 0.5 is used to shift down the transfer function.

The parameters, α and β, are used to tune the curve shapes of the first and second sigmoid functions respectively. Generally, some image statistics such as global mean or global standard deviation are used for adaptiveness of the image. But, the image under consideration consists of underexposed and also overexposed regions. To implement these image statistics will misguide. Therefore, these image statistics cannot be implemented to this image. To set the adaptiveness of MWIS transfer function, intensity image is divided into subimages. The sizes of the subimages are determined based on the image enhancement experiments and can be expressed as

$$m = 0.0625 \times M$$
$$n = 0.0625 \times N \quad (8)$$

where m and n are the size of the subimage, M and N are the size of the intensity image. The size of the subimage is 16×16 for a 256×256 intensity image, 32×32 for a 512×512 intensity image.

After constructing subimages we determine the parameters, α and β, based on the mean of the darkest and the brightest subimages respectively. The relationship between parameters and means of the subimages is determined based on large number of image enhancement experiments and evaluation by using statistical methods proposed by Jabson *et al.* [16]. For this adaptive algorithm the parameters can be expressed as

$$\alpha = \frac{21.4242 - 3 \times \sqrt{L_{m\_\min}}}{7.14.14} + 0.5 \quad for \quad 0 \le L_{m\_\min} \le 51$$
$$\alpha = 0.5 \quad for \quad 51 < L_{m\_\min} \le 255 \quad (9)$$

$$\beta = \frac{21.4242 - 3 \times \sqrt{1 - L_{m\_\max}}}{7.14.14} + 0.5 \quad for \quad 204 \le L_{m\_\max} \le 255$$
$$\beta = 0.5 \quad for \quad 0 \le L_{m\_\min} < 204 \quad (10)$$

for 8- bit images, where $L_{m\_\min}$ is the mean of the darkest subimage and $L_{m\_\max}$ is the mean of the brightest subimage.

According to the Equations (9) and (10) ;
If $L_{m\_\min}$ is 0, α is 3.5 (maximum curvature).
If $L_{m\_\min}$ is between 0 and 51, α is nonlinearly adjusting between 0.5 and 7.5.
If $L_{m\_\min}$ is between 51 and 255, α is 0.5 (minimum curvature).
If $L_{m\_\max}$ is 255, β is 7.5 (maximum curvature).

If $L_{m\_\max}$ is between 204 and 255, β is nonlinearly adjusting between 0.5 and 3.5.

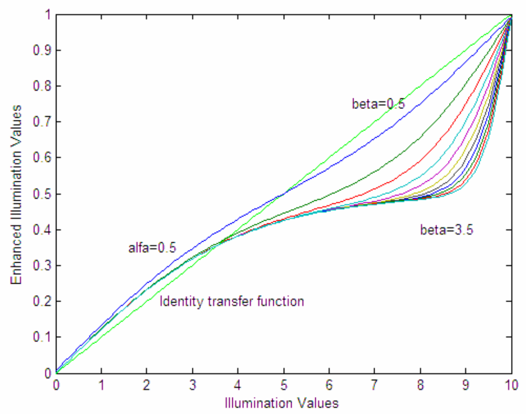
If $L_{m\_\max}$ is between 0 and 204, β is 0.5 (minimum curvature).

A set of various curve shapes of WIS transfer function is provided in Figure 2 with different α and β values in Equations (9) and (10).

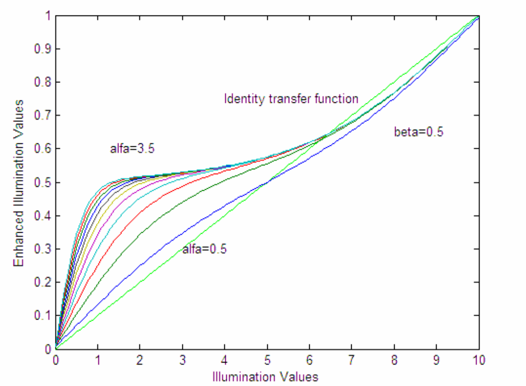
Obviously, if the image does not have very dark and bright regions (i.e. $\alpha = 0.5$ and $\beta = 0.5$), MWIS transfer function will have the shape of almost an identity transfer function as seen in Figure 2. Therefore, the pixels are only normalized to the range [0 1] with a small changing.

MWIS transfer function is used to pull up the illumination of underexposed pixels and to pull down the illumination of overexposed pixels; meanwhile all pixels are normalized to the range [0 1]. Therefore, dynamic range compression of the illumination is realized.

After obtaining illumination enhancement, there are two ways to apply contrast enhancement. First one is as in IRME, computing the reflectance using Equation (3-2) and after contrast enhancement of illumination, to combine the illumination and reflectance using the same equation. Second is combining the illumination and reflectance before contrast enhancement and then applying contrast enhancement. In MWIS algorithm, the second method is used. By this way, the visually significant image features (high frequency components) are combined with enhanced illumination and this combination provides to process not only illumination component, but also reflectance component during contrast enhancement. This combination also provides to spread out the pixels that have been gathered about the threshold point during illumination enhancement process.



(a) MWIS transfer function with $\alpha = 0.5$



(b) MWIS transfer function with $\beta = 0.5$

Figure 2. A set of various curves of MWIS transfer function.

This process can be summarized as rejoining through a multiplication in order to obtain enhanced intensity image and can be expressed as

$$I_{enh}(x, y) = L''_{enh}(x, y)R(x, y) \tag{11}$$

During this process, a few number of bright pixels which are surrounded by dark pixels leave out the range [0 1]. So, they are simply clipped.

B. Contrast Enhancement

In enhancement process, the contrast of the image is degraded, so the appearance of the image is grayed out. In order to improve the overall quality of the images, contrast enhancement process must be applied to restore or even higher than that of the original image. The conventional global contrast enhancement methods simply increase the intensity for bright pixels and decrease the intensity for the dark pixels [7]. This process is the opposite of the required process for our image. Increase in the intensity for bright pixels and decrease in the intensity for the dark pixels can result with significant expanded dynamic range. From the other point of view, these methods have limited performance for bringing out fine details where adjacent pixels have small intensity differences about threshold point after intensity enhancement process. Therefore, it is needed to implement a surrounding pixel (neighborhood)-dependent contrast enhancement technique. A surrounding pixel-dependent contrast enhancement technique might supply sufficient contrast, even higher than that of the original image, and maintaining the dynamic range compression that was set in the previous step. This adaptive process must be based on the intensity information of the processed (center) pixel and its surrounding pixels.

After illumination enhancement process, some pixels, which values close to the threshold point, had very small intensity differences with their adjacent pixels. These differences are elevated combining illumination and reflectance of the image, but this elevation was not sufficient. With surrounding pixel-dependent contrast enhancement technique, pixels with the same intensity may have different outputs depending on their surrounding pixels. For example, considering two pixels in which one of them is surrounded by darker, the other is surrounded by brighter pixels, while the pixel, which is surrounded by darker, will be boosted, the other will be lowered. By this way, image contrast and fine details can be enhanced.

In the MWIS algorithm, the contrast enhancement process, which was used in AINDANE and IRME, is implemented due to its high quality contrast process and control in the dynamic range expansion.

In the algorithm, to obtain the intensity information of surrounding pixels, 2D discrete spatial convolution with a Gaussian kernel as explained in Equations (3) and (4) is used.

After obtaining surrounding intensity information, it is compared with the intensity value of the center pixel. The result is used to identify the value of corresponding enhanced intensity pixel, $I_{enh}(x, y)$, which was obtained in previous part. These two process can be defined as

$$S(x, y) = 255 \times I_{enh}(x, y)^{E(x,y)} \qquad (12)$$

where $S(x, y)$ is the pixel intensity value after contrast enhancement and $E(x, y)$ is the ratio of the surrounding intensity information over input image,

$$E(x, y) = \left[\frac{I_{conv}(x, y)}{I(x, y)}\right]^{P} \qquad (13)$$

In this way, if the center pixel's intensity is higher than the average intensity of surrounding pixels, the corresponding pixel on the intensity-enhanced image, $I_{enh}(x, y)$, will be pulled up, otherwise it will be pulled down. In fact, this process is an intensity transformation process. Considering the enhanced-intensity pixels are in the range [0 1] and the power of these pixels as in Figure 3;

(1) If $E(x, y)$ is less than 1, $I_{enh}(x, y)^{E(x,y)}$ will be larger than $I_{enh}(x, y)$. (i.e. the center pixel is brighter than the surrounding pixels)

(2) If $E(x, y)$ is much than 1, $I_{enh}(x, y)^{E(x,y)}$ will be smaller than $I_{enh}(x, y)$.(i.e. the center pixel is darker than the surrounding pixels)

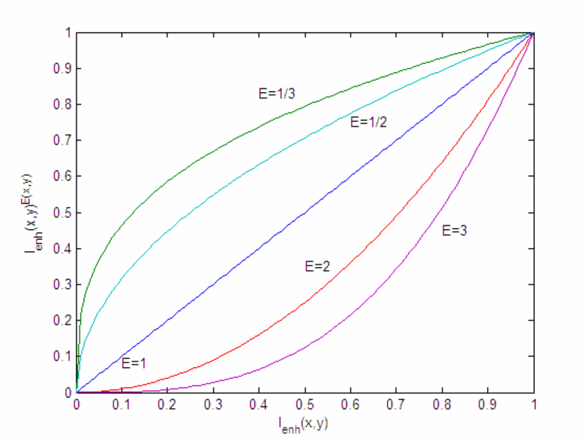


Figure 3. Intensity transformation for contrast enhancement.

In AINDANE and IRME, the parameter, *P*, is used to tune the contrast enhancement process based on the global standard deviation of the input intensity image. As pointed out before, in the interest image is overexposed and underexposed regions are in the same image. Therefore, global standard deviation cannot be considered as an indication for this type of images. In the algorithm, *P = 1* gives the best results. Also, it can be adjusted manually based on the interested image. If the contrast is very poor in dark or bright areas, it may be larger than 1, and if the contrast is sufficient, it may be a less than 1.

In case of better results in visibility at the expense of loosing some details, multiple convolution results are necessary in order to achieve a graceful balance between dynamic range compression and tonal rendition. Then, in the contrast enhancement process, it can be preferred to use linear combination of multiple convolution results using different scales. Generally, enhancement with a small scale (i.e. a few neighboring pixels can provide intensity information of about the nearest neighborhood pixel) convolution tends to enhance local contrast or fine details and enhancement with a large scale (i.e. large number of neighboring pixels can provide intensity information of the entire image) convolution can provide a global tonality, smooth and natural looking close to the original image. A medium scale can provide a mixture of both details and image rendition. Obviously, convolution with multiple scales can yield more complete information on the image's intensity distribution, and hence lead to more balanced image enhancement. However, in the extremely high contrast image, the influences of the dark and bright pixels to each other may be very much and the image may be composed of many detailed dark regions and bright regions. Also, large neighboring may expand the dynamic range for bright regions, which was set in the intensity enhancement part of the algorithm. Therefore, in the algorithm $c = 5$ is used.

The contrast enhancement with multiscale convolutions can be described by the following equations:

$$F_i(x,y) = K \exp\left(-\frac{(x+y)^2}{c_i^2}\right) \tag{14}$$

$$I_{conv,i}(x,y) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I(m,n) F_i(m+x, n+y) \tag{15}$$

$$S_i(x,y) = 255 I_{enh}^{E_i(x,y)} \tag{16}$$

$$S(x,y) = \sum_i w_i S_i(x,y) \tag{17}$$

where c_i $(i = 1,2,3,..)$ determines different scales and w_i is the weight factor for each contrast enhancement output. By default, $w_i = 1/n$, (n is the number of the scales).

C. Color Restoration

The human visual system has a complex nonlinear mechanism that determines the perceived color by spatial comparisons of color signals across the scene. Therefore, it is a complex problem for digital vision. To deal with this problem various color restoration methods exist. They involve strong assumptions, such as constant illumination, that are in general, unsatisfied in complex environments.

In the MWIS algorithm, among the basic linear and nonlinear approaches for color consistency, a basic linear color restoration process based on the chromatic information of the input image is applied. This process can be expressed as

$$S_j(x,y) = S(x,y) \frac{I_j(x,y)}{I(x,y)} \tag{18}$$

where j represents red, green, blue spectral band.

4. EXPERIMENTAL RESULTS AND DISCUSSION

MWIS algorithm was applied to enhance various number of images for performance evaluation and comparison with the other algorithms.

In MWIS algorithm, estimated illumination was averaged with the intensity for bright pixels to abstain from the effect of the sudden change of illumination. Figure 4 illustrates the effects of sudden change of illumination.

The original image is illustrated in Figure 4(a), it is overexposed and some details cannot be seen clearly. The image in Figure 4(b), is obtained by enhancing the estimated illumination of the image. Although, it is enhanced, obvious halo effect is observed around the characters and also the image is blurred. The image enhanced with illumination-intensity averaging is well obtained without producing severe halo effect in Figure 4(c). The detail parts, which cannot be seen in the original image, are clearly observed and read.

(a) Original image

(b) Enhanced image with illumination estimation

(c) Enhanced image with illumination-intensity averaging

Figure 4. Effects of sudden change of illumination.

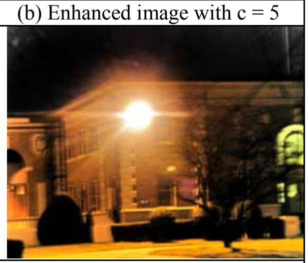
The proposed algorithm was tested with single convolution results to obtain detailed images due to the goal of the algorithm. In Figure 5, the contrast enhancement results performed with various scales are illustrated.

The original image (Figure 5(a)) composed of some underexposed regions (upper and lower part of the image) and overexposed regions (middle part of the image). The enhancement result with a small convolution scale (c = 5) is illustrated in Figure 5(b). While the fine details enhanced well, there is a lack of global tonality. The Figure 5(d) shows the enhanced image with a large convolution scale (c = 220).

(a) Original image

(b) Enhanced image with c = 5

(c) Enhanced image with c = 80



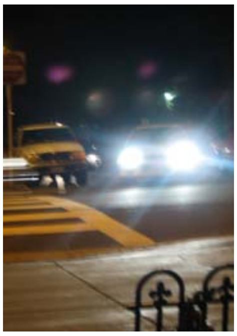
(d) Enhanced image with c = 220

Figure 5. Comparison of the enhancement results with different convolution scale.

The enhanced image has a global tonality closing to the original image for smooth and natural looking results, but the detailed parts (the upper and lower part of the image) cannot be seen clearly. A medium scale (c = 80), provided a mixture of details as illustrated in Figure 5(c). And Figure 5(e) illustrates the enhanced image with multiple convolution scales ($c_1 = 5$, $c_2 = 80$, $c_3 = 120$). The multi scale convolutions produced more balanced image, since they supply more complete information on the image's intensity distribution.

P is another parameter used for contrast enhancement in the algorithm. It can be used for low contrast images to increase the good visual effect of the image. In AINDANE and IRME, this parameter is an image-dependent parameter based on the global standard deviation. In the MWIS algorithm, this parameter cannot be used as an adaptive control parameter due to interest image characteristics. Therefore, it is used to adjust the contrast manually for specific usage.

The image in Figure 6(a) has poor contrast for dark regions. Although, the standard deviations for local dark regions are less than 5, those of the regions near the headlight are more than 50. So, the global standard deviation misguides the algorithm.



(a) Original image

(b) Enhanced image with P = 0.5

(c) Enhanced image with P = 1

(d) Enhanced image with P = 2

Figure 6. Comparison of the enhancement results with different "P" values.

The image in Figure 6 illustrates the effect of the parameter P on the image enhancement. Figure 6(b) is the result of the image enhancement with P = 0.5. After enhancement, the dark regions (the left car and the road) do not have sufficient contrast. Figure 6(c) illustrates the enhancement result with P = 1. The contrast of the dark regions is more sufficient than Figure 6(a). The desired contrast for dark regions can be obtained with P = 2 (Figure 6(d)), but the effect of the headlights which were treated in Figure 6(b) and 6(c) tends to brighten as original image.

The MWIS algorithm has several advantages over MSRCR in terms of flexibility in algorithm tuning, since it shares certain similarities with AINDANE and IRME. But the main beneficial point of the MWIS algorithm over MSRCR, LDNE, AINDANE and IRME is enhancing the overexposed regions. The algorithm compared with these algorithms on the interest image. In Figure 7, a sample image provided for comparison among the performance of the MSRCR, AINDANE, and IRME.

The original image in Figure 7(a), has some overexposed regions near the lamp and some dark regions at the corners. These regions need to enhance. The enhancement result with MSRCR introduced unnatural color or artifacts in dark areas as illustrated in Figure 7(b). Also, the bright region near to lamp still cannot be seen. It can be observed that the images processed with AINDANE (Figure 7(c)) and IRME (Figure 7(d)) have a higher visual quality than those processed by MSRCR.

(a) Original image

(b) Enhanced image with MSRCR

(c) Enhanced image with AINDANE

(d) Enhanced image with IRME

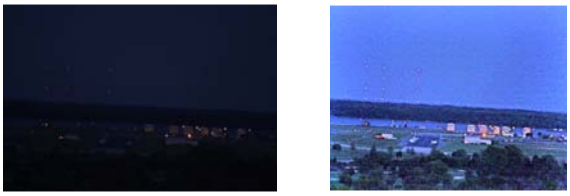
(e) Enhanced image with MWIS algorithm

Figure 7. Comparison of the performance of different enhancement algorithms.

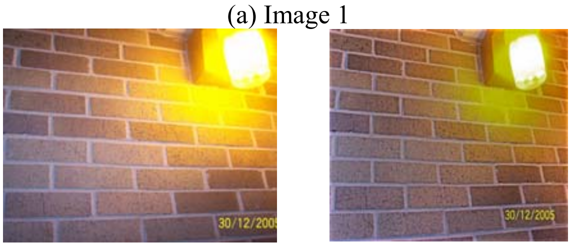
They yield higher color accuracy and a better balance between the luminance and the contrast across the whole image. But, they are not sufficient to enhance overexposed regions. The result of the proposed algorithm is illustrated in Figure 7(e). The algorithm produced sufficient luminance enhancement in both dark and bright regions and also demonstrate high contrast, since it has flexibility and adaptiveness of AINDANE and IRME.

The original images and enhanced images by the algorithm were evaluated using the statistical method [16] proposed by Jobson *et al*. This statistical method is a connection between the numerical and the visual representations. The method is based on some combination of high regional visual lightness and the contrast. For regional statistics, the images were divided into non-overlapping blocks with size 16×16. To measure the quantitative evaluation of the algorithm, a large number of images are tested over this statistical method. The evaluation of six original images and their corresponding enhanced images with MWIS algorithm in Figure 8 are plotted in Figure 9.

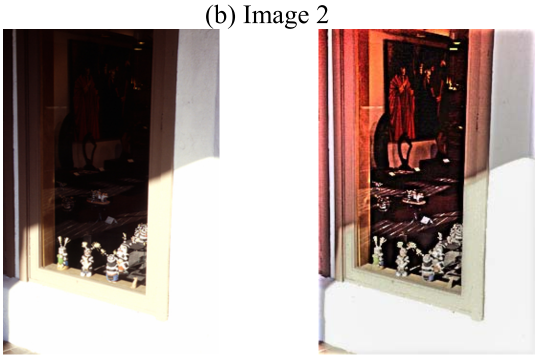
The effects of the algorithm are clearly depicted by transferring images towards to visually optimal region. Since the interest images have very dark and very bright or one of these properties, all of the images are not inside visually optimal region.



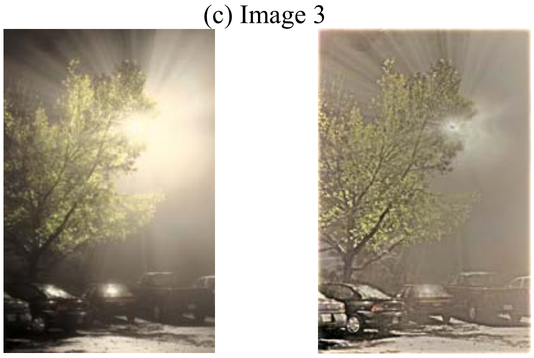
(a) Image 1



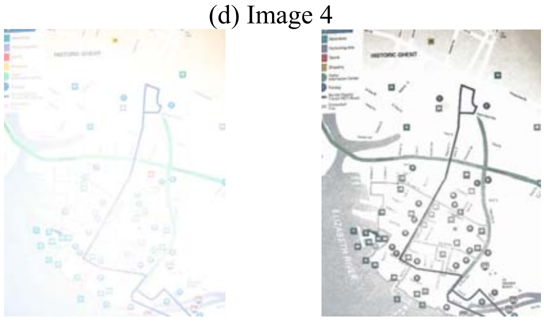
(b) Image 2



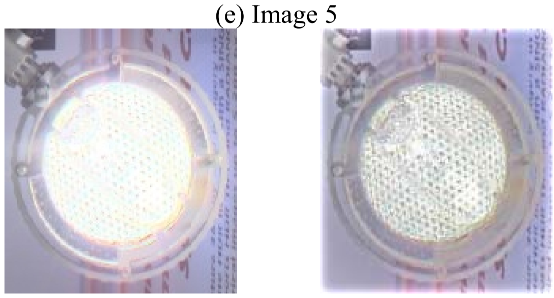
(c) Image 3



(d) Image 4



(e) Image 5



(f) Image 6

Figure 8. Images used in quantitative evaluation of MWIS algorithm. Left column: Original images. Right column: Enhanced images with MWIS algorithm.

For example, after image enhancement, the nearest square to the origin, Image 1 evaluated in terms of lightness and contrast sufficiently, but the enhanced image is not inside the visually optimal region. Another sample is the brightest image, Image 5. Although, it did not transfer into the visually optimal region, it evaluated in terms of lightness and contrast towards to visually optimal region.

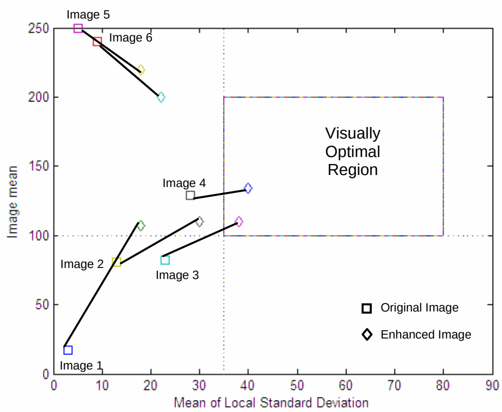


Figure 9. Image quality evaluations.

5. CONCLUSION

In this paper, a new image enhancement algorithm for extremely non-uniform lighting images based on the application of MWIS transfer functions has been presented.

The intensity enhancement, contrast enhancement and color restoration issues were considered as separate steps. This consideration makes the algorithm more flexible and adaptable. The input intensity image separated into the illumination and reflectance components preserving the important features of the image. The estimated illumination component is initially processed through a suitable nonlinear function designed in order to improve the illumination in the dark areas and also reduce the illumination in bright areas. After the combination of illumination and reflectance, the enhanced intensity image is treated through a surrounding pixel dependent contrast enhancement technique. Lastly, to obtain output color image, the enhanced intensity image was processed using a linear color restoration operation based on the chromatic information contained in the input image.

Considering the goal of the algorithm, it is focused on the intensity enhancement part of the algorithm. In this part of the algorithm, a very flexible nonlinear WIS transfer function was developed to achieve the enhancement process for extremely non-uniform lighting conditions. The adaptiveness of the transfer function, depending on the statistical information of the input image and its subimages, makes the algorithm more flexible and easier to control. For the interest image, the estimation of the illumination is very important, since there might be many regions where sudden change of illumination exists. This may be the reason of halo effects in bright regions. Therefore, an average of illumination and intensity for very bright regions is used as estimated illumination. In this way, the influence of the dark pixels on the neighboring bright pixels is decreased and therefore, the halo effects are diminished in bright regions.

In order to make experimental results more persuasive, different images are selected to test the algorithm: images of different scene and under different lighting conditions. The experimental results showed the improved performance with respect to other algorithms in overexposed regions. The MWIS algorithm not only enhances the dark regions, but also enhances the bright regions.

Based on the enhancement results, it is observed that the MWIS algorithm as proposed in this thesis, yields visually optimal results on images captured under extremely lighting conditions. The algorithm would be a promising image enhancement technique that can be useful in many applications.

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