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Numan Unaldi
Hava Harp Okulu

Vijayan K. Asari
University of Dayton

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Numan UNALDI[a,b], Vijayan K. Asari [a], Zia-ur Rahman [a]
[a] Department of Electrical and Computer Engineering, ODU, Norfolk, VA, USA 23529
[b] Aeronautics and Space Technologies Institute, HHO, 34807 Yesilyurt, Istanbul, Turkey
{nunal001, vasari, zrahman}@odu.edu

ABSTRACT

In this paper, a new wavelet-based dynamic range compression algorithm is proposed to improve the visual quality of digital images captured in the high dynamic range scenes with non-uniform lighting conditions. Wavelet transform is used especially for dimension reduction such that a dynamic range compression with local contrast enhancement algorithm is applied only to the approximation coefficients which are obtained by low-pass filtering and down-sampling the original intensity image. The normalized approximation coefficients are transformed using a hyperbolic sine curve and the contrast enhancement is realized by tuning the magnitude of the each coefficient with respect to surrounding coefficients. The transformed coefficients are then de-normalized to their original range. The detail coefficients are also modified to prevent the edge deformation. The inverse wavelet transform is carried out resulting in a low dynamic range and contrast enhanced intensity image. A color restoration process based on relationship between spectral bands and the luminance of the original image is applied to convert the enhanced intensity image back to a color image.

Keywords: Wavelet based image enhancement**,** dynamic range compression, local contrast enhancement.

1. INTRODUCTION

It is well known that human eyes perform much better than cameras when imaging real world scenes, which generally presents high dynamic range that can span more than six orders of magnitude. Human eyes have about 10^8:1 absolute range from fully adapted dark vision to fully adapted lighting conditions at noon on the equator. They can see about 3×10^4:1 range of luminance when adapted to a normal working range. This is achieved through a series of adaptive mechanisms for brightness perception. First, the size of pupil is variable to accommodate different levels of radiance from different regions in a scene while the camera aperture is fixed when capturing the scene. When staring at a highly-bright region in the scene, the pupil will shrink to compress the dynamic range so that the eyes can deal with it. Secondly, and more importantly, the major dynamic range compression process is taking place via the lateral processing at the retinal level [1]. Finally, the early visual cortex is also found participating in some of the dynamic range processing.

Currently available imaging devices can measure only about three orders of magnitude. In addition, image display devices, like monitors and printers, also demonstrate limited dynamic range. As a result, images captured in high dynamic ranges scenes commonly suffer from poor visibility due to either overexposure causing saturation or underexposure resulting in low contrast dark images in which some important features are lost or become hard to detect by human eyes. Computer vision algorithms also have difficulty processing those images.

To cope with the high dynamic range scenes given the limited dynamic ranges of cameras, monitors and printers, various image processing techniques which compress the dynamic range have been developed. Some of those are global histogram modification techniques, such as gamma adjustment, logarithmic compression, and levels/curves methods. However, those conventional methods generally have very limited performance such that some features may be lost during the image processing, or some cannot be sufficiently enhanced. The resulting images suffer from degraded global and local contrast which is related with the visual quality and the fine features.

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Among the contrast enhancement techniques, histogram equalization (HE) and its modified versions are commonly used for enhancement. Although HE works well for scenes that have uni-modal or weakly bi-modal histograms; its performance is poor for scenes with strongly bi-modal histograms. To make it work for multi-modal histograms, adaptive histogram equalization (AHE) was introduced [2]. In AHE which is also called localized or windowed HE, histogram equalization is performed locally within an adjustable size window. AHE provides local contrast enhancement and performs better than normal HE. However, AHE suffers from intensive noise enhancement in "flat" regions and "ring" artifacts at strong edges due to its strong contrast enhancement [3]. In contrast limiting AHE (CLAHE [4]), undesired noise amplification is reduced by selecting the clipping level of the histogram and controlling local contrast enhancement. Bound artifacts in CLAHE can be eliminated by performing background subtraction [5]. Multi-scale AHE (MAHE)[6] is the most advanced variation of HE. Unlike traditional single scale techniques, wavelet-based MAHE is capable of modifying/enhancing the image components adaptively based on their spatial-frequency properties. Those advanced HE variations generally have very strong contrast enhancement, which is especially useful in feature extraction applications like medical imaging for diagnosis. They are not commonly used in processing color images probably because their strong contrast enhancement may lead to excessive noise or artifacts and cause the image to look unnatural.

In order to obtain better performance, more advanced image enhancement techniques to compress the dynamic range maintaining or even boosting local contrast have been developed. Retinex based algorithms are examples of such techniques based on E. Land's theory [7] of human visual perception of lightness and color. Since the introduction of Retinex, several variants [8]-[11] on the original method have been developed mainly to improve the computational efficiency while preserving the basic principles.

MSRCR (Mutiscale Retinex with Color Restoration) [12]-[14], proposed by Jobson, *et al*, a widely cited image processing technique which is a Retinex based algorithm. MSRCR uses logarithmic compression and spatial convolution to implement the idea of Retinex. It aims to synthesize local contrast enhancement, color constancy, and lightness/color rendition for digital color image enhancement. MSRCR works well with a large variety of images.

AINDANE (Adaptive and Integrated Neighborhood Dependent Approach for Nonlinear Enhancement) [15] and IRME (Illuminance-Reflectance Model for Nonlinear Enhancement) [16] are two other novel techniques proposed by Li et al. They are both constituted by two separate processes viz. adaptive luminance enhancement and adaptive contrast enhancement to provide more flexibility and better control over image enhancement. AINDANE produces better results for most natural images when compared to IRME, while IRME is the fastest of the all retinex-based algorithms including AINDANE and it was primarily designed for real-time video enhancement on PC platforms.

In this paper, we introduce a novel fast and robust Wavelet-based Dynamic Range Compression with Local Contrast Enhancement (WDRC) algorithm based on the principles introduced by MSRCR and AINDANE to improve the visibility of digital images captured under non-uniform lighting conditions. The scheme of the proposed algorithm is shown in Fig.1. We give the details of the proposed algorithm in section 2. The experimental results and discussion are presented in sections 3, and the conclusions in section 4.

2. ALGORITHM

The proposed enhancement algorithm consists of four main stages, three of which are applied in discrete wavelet domain:

1. Luminance enhancement via dynamic range compression of approximation coefficients.
2. Local contrast enhancement using averaged luminance information of neighboring pixels which is inherited to approximation coefficients
3. Detail coefficients modification.
4. Color restoration.

For input color images, the intensity image $I(x,y)$ is obtained by employing the following transformation:

$$I(x, y) = \max[r(x, y), g(x, y), b(x, y)] \tag{1}$$

where $\boldsymbol{r}$, $\boldsymbol{g}$ and $\boldsymbol{b}$ are the RGB components of color image in the RGB color space. This is the definition of the value (V) component in HSV color space. The enhancement algorithm is applied on this intensity image.

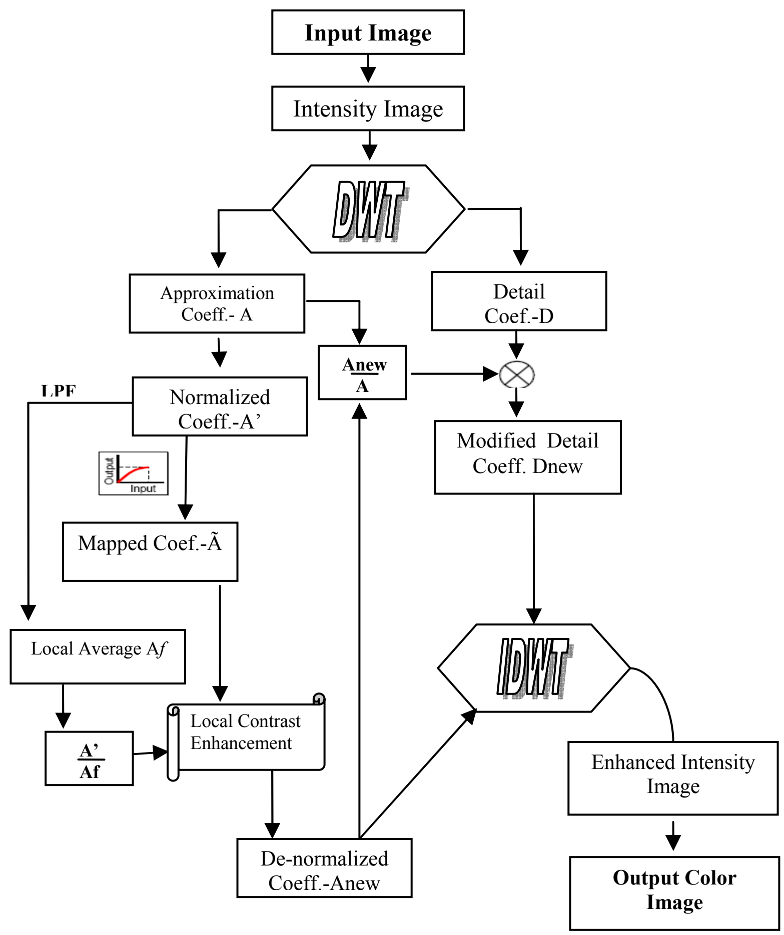

Fig. 1. The proposed algorithm

2.1 Dynamic Range Compression

According to orthonormal wavelet transform, the luminance values are decomposed by Eq. (2):

$$I(x,y)=\sum_{k,l\in z}a_{J,k,l}\Phi_{J,k,l}(x,y)+\sum_{j\geq J}\sum_{k,l\in z}d^{h}{}_{j,k,l}\Psi^{h}{}_{j,k,l}(x,y)+\sum_{j\geq J}\sum_{k,l\in z}d^{v}{}_{j,k,l}\Psi^{v}{}_{j,k,l}(x,y)+\sum_{j\geq J}\sum_{k,l\in z}d^{d}{}_{j,k,l}\Psi^{d}{}_{j,k,l}(x,y) \tag{2}$$

where $a_{J,k,l}$ are the approximation coefficients at scale J with corresponding scaling functions $\Phi_{J,k,l}(x,y)$, and $d_{j,k,l}$ are the detail coefficients at each scale with corresponding wavelet functions $\Psi_{j,k,l}(x,y)$. While the first term on the right-hand side of (2) represents the coarse-scale approximation to *I (x , y),* the second, the third, and the fourth terms represent the detail components in horizontal, vertical and diagonal directions, respectively.

Based on some assumptions about image formation and human vision behavior, the image intensity *I(x, y)* can be simplified as a product of the reflectance *R(x, y)* and the illuminance *L(x, y)* at each point *(x, y).* The illuminance *L* is assumed to be containing the low frequency component of the image while the reflectance *R* mainly includes the high frequency component, since *R* generally varies much faster than *L* does in most parts of an image with a few exceptions, like shadow boundaries. In most cases the illuminance has several orders larger dynamic range when compared to reflectance. By compressing only the dynamic range of the illuminance and preserving the reflectance, dynamic range compression of the image can be achieved. Accurate estimation of illuminance, which is difficult to be determined, can be approximated by low pass filtering the image.

The wavelet transform with which any image can be expanded as a sum of its approximate image at some scale J along with corresponding detail components at scale J and at finer scales is used especially for dimension reduction in our algorithm. Besides, we use the approximate image represented by normalized approximation coefficients, which can be obtained by low pass filtering and down-sampling the original image in the wavelet transform, to estimate the down-sampled version of the illuminance.

A raised hyperbolic sine function given in (4) which maps the normalized range [0,1] of $a_{J,k,l}$ to the same range is used for compressing the dynamic range represented by the coefficients. We have chosen hyperbolic sine function for dynamic range compression since the function is 'two-sided' that allows us to pull-up small coefficients and pull-down large coefficients to some extent at the same time. This is consistent with the human visual system that has mechanisms through which it can adapt itself allowing good visual discrimination in all lighting conditions. The normalized and compressed coefficients at level J can be obtained by

$$\bar{a}_{J,k,l} = \left[\frac{\sinh(4.6248.a'_{J,k,l} - 2.3124) + 5}{10} \right]^r \tag{3}$$

where $a'_{J,k,l}$ are normalized coefficients given by (4) and r is the curvature parameter which adjusts the shape of the hyperbolic sine function.

$$a'_{J,k,l} = \frac{a_{J,k,l}}{255 \times 2^J} \tag{4}$$

In Fig 2. the hyperbolic sine function with different curvature parameters is shown. To ease the comparison, identity transformation (r=0, $\bar{a}_{J,k,l} = a'_{J,k,l}$) is also given. For values of r less than 1, small pixel values are pulled up much more than large pixel values are pulled down, and for values greater than 1 vice versa. We determined r=0.5 as a default value, which provides good range compression especially in shadowed scenes. We found the greater values of r useful for bright scenes with no dark regions and for scientific applications such as medical image enhancement especially when the region of interest is too bright.

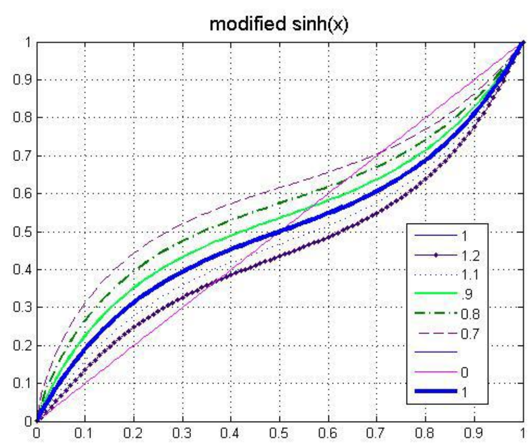

Fig. 2. Raised hyperbolic sine function

After applying the mapping operator to the coefficients, if we de-normalize the new coefficients and take the inverse wavelet transform, the result will show a compressed dynamic range with a significant loss of contrast. The new image will look washed-out. Such an example is shown in Fig 3.(b) Thus, we need to increase the local contrast to get a high visual quality.

Fig. 3. Results of the proposed algorithm at each step Top, left: Original image; right: Range compressed image; bottom left: Local contrast enhanced image; right: Image with modified detail coefficients.

2.2 Local Contrast Enhancement

The global contrast enhancement techniques which modify the histogram of the image by stretching it or boosting the bright pixels and decreasing the value of dark pixels globally can not generally produce satisfying results. Those methods have limited performance in enhancing fine details especially when there are small luminance differences between adjacent pixels. Therefore, the surrounding pixels should be taken into account when one pixel is being processed. We used the centre/surround ratio introduced by Land [8], and efficiently modified by Rahman et. al.[13] to achieve the compressed dynamic range preserving or even enhancing the local contrast. The center/surround ratio is used as a variable gain matrix, by simply multiplying with the modified coefficients when the ratio is less than 1 and by applying inverse of this matrix as a power transform to the coefficients when the ratio is greater than 1. In such a way, the result images will not suffer either halo artifacts, or saturation caused by over-enhancement. In this method, depending on their surrounding pixel intensity, pixels with the same luminance can have different outputs. When surrounded by darker or brighter pixels, the luminance of the pixel being processed (the center pixel) will be boosted or lowered respectively. In such a way, image contrast and fine details can be sufficiently enhanced while dynamic range expansion can be controlled without degrading image quality.

The local average image represented by modified approximation coefficients is obtained by filtering the normalized coefficients obtained from the wavelet decomposition of the original image with a Gaussian kernel. We have chosen Gaussian kernel like in MSRCR which proved to give good results over a wide range of space constants. The standard deviation (also called scale or space constant) of the 2D Gaussian distribution determines the size of the surround. The 2D Gaussian function *G(x, y)* is given by,

$$G(x,y) = \kappa e^{\left(\frac{-\left(x^2+y^2\right)}{\sigma^2}\right)} \tag{5}$$

where κ is determined by

$$\sum_x \sum_y G(x,y) = 1 \tag{6}$$

and σ is the surround space constant. Surrounding intensity information is obtained by 2D convolution of (5) with image A', whose elements are the normalized approximation coefficients $a'_{J,k,l}$ given by (4) such as

$$A_f(x,y) = A'(x,y) * G(x,y) = \sum_{x'=0}^{M-1} \sum_{y'=0}^{N-1} A'(x',y')G(x-x',y-y') \tag{7}$$

The ratio between A' and A_f determines whether the center coefficient is higher than the average surrounding intensity or not. If it is higher, the corresponding coefficient will be increased, otherwise it will be lowered. As stated above, the size of the surrounding which has a direct effect on the contrast enhancement result is controlled by the space constant σ of the surround function G. The local contrast enhancement is carried out as follows:

$$A_{new} = \begin{cases} \overline{A}.R * 255 * 2^J & \text{for } R < 1 \\ \\ \overline{A}^{(\frac{1}{R})} * 255 * 2^J & \text{for } R > 1 \end{cases} \tag{8}$$

where, R is the centre/surround ratio, $\overline{A}$ is the matrix whose elements are the output of the hyperbolic sine function given by (3) and A_{new} is the new coefficient matrix which will replace the approximation coefficients $a_{J,k,l}$ obtained by the decomposition of the original image at level J. R is given by

$$R = \left(\frac{A'}{A_f}\right)^d \tag{9}$$

with the parameter d which is an enhancement strength constant with a default value of 1. It can be tuned for an optimal result. When it is greater than 1, the result contrast will be high with a cost of increased noise. When it is less than 1, the resulting image will have less contrast with less noise. In Fig.3(c) the result of the contrast enhancement algorithm after taking the inverse wavelet transform of the modified coefficients and applying a linear color restoration process is given. In Fig.4, 1D comparison of the range compression and the contrast enhancement results are shown. The curves show the pixel values in the middle row of the original, dynamic range compressed and enhanced intensity images, respectively.

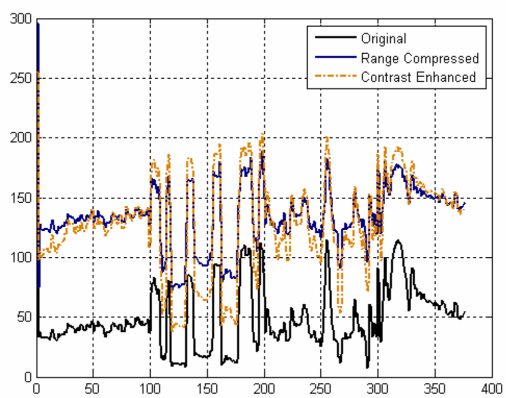

Fig. 4. Result of the proposed algorithm. Intensity variations along the line passing through the center of an image.

The contrast enhancement transformation given in (8) consists of two different equations: The first one is an adaptive multiplicative gain and it is used when the centre/surround ratio is less than 1. Multiplication with such a number will lower the coefficients. The second equation is adaptive power transform with different values for each coefficient and is valid when the center coefficient is greater than the local average. Since the coefficients are normalized to [0,1] and the term $\left(\frac{1}{R} < 1\right)$ is always satisfied, the power transform given in (8) will always produce a higher value but less than or equal to 1. This prevents saturation and halo errors that would occur if the first equation in (8) was used instead. The second equation could be used instead of the first one as in AINDANE, but it would not provide as much contrast enhancement as the multiplicative gain.

Using a single scale is incapable of simultaneously providing sufficient dynamic range compression and tonal rendition[13]-[14], therefore different scale constants (e.g. small, medium, large) of the Gaussian kernel can be used to gather surround information and the contrast enhancement process given by (5)-(9) is repeated for each scale. The final output is a linear combination of the new coefficients calculated using these multiple scales. This needs three times more calculations compared to using only one scale. Instead of using three convolutions, the same result can be approximated using a specifically designed Gaussian kernel. Such kernel which we name ‘Combined-scale Gaussian (CG)’ is a linear combination of three kernels with three different scales.

$$G(x,y) = \sum_{k=1}^{3} W_k \kappa_k \cdot e^{\left(\frac{-\left(x^2+y^2\right)}{\sigma_k^{\,2}}\right)} \tag{10}$$

with $W_k = \frac{1}{3}$. The CG kernel obtained using three scales (2, 40, 120) is shown in Fig.5.

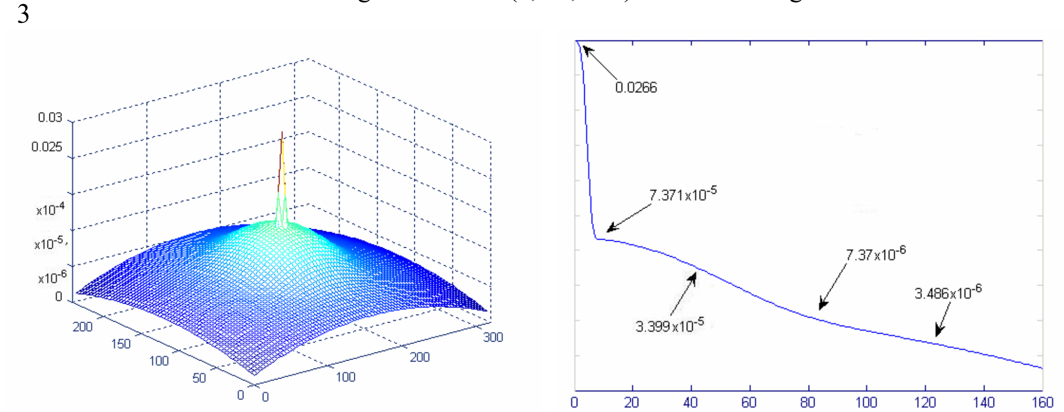

Fig. 5. Spatial form of CG operator. Left: 3-D representation, right: Cross-section to illustrate the surround (Both representation are distorted to visualize the surround)

2.3 Detail Coefficient Modification

Contrast enhancement through detail coefficient modification is a well-established technique and a large variety of application can be seen in literature [17]-[18]. In such a contrast enhancement technique generally small valued coefficients, which also represent the noise content are weakened or left untouched while large valued ones are strengthened by linear or non-linear curve mapping operators. Determining the threshold that separates the small and large coefficients is still merit of interest. Modifying these coefficients is very susceptible and may lead to undesired noise magnification or unpredictable edge deterioration such as jaggy edges. Thus, the inverse wavelet transform with the modified approximation coefficients will suffer from edge deterioration if the detail coefficient is not modified in an appropriate way. To meet this requirement, the detail coefficients are modified using the ratio between the enhanced and original approximation coefficients. This ratio is applied as an adaptive gain mask such as:

$$D^h{}_{new} = \frac{A_{new}}{A} D^h \qquad D^v{}_{new} = \frac{A_{new}}{A} D^v \qquad D^d{}_{new} = \frac{A_{new}}{A} D^d \tag{11}$$

where A and A_{new} are the original and enhanced approximation coefficients at level 1, respectively. D^h, D^v, D^d are the detail coefficient matrices for horizontal, vertical and diagonal details at level 1, and $D_{new}{}^h, D_{new}{}^v, D_{new}{}^d$ are the corresponding modified matrices, respectively. If the wavelet decomposition is carried out for more than one level, equation (12) is used instead.

$$D^h{}_{new,j} = \frac{A_{new,j}}{Aj} D_j{}^h \qquad D^v{}_{new,j} = \frac{A_{new,j}}{A_j} D_j{}^v \qquad D^d{}_{new,j} = \frac{A_{new,j}}{A_j} D_j{}^d \tag{12}$$

with $j=J,J$-1,….2,1. Here A_j and $A_{new,j}$ is determined by 1 level reconstruction using A_{j+1} and D_{j+1} for A_j; $A_{new,j+1}$ and $D_{new,j+1}$ for $A_{new,j}$ at each step. Applying the wavelet algorithm more than 1 step will be computational inefficient. In our implementations 1 level decomposition for illumination estimation yielded fast results with high visual quality. In Fig.3(c)–(d) result obtained without and with detail coefficient modification is given. The need for this step is more apparent in the examples given in Fig. 6.

Fig 6. Examples showing the effect of detail modification. Original images left, enhancement without and with detail coefficient modification middle and right images, respectively.

2.4 Color Restoration

Color restoration process is straight forward. For converting the enhanced intensity image to RGB color image, the ratio between original and enhanced intensity image along with the chromatic information of the original image are employed. The RGB values $(r_{enh}, g_{enh}, b_{enh})$ of the restored color image are obtained by,

$$r_{enh} = \frac{I_{enh}}{I} r \qquad g_{enh} = \frac{I_{enh}}{I} g \qquad b_{enh} = \frac{I_{enh}}{I} b \tag{13}$$

Here I is given by (1) and I_{enh} is the resulting enhanced intensity image derived from the inverse wavelet transform of the modified coefficients. Thus, the color consistency between the original color image and the enhanced color image can be achieved.

3. RESULTS AND DISCUSSION

The proposed algorithm has been applied to process numerous color images captured under varying lighting conditions. From our observations we can conclude that the algorithm is capable of removing shades in the high dynamic range images while preserving or even enhancing the local contrast well. Besides, the produced colors are consistent with the colors of the original images. In this section more results obtained by the proposed algorithm to show its ability in producing dynamic range compressed images preserving the local contrast and good rendition will be given. Examples given in Fig. 7. show that the proposed enhancement algorithm is capable of removing the shades and providing better results in terms of visual quality. The local contrast is preserved, even improved in all these examples. The processed images are sharper than the original ones. Fig 8. shows two examples of the real-world scenes that violate the gray-world assumption. Although the scenes are dominated by one color channel (mostly-green), the proposed enhancement algorithm can provide results that have very appealing color rendition and the results do not suffer from graying-out of the uniform areas.

Fig 7. Image enhancement results by proposed algorithm. Top: Original images, bottom: Enhanced Images

Fig 8. Image enhancement results by proposed algorithm. Left: Original images, right: Enhanced Images

Fig 9. Image enhancement results by proposed algorithm. Left: Original images, right: Enhanced Images

Two examples for scenes that have very rich color mixture are given in Fig 9. The illumination is also balanced in both scenes. Both enhancement results preserve the color information well, providing sharper results. The background that has low illumination in the first image becomes more visible with realistic and balanced colors in the enhanced image. Both enhanced images are brighter than the original ones.

The main advantage of the proposed algorithm is its speed. Since the convolutions which take most of the processing time are only applied to approximation coefficients, the processing time is reduced to almost half the processing time required for IRME which is known to be designed for real time video processing on PC platforms.

The proposed algorithm successfully accomplishes color rendition, dynamic range compression with local contrast enhancement simultaneously except for some "pathological" scenes that have very strong spectral characteristics in a single band. Two examples for such scenes are given in Fig 10. Although the enhanced results are sharper than the original images and the colors of the enhanced results are consistent with the colors in the original images, they are not the colors observed in real-life scenes. This drawback of the proposed algorithm is shared with AINDANE and IRME as well, since these algorithms, like the proposed one, exploit only the luminance component of the image to be enhanced. The "pathology" in the original image is inherited to the enhanced image via linear color restoration process. The algorithm is not "color constant". Color constancy implies the observed scene is independent of the spectral characteristics of the illumination to some extent. The observed scenes in given examples would let the real-world colors be more visible.

4. CONCLUSIONS

A wavelet based fast image enhancement algorithm which provides dynamic range compression preserving the local contrast and tonal rendition has been developed to improve the visual quality of the digital images. It is also a good candidate for real time video processing applications. Although the colors of the enhanced images produced by the proposed algorithm are consistent with the colors of the original image, the proposed algorithm fails to produce color constant results for some "pathological" scenes that have very strong spectral characteristics in a single band. The linear color restoration process is the main reason for this drawback. Hence, a different approach is required for the final color restoration process. A new version of the proposed algorithm which deals with this issue is presently being developed.

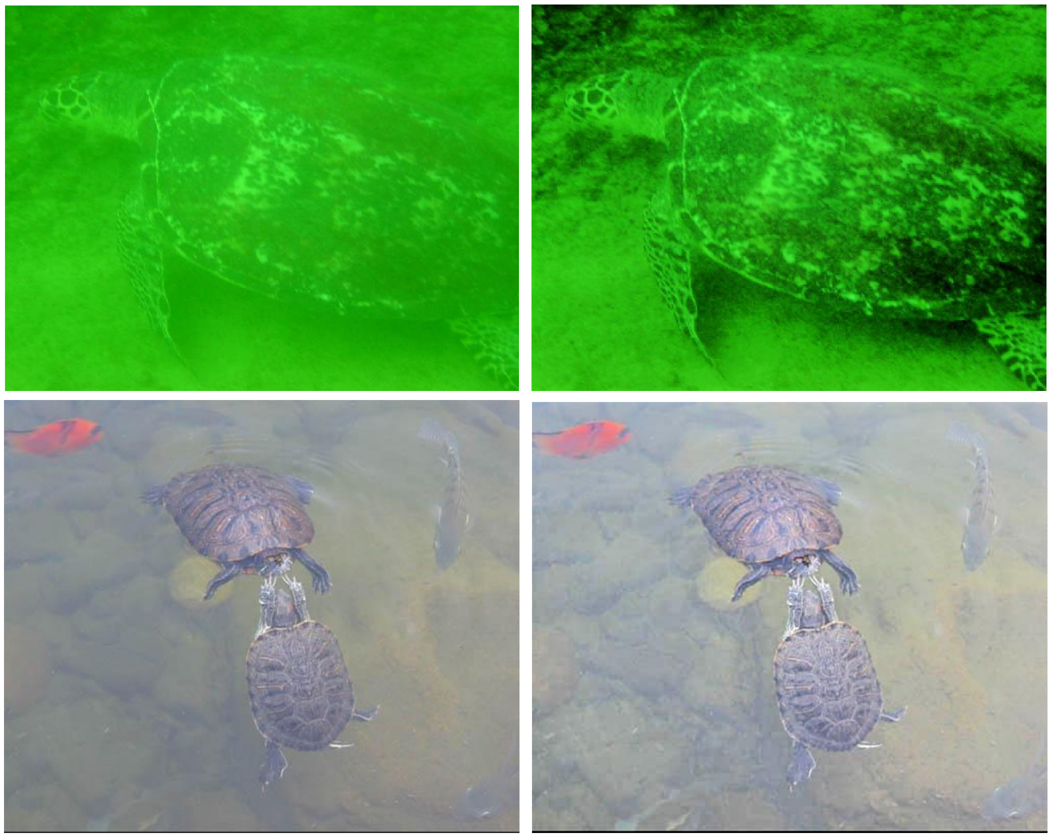

Fig 12. Enhancement results of the "Pathological images". Left: Original images, right: Enhanced Images

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