A Locally Tuned Nonlinear Technique for Color Image Enhancement

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*Abstract: - A*n innovative technique for the enhancement of digital color images captured under extremely non-uniform lighting conditions is proposed in this paper. The key contributions of this technique are adaptive intensity enhancement, contrast enhancement and color restoration. Simultaneous enhancement of extreme dark and bright intensity regions in an image is performed by a specifically designed Locally Tuned Sine Non-Linear (LTSN) function. The intensity of each pixel's magnitude is tuned based on its surrounding pixels to accomplish contrast enhancement. Retrieval of the color information from the enhanced intensity image is achieved by a linear color restoration process which is based on the chromatic information of the input image. Experimental evaluations show that the proposed algorithm can be effectively used for improving the visibility of night time surveillance video sequences with frames having extreme bright and dark regions.

Key-Words: - dynamic range compression, intensity transformation, image enhancement, adaptive intensity enhancement, contrast enhancement, sine nonlinearity

1 Introduction

Human eye manifests an unprecedented performance when compared to the digital cameras while imaging real world scenes that produces high dynamic range (HDR) maps spanning more than six orders of magnitude. Eye adjusts itself to the existing variations in lighting and changes its mode of operation as the light reduces from the day to night adapting locally while cameras set exposure globally. The pupil shrinks to constringe the dynamic range so that eyes can deal with it. This sensitivity of eye automatically adjusts itself to the changes in the illumination. The advent of contemporary cameras with their clean-room construction and coated optics cannot rival human vision when it comes to low flare and absence of multiple paths in harsh lighting environments. The possible exception being cinema where there has been a little advancement of achieving greater dynamic range in image capture stage, as the common displays and viewing environments limit the range of what can be presented to only about two orders of magnitude between the maximum and minimum luminance. Some instances of such scenes being sunlight overexposed and underexposed areas, scenes that possess both indoor and outdoor details and scenes with lighted signs during night times. Hence, the utmost aim is natural image synthesis to recreate the viewer's phenomenon of the high dynamic range scenes.

Compressing the high dynamic range scenes is a possible solution to handle the limited dynamic ranges (LDR) of the current devices such as printers, monitors, and CRTs. Developments in this field paved way to various methods to implement this concept, like gamma adjustment, logarithmic compression, histogram equalization and levels/ curves methods. The limited performance of these methods led to the cases where some features might be lost or some left un-enhanced. Global processing is the basis on which they work, lacking the local contrast enhancement that preserves or enhances significant image details. Progressive image enhancement techniques have been developed and implemented which not only accounts in compressing the dynamic range but also improving the local contrast achieving high quality of vision.

Any real world scene that has extremely high illumination underexposes the dark regions and makes low contrast details less visible than they would be to the eye. Hence, preserving both the dark and light regions of any high contrast scene can be made viable by implementing the proposed algorithm. In this paper, section 2 deals with related work mentioning various image enhancement techniques. We discuss the proposed enhancement algorithm named LTSNE in section 3. The experimental results and discussion on performance and computational speed are presented in sections 4 and 5, and the conclusions in section 6.

2 Related Work

The major dynamic range process takes place via lateral processing at the retina level [1]. Many image enhancement techniques have been developed such as Adaptive Histogram Equalization (AHE), contrast-limiting AHE (CLAHE) [2] and Multi-Scale Retinex (MSR) [3]. MSR performs well in terms of dynamic range compression, but it fails to meet with the gray world assumption. Further, there is a notable defect in color rendition. So color restoration for multiscale retinex method becomes very important. In MSRCR [4,5] 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. Multi-scale Luminance Retinex [6] method was proposed to separate two components of MSRCR. Luma-Dependent Nonlinear Enhancement (LDNE) [7] algorithm is a luminance based multi-scale center/surround retinex algorithm. This method suppresses unwanted noise in enhancement process by adding convolution results of luminance and different scales. It also performs color saturation adjustment for producing more natural colors. Further luminance control is achieved to prevent unwanted luminance drop. AINDANE (Adaptive Integrated Neighborhood Dependent Approach for Nonlinear Enhancement) [8] involves itself in adaptive luminance enhancement and adaptive contrast enhancement. The enhanced image can be obtained by a linear color restoration process based on the chromatic information in the original image. Cosine nonlinearity is used to enhance the HDR images in [9] which results in halo artifacts.

In Computer Graphics the problem of reproducing the HDR images on LDR devices is addressed by tone mapping [10]. Larson *et al*. developed a tone-mapping operator based on iterative histogram adjustment and spatial filtering process, the main goal of which is to produce images that preserve visibility in high dynamic range scenes. Chui *et al*. suggested that the tone mapping should be neighborhood dependent. Schlik [11] developed Chui's algorithm by utilizing a first degree rational polynomial function to map high-contrast scene illuminance to display system values, which is not adaptive for contrast enhancement in all images. To eliminate the halo effects that are likely to appear in the above methods, Tumblin and Turk [12] developed a Low Curvature Image Simplifier (LCIS) method that accepts inputs from real world scenes and produces output for any device. Fattal et al [13] used the gradient field of the luminance image for HDR compression by attenuating the magnitudes of large gradients.

3 Proposed Algorithm

The LTSNE algorithm constitutes three important stages that lead to better enhancement results, {i) adaptive intensity enhancement, (ii) contrast enhancement, and (iii) color restoration.

3.1 Adaptive Intensity Enhancement

The foremost step in this stage is the conversion of color images to gray scale images which is on the basis of eqn. (1)[8]. This technique is the NTSC standard to obtain the luminance (intensity) details of color images on an additive color device.

$$I(x,y)=\frac{76.245\times I_R(x,y)+149.685\times I_G(x,y)+29.07\times I_B(x,y)}{255} \quad (1)$$

where $I_R(x, y)$, $I_G(x, y)$, and $I_B(x, y)$ represents the R, G, and B values respectively for a pixel at location (x, y). Image intensity $I(x, y)$ is normalized as:

$$I_n(x,y)=\frac{I(x,y)}{255} \quad (2)$$

To decrease the illumination values of the high-illumination pixels simultaneously increasing the illumination values of the low-illumination pixels, the intensity images are treated with enhancement and compression processes respectively using a specifically designed non-linear transfer function.

$$I_E(x,y)=\mathrm{Sin}^2(I_n(x,y)^q*\pi/2) \quad (3)$$

From the above equation we can observe that, the non-linear transfer function is image dependent with a parameter q, and is related to the mean of the pixel described as:

$$q=\tan(\frac{I_{M_n}(x,y)*\pi}{c_1})+c_2 \quad (4)$$

where c_1 and c_2 are experimental constants. As c_1 equals to 2, q value becomes infinite. c_1 should be greater than 2. To have the boundary for maximum value of q, in Fig. 1 the range of c_1 for various q values is 2.1 to 2.4. As it increases from 2.1 to 2.4 the amount of pull down intensity will decrease for brighter pixels. So for better results, c_1 (by experiments) is set to 2.25. If it reaches to 2 the over-exposed (white) areas become black because of high values of q. On the contrary, for values which are closer to 0 the noise in the extreme dark regions becomes enhanced. So the mean value below 0.2 is considered as extreme dark regions and q for those pixels can be calculated by:

$$q=\frac{[\log(2*I_{M_n}(x,y))+2]}{2} \quad (5)$$

where c_2 can be calculated by equating the q value at 0.2 in eqn. (4) to eqn. (5) to maintain the continuity. $I_{M_n}(x, y)$ is the Normalized Mean value of the pixel intensity at (x, y).

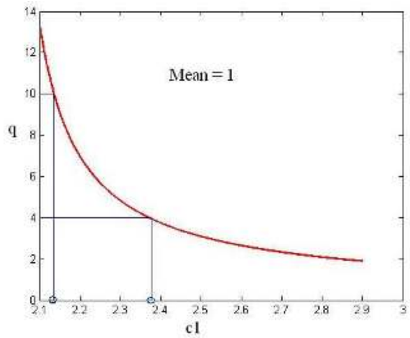


Fig.1 c_1 vs. q curve for mean equals to 1.

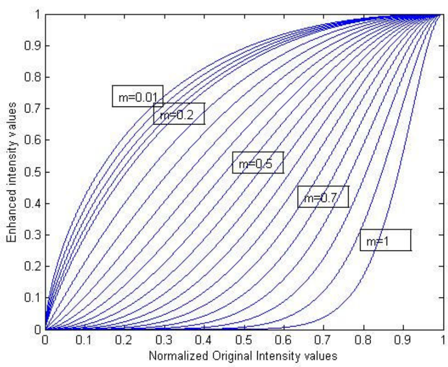


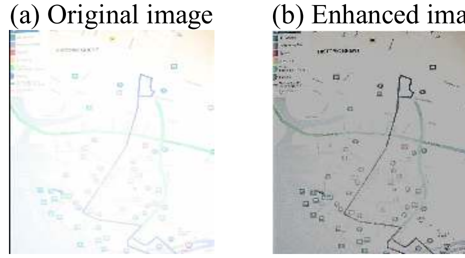
Fig.2 Curves of the nonlinear transfer function corresponding to various mean values for c1=2.25 and c2=0.0085.

The extreme bright pixels (region) that has a mean value closer to 1 will be processed by the curve with a specific q value. The q and mean dependency is empirically determined. The transfer function is a squared sine function. It can be observed from the curves in Fig. 2 that this transformation greatly boosts the luminance of darker pixels (regions) simultaneously decreasing the luminance of brighter pixels (regions). Similar curves produced by different kinds of functions will have effects that are similar on luminance enhancement, when used as a transfer function. These transfer functions achieve greater dynamic compression besides producing very good enhancement results. The influence of the mean on the transfer function is illustrated in Fig. 2. Whenever the mean falls below 0.3 (in the case of dark and extreme dark regions), the luminance needs to be further enhanced. Similarly when the mean raises above 0.7 (in the case of bright and extreme bright regions) the luminance need to be compressed. Further, the luminance will be mostly unaltered for mean values closer to 0.5. All these results can be achieved by the effect of the above cases (for different mean values) in Fig. 2 when applied to the original luminance image. The graph indicates that darker regions (with smaller mean values) have enhanced luminance and brighter regions (with larger mean values) have compressed luminance in order to preserve all the finer details in extreme dark and bright regions in the same image. The mean image is obtained by filtering the image with a Gaussian mask which is defined as:

$$G(x, y) = K \cdot e^{\left(\frac{-(x^2+y^2)}{c^2}\right)} \tag{6}$$

where K is determined by $\iint G(x, y)dxdy = 1$. With a single scale Gaussian mean with smaller c values, the details in the image are clearly visible but they suffer in halo artifacts and poor Global impression. For larger c values Global impression is maintained but the details are not clear. In order to have a better balance between Global impression, visibility details and to minimize the halo artifacts, Multi scale Gaussian mean is considered for the calculation of q. It has been observed that for three scales the proposed algorithm produces better results.

(a) Original image (b) Enhanced image



(c) Original image (d) Enhanced image

Fig.3 Image enhancement by LTSNE

The filtering of the original intensity image *I(x, y)* of size M×N is performed by discrete 2D convolution with a Multi scale Gaussian function as:

$$I_M(x, y) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I(m, n)\, G_i(m+x, n+y) \tag{7}$$

where G_i is the weighted sum of i Gaussian functions with different scales (i=3 in this case). The image is normalized to make the range between 0 and 1 and hence $I_{M_n}(x, y)$ can be obtained.

3.2 Contrast Enhancement

Contrast enhancement is performed in a similar way as in AINDANE [8]. This process restores the contrast of the luminance-enhanced images, which were degraded in the previous process. A surrounding pixel (neighborhood) dependent contrast enhancement technique implementation is performed to achieve sufficient contrast for image enhancement which restores the dynamic range compression. While an image is processed with such a method, pixels with the same luminance posses different outputs depending on their neighboring pixels. When surrounded by darker or brighter pixels, the luminance of a pixel being processed (the center pixel) would be boosted or lowered respectively. In this way, picture contrast and finer details can be sufficiently enhanced while dynamic range expansion can be controlled while maintaining the image quality. If the center pixel's intensity is higher than the average intensity of surrounding pixels, in the original image, the corresponding pixel on the luminance-enhanced image will be pulled up otherwise it will be pulled down. The center-surround contrast enhancement is performed as defined in the following equations:

$$S(x,y) = 255 . I_{M_n}(x,y)^{E(x,y)} \quad (8)$$

where the exponent is defined by:

$$E(x,y) = r(x,y)^P = \left(\frac{I_M(x,y)}{I(x,y)} \right)^P \quad (9)$$

S(x, y) is the pixel intensity after contrast enhancement and *r(x, y)* is the intensity ratio between $I_M(x,y)$ and *I(x, y)*. *P* is an image dependent parameter used to tune the contrast enhancement process.

3.3 Color Restoration

The above two stages of luminance and contrast enhancement took place in the luminance space. The enhanced color image can be obtained through a linear color restoration process based on the chromatic information contained in the input image. Mathematically, the color restoration process for images in RGB color space can be expressed as:

$$S_j(x,y) = S(x,y) \frac{I_j(x,y)}{I(x,y)} \cdot \lambda_j \quad (10)$$

where $j = r, g, b$ represents the R, G, B spectral band respectively, and S_r, S_g and S_b are the RGB values of the enhanced color image. A parameter λ is introduced here in order to adjust the color hue of the enhanced color images. λ is a constant very close to 1, which takes different values in different spectral bands. When all λs are equal to 1, eqn. (10) can preserve the chromatic information of the input color image for minimal color shifts.

4 Results and Discussion

The proposed algorithm has been applied to process various color images captured by digital cameras under varying lighting conditions. The key advantage of LTSNE is enhancement of overexposed regions. LTSNE possesses various adjustable parameters that have been tuned finely by continuous experimentation for achieving consistent and higher quality image results. Some of the parameters are image dependent and are introduced to make the algorithm more adaptive. For example, the parameter q in eqn. (3) is controlled by the mean value and hence used to adjust luminance enhancement to avoid excessive or insufficient luminance enhancement. In Fig. 3 the enhanced image processed by LTSNE looks clearer than the original image in terms of contrast. p is another parameter involved for contrast enhancement in LTSNE which was previously found in AINDANE. Here from the experiments it can be observed that p value is nearly 0.2 for most of the images in this algorithm because the contrast reduction was performed locally. By applying LTSNE the details in the overexposed regions are clearly visible.

In Fig. 4, sample image is provided for comparison among the performance of MSRCR, AINDANE and LTCNE. Commercial software Photo Flair (www.trueview.com) is used to implement MSRCR. It can be observed that the images produced by LTSNE possess more details with high visual quality (in terms of details in both underexposed and overexposed regions) than those processed by MSRCR and AINDANE.

In Fig. 5, sample images taken under varying lighting conditions are used for evaluating the effectiveness of the proposed algorithm. The images in Figs. 5(a), 5(c), and 5(e) were captured in non-uniform lighting conditions. The enhanced images (Figs. 5(b), 5(d), and 5(f)) obtained by LTSNE show that the faces in all the three images are clearly visible. Figs. 5(g) and 5(i) are the images containing extreme bright and dark regions. The details near the light (over exposed regions) are clearly visible and darker regions are also enhanced well in Figs. 5(h) and 5(j).

4.1 Statistical Evaluation

A statistical method [14] is used to compare the performance of different enhancement algorithms. The mean and mean of standard deviations of the original images and the enhanced images are plotted in Fig. 6. The numbers 1, 2 and 3 inside the diamonds represent the images enhanced using the MSRCR, AINDANE and LTSNE algorithms respectively.


(a) Original Image


(b) Enhanced by MSRCR


(b) Enhanced by AINDANE


(b) Enhanced by LTSNE

Fig.4 Image enhancement comparison

Image 1 is transferred to the visually optimal region through all three types of enhancement algorithms. Since LTSNE compresses the bright regions, the enhanced image with LTSNE possess lower image mean than the others. AINDANE and LTSNE can transfer image 2 to the visually optimal region. Since AINDANE enhances the brighter region of the image, its mean is higher than the enhanced image using LTSNE. Image 3 is an extremely bright image and bright regions need to be compressed. AINDANE enhances the extremely brighter pixels and LTSNE compresses them. This causes the LTSNE result fall closer to the visually optimal region.

5 Computational Speed

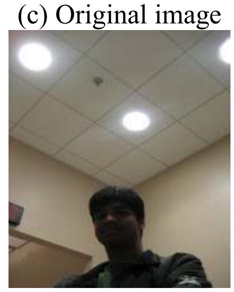
The processing time needed for enhancement of the images of different sizes using LTSNE is compared with that of AINDANE and MSRCR. The computing platform is an Intel Pentium 4 system, which has a CPU running at 3.06 GHz and 1GB memory. The operating system is Windows XP® Professional Edition. A commercial digital image processing software PhotoFlair® ver 2.0 (*TruView Imaging Company*) is used to process images by MSRCR. Windows versions of AINDANE and LTSNE implemented in C^{++} are applied to process the same set of images. The processing time needed to enhance images of various sizes is provided in Table 1 for performance comparison of LTSNE, AINDANE and MSRCR.

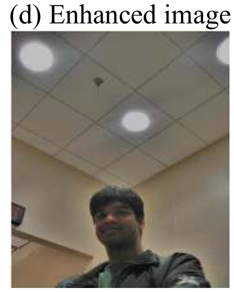

(a) Original image


(b) Enhanced image

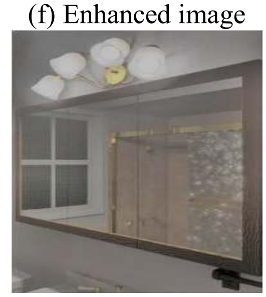

(c) Original image


(d) Enhanced image


(e) Original image


(f) Enhanced image


(g) Original image


(h) Enhanced image


(i) Original image


(j) Enhanced image

Fig.5 Image enhancement results by LTSNE

Generally, the processing time of LTSNE is less compared to AINDANE and MSRCR. This is due to the fact that FFT computations occupy most of the processing time. Only the intensity image (equivalent to one color band) is processed with FFT in AINDANE to obtain neighborhood averaging where as all the three color bands are processed independently with FFT in MSRCR. But in LTSNE the processing time is reduced to a considerable extent due to the adaptive intensity enhancement process which involves fewer complex functions. Therefore, LTSNE is better suitable for fast applications.

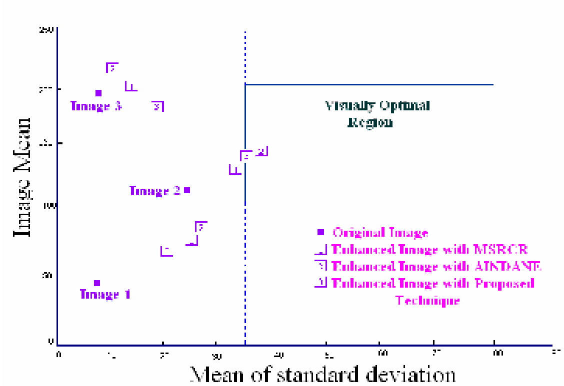


Fig.6 Comparison of statistical characteristics of LTSNE with other image enhancement techniques.

Table 1 Comparison of AINDANE, MSRCR and LTSNE in processing time.

Image size (pixels)	Processing time by AINDANE (seconds)	Processing time by MSRCR (seconds)	Processing time by LTSNE (seconds)
360×240	0.25	1.2	0.19
640×480	1.4	4	0.687
1024×768	2.8	8	1.716
2000×1312	6.7	18	4.572

6 Conclusion

A new nonlinear image enhancement algorithm named LTSNE has been developed to improve the visual quality of digital images captured under extreme lighting conditions. The image enhancement algorithm is composed of three separate processes: the adaptive luminance enhancement (dynamic range compression), contrast enhancement and color restoration. The combination of the three processes is believed to make the algorithm more flexible and easier to control. Adaptive-ness of the algorithm depending on the statistical information (mean) of the input images has been realized in LTSNE to automatically refine the image quality. LTSNE has been tested with a large number of images. The enhanced images processed by LTSNE have improved visual quality compared with those produced by other techniques in terms of better balance between luminance and contrast. Color is better preserved compared to MSRCR. Moreover, the processing speed of LTSNE is much faster than that of AINDANE and MSRCR. LTSNE algorithm would be a promising image enhancement technique that could be useful in many security surveillance applications.

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