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Adaptive Monte Carlo Retinex Method for Illumination and Reflectance Separation and Color Image Enhancement

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Abstract

A novel stochastic Retinex method based on adaptive Monte Carlo estimation is presented for the purpose of illumination and reflectance separation and color image enhancement. A spatially-adaptive sampling scheme is employed to generate a set of random samples from the image field. A Monte Carlo estimate of the illumination is computed based on the Pearson Type VII error statistics of the drawn samples. The proposed method takes advantage of both local and global contrast information to provide better separation of reflectance and illumination by reducing the effects of strong shadows and other sharp illumination changes on the estimation process, improving the preservation of the original photographic tone, and avoiding the amplification of noise in dark regions. Experimental results using monochromatic face images under different illumination conditions and low-contrast chromatic images show the effectiveness of the proposed method for illumination and reflectance separation and color image enhancement when compared to existing Retinex and color enhancement techniques.

1. Introduction

An ongoing challenge in computer vision is alleviating unwanted global and local illumination variations. In practical computer vision applications such as video surveillance [1] and face recognition [2], images and videos are often acquired in different unconstrained environments where illumination can vary significantly within the acquired scene. For example, lighting in outdoor environments can change significantly over the course of the day, resulting in images of the same scene acquired at different times of the day to appear very different from an image intensity perspective. Similarly, the same objects can appear very different due to differing or changing lighting conditions in indoor environments. Such global and local illumination variations make it difficult for computer vision algorithms to recognize objects in a reliable and consistent manner. In the realm of photography, obtaining images with good contrast is desired, which is often not possible to capture directly due to illumination variations in the scene. Therefore, methods for alleviating the effects of global and local illumination variations are sought.

One particularly effective class of approaches for reducing the effects of illumination variations is that based on Retinex theory [3], where images are decomposed into their individual illumination and reflectance components prior to further processing. Then the reflectance information can be used to achieve reliable object recognition that is invariant to illumination conditions. Also, the illumination information can then be modified independent of the reflectance information to achieve improved image contrast while avoiding a washed-out appearance.

Retinex methods can be generally divided into two main groups: i) global Retinex methods, and ii) local Retinex methods. In global Retinex methods [4, 5, 6], pixel intensity information along multiple random walks around the image (with each walk ending at the pixel being estimated) are used to estimate the reflectance of the image, from which the illumination of the image can be subsequently estimated. The primary difference between global Retinex methods is in the path geometry used. By exploiting global information in the reflectance and illumination separation process, global Retinex methods are able to better preserve the original photographic tone of the image. However, global Retinex methods tend to have poor detail recovering, particularly in dark regions [7]. In local Retinex methods [8, 9, 10, 11], the neighboring pixel intensities are used to estimate the illumination of the image, from which the reflectance of the image can be subsequently estimated. The primary difference between local Retinex methods is

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in the way in which the illumination information is estimated. These include single scale Gaussian estimation [9], multi-scale Gaussian estimation [10], and bilateral estimation [11]. By exploiting local contrast information in the reflectance and illumination separation process, local Retinex methods are able to better recover fine image details when compared to global Retinex methods. However, since only local information is used, the original photographic tone of the image is often not well maintained. Furthermore, existing local Retinex methods are commonly based on the assumption that illumination varies slowly. However, this assumption is violated in situations where strong shadows result in sharp illumination changes, resulting in false discontinuities in the estimated reflectance at these locations. Finally, a problem faced by both global and local Retinex methods is the amplification of noise in dark regions, which can have significant negative effects on both image quality and recognition capabilities of existing computer vision algorithms. The underlying goal of the proposed method is to combine the advantages of both global and local Retinex approaches to address the aforementioned issues.

In this paper, we propose a novel approach to illumination and reflectance separation using an adaptive Monte Carlo Retinex method. By utilizing both global and local contrast information to estimate the illumination and reflectance information of an image in a stochastic manner, the proposed method aims to reduce the effects of strong shadows and other sharp illumination changes on the estimation process, improve the preservation of the original photographic tone, and avoid the amplification of noise in dark regions. It is important to note that the stochastic nature of the proposed method should not be confused with purely global Retinex approaches which also utilizes random sampling. Unlike these methods, the proposed method also utilizes local information to better recover image detail. This paper is organized as follows. A quick review of Retinex theory is presented in Section 2. The mathematical background behind the proposed method is presented in Section 3. Experimental results are presented and discussed in Section 4. Finally, conclusions are drawn and future work is discussed in Section 5.

2. Retinex Theory

The basic postulates of the Retinex theory used in existing Retinex approaches can be defined as follows. The first postulate states that there are three independent mechanisms in the vision system for processing each of the three color channels. Based on this postulate, each of the three color channels can be processed independent of each other. The second postulate states that the intensity image I corresponding to a particular color channel is proportional to the product of illumination L and a reflectance R,

$$I \sim L \cdot R. \tag{1}$$

Based on this postulate, the illumination component L and reflectance component R of an intensity image I can be estimated by first estimating either one of the components and then computing the second component as the ratio between I and the estimate of the first component. In the global Retinex approach, the reflectance R at a particular pixel $\underline{x} = (x, y)$ is first estimated as the normalized sum of ratios between the intensity I at $\underline{x}$ and the highest intensity traveled by each of the M random walks $\{p_i : i = 1, \ldots, M\}$ along the image, where each random walk ends at $\underline{x}$,

$$\hat{R}(\underline{x}) = \frac{1}{M} \sum_{i=1}^{M} \frac{I(\underline{x})}{I(\underline{h}_i)}, \tag{2}$$

where h_i is point along path p_i with the highest intensity. In the local Retinex approach, the illumination I at a particular point $\underline{x}$ is first estimated as the weighted mean over a local neighborhood $\aleph$ centered at $\underline{x}$,

$$\hat{L}(\underline{x}) = \sum_{q \in \aleph} w(\underline{q}, \underline{x}) I(\underline{q}), \tag{3}$$

where w is the weight associated with neighboring point $\underline{q}$ based on its relationship with $\underline{x}$. In typical local Retinex methods, the weight w is dependent on the spatial distance between $\underline{x}$ and $\underline{q}$. Based on the estimated illumination $\hat{L}$, the reflectance $\hat{R}$ of the image is typically estimated in its logarithmic form r as the difference between the logarithms of I and $\hat{L}$,

$$\hat{r}(\underline{x}) = \log(I(\underline{x})) - \log\left(\hat{L}(\underline{x})\right) \tag{4}$$

A general overview of the local Retinex approach is shown in Fig. 1.

3. Adaptive Monte Carlo Retinex

As discussed in Section 1, global and local Retinex methods each have their own advantages, which are complementary to each other. While global Retinex methods provide better preservation of the original photographic tone of the image, local Retinex methods provide better recovery of image detail, particulary in dark regions. As such, a hybrid method that possesses the advantages of both the local and global Retinex methods is desired. One possible approach to achieving this goal is to integrate the random sampling aspect of the global Retinex approach into the local Retinex approach. This can be accomplished by extending the neighborhood $\aleph$ used in the estimation of L such that the $\aleph$ is comprised of a set of random points $\{\underline{q}_1, \underline{q}_2, \ldots, \underline{q}_N\}$ sampled from a random field S representing all possible pixels in the image. Based on this new formulation of $\aleph$,

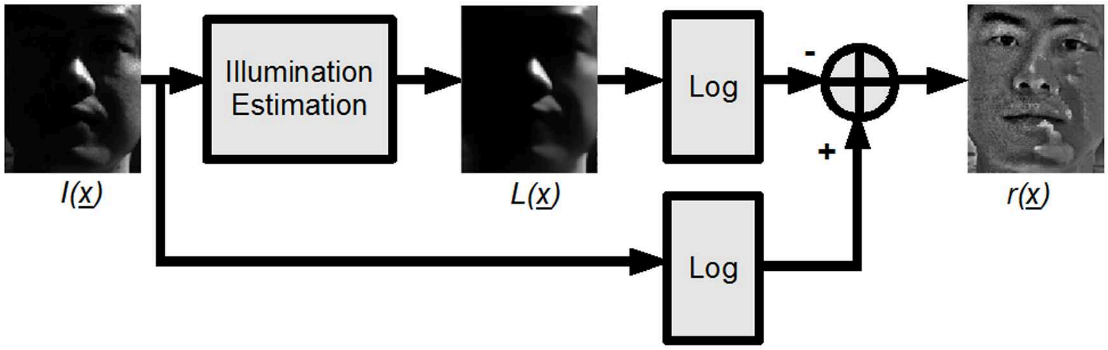

Figure 1. General overview of the local Retinex approach. First, the illumination information is estimated using a local weighted mean approach. Based on the estimated illumination information, the reflectance of the image is estimated in logarithmic form.

the estimate of L then becomes a weighted mean of the intensities at the N random points in the image,

$$\hat{L}(\underline{x}) = \sum_{i=1}^{N} w(\underline{q}_i, \underline{x}) I(\underline{q}_i). \tag{5}$$

This new formulation of $\hat{L}$ allows for the utilization of global information from across the image while enforcing locality (e.g., spatial locality) through the weighting scheme. One of the main drawbacks of the formulation described in Eq. (5) is that, using existing local Retinex convention, spatial locality is enforced on a pixel basis between $\underline{x}$ and $\underline{q}$. This is based on the common assumption that illumination varies slowly. However, this assumption is violated in situations where there are sharp illumination changes, such as strong shadows, resulting in false discontinuities in the estimated reflectance at these locations. To accommodate for sharp illumination changes while still benefiting from the detail recovery advantages gained from enforcing spatial locality, we propose that the weight not be determined based on the spatial distance between $\underline{x}$ and $\underline{q}$, but instead be determined by the accumulated error between the neighborhoods $\aleph_{\underline{x}}$ and $\aleph_{\underline{q}}$,

$$\hat{L}(\underline{x}) = \sum_{i=1}^{N} w(\aleph_{\underline{q}_i}, \aleph_{\underline{x}}) I(\underline{q}_i). \tag{6}$$

By removing the spatial locality constraint between $\underline{x}$ and $\underline{q}$, the assumption of slow illumination variation is no longer made and so discontinuities due to sharp illumination changes is well preserved in the estimated illumination of the image. Therefore, the effect of strong shadows and other sharp illumination changes on the estimated reflectance is effectively reduced. Furthermore, by determining the weight on local neighbors instead of individual points, the detail recovery performance of the local Retinex approach is retained.

Based on the formulation described in Eq. (6), the adaptive Monte Carlo Retinex method can be described as follows. Given an image I, consider a random field S representing all possible pixels within $I(\underline{x})$, and X be a random variable in S. For a given point x_c, a set of N random points $\{\underline{q}_1, \underline{q}_2, \ldots, \underline{q}_N\}$ are generated from S based on a spatially-adaptive probability density function p,

$$p(\underline{x}|\underline{x}_c) = \frac{1}{(\underline{x} - \underline{x}_c)^{\alpha}}, \tag{7}$$

where $\underline{x}_c$ is the point in L being estimated and α is the sampling density decay factor (based on empirical testing, a suitable decay factor is kept constant at $\alpha = 1.3$). This spatially-adaptive sampling scheme encourages spatial locality by decreasing the sampling density as we move away from $\underline{x}_c$, while still taking advantage of global information by allowing for the possibility of distant points in the image being sampled.

Given the set of N random points $\underline{q}_1, \underline{q}_2, \ldots, \underline{q}_N$, the weight w associated with $\underline{q}_i$ in estimating $L(\underline{x}_c)$ can be computed as the exponential of the negative cumulative Pearson Type VII error [12] between the respective local neighborhoods $\aleph_{\underline{q}_i}$ and $\aleph_{\underline{x}_c}$

$$w(\aleph_{\underline{q}_i}, \aleph_{\underline{x}_c}) = \exp\left[\frac{-\Phi(\aleph_{\underline{q}_i}, \aleph_{\underline{x}_c})}{d}\right], \tag{8}$$

where d is the weight decay constant (based on empirical testing, a suitable constant is kept at $d = 0.15$) and,

$$\Phi(\aleph_{\underline{q}_i}, \aleph_{\underline{x}_c}) = \quad \sum \ln\left(\sqrt{1 + \left(I(\aleph_{\underline{q}_i}) - I(\aleph_{\underline{x}_c})\right)^2}\right).$$

Based on this weighting scheme, the Monte Carlo estimate of L at $\underline{x}_c$ based on the set of random points $\underline{q}_1, \underline{q}_2, \ldots, \underline{q}_N$ can be computed as

$$\hat{L}(\underline{x}_c) = \frac{\sum_{i=1}^{N} I(\underline{q}_i) w(\aleph_{\underline{q}_i}, \aleph_{\underline{x}_c})}{\sum_{i=1}^{N} w(\aleph_{\underline{q}_i}, \aleph_{\underline{x}_c})}. \qquad (9)$$

Finally, the reflectance of the image can then be estimated using the formulation described in Eq. (4).

4. Experimental Results

To evaluate the effectiveness of the proposed adaptive Monte Carlo Retinex method, two sets of experiments were devised. The first set of experiments involves performing illumination and reflectance separation on monochromatic face image test sets constructed based on the Yale Face Database B [13]. Each face test set consists of single light source images of a human subject under three different ambient illumination conditions. For comparison purposes, the single scale Retinex (SSR) method proposed by Jobson et al. [9], the multi scale Retinex (MSR) method proposed by Jobson et al. [10], and the bilateral filtering Retinex (BFR) method proposed by Elad [11] were also tested. All of the tested methods are implemented using the parameters proposed in the original works. Proper illumination and reflectance separation is very important in computer vision as it allows for object recognition that is robust to local and global illumination variations. The second set of experiments involves performing color image enhancement using the proposed method on two low-contrast chromatic images from the work by Elad [11] and Yamasaki et al. [1] respectively. For comparison purposes, color image histogram equalization was also tested for color image enhancement. Proper color image enhancement is very important in improving the perceptual quality of an image while maintaining the tone of the original image.

The illumination and reflectance separation results for the monochromatic face image test sets are shown in Fig. 2, Fig. 3, and Fig. 4. The strong shadows are better preserved in the estimated illumination using the proposed method in all test cases. This preservation of strong shadows in the illumination component is much desired as they are due to sharp illumination changes and as such should be retained in the illumination component as opposed to appearing in the reflectance component. Consequently, the estimated reflectance using the proposed method exhibits noticeably less illumination-related artifacts than the other tested methods. This is particularly noticeable in Fig. 2, where the strong shadow artifacts present near the nose of the human subject exhibited by the other tested methods is noticeably reduced in the proposed method. This allows for a more consistent representation that is more robust to illumination variations in the environment. Therefore, these results demonstrate the effectiveness of the proposed method for separating the illumination and reflectance components in an image under varying illumination conditions.

The color image enhancement results for the low-contrast chromatic images are shown in Fig. 5 and Fig. 6. While both the proposed method and color image histogram equalization noticeably improves the contrast for both test images, the proposed method does a significantly better job at preserving the original photographic tone of the image. This is particularly noticeable in Fig. 5, where the image produced by color image histogram equalization appears over-exposed, while the image produced by the proposed method provides good contrast while preserving the original photographic tone of the image. Furthermore, the images produced by the proposed method exhibit noticeably less noise in dark regions. This is evident in Fig. 5, where blocking artifacts become very visible in the histogram equalized image but not noticeable in the image produced by the proposed method. Similarly, noise artifacts are noticeably amplified in the dark regions of Fig. 6 in the histogram equalized image, which is not the case for the proposed method. These results illustrate the effectiveness of the proposed method in enhancing the contrast of color images while preserving the original photographic tone of the image and avoiding noise amplification in dark regions.

5. Conclusions

In this paper, a novel Retinex method based on adaptive Monte Carlo estimation is presented. A spatially-adaptive scheme is introduced for sampling random points from the image field. An adaptively weighted Monte Carlo estimation scheme for estimating the illumination and reflectance components of an image is introduced based on the drawn set of random points. By exploiting both global and local image information, the proposed method is designed to provide better illumination and reflectance separation by reducing the effects of sharp illumination changes and noise on the estimation process, while still preserving the original photographic tone of the image. Experimental results demonstrate that the proposed method achieves improved illumination and reflectance separation as well as color image enhancement when compared to existing Retinex and color enhancement techniques. Future work involves investigating alternative point sampling approaches and weighting schemes, as well as applying the proposed method to illumination invariant object tracking.

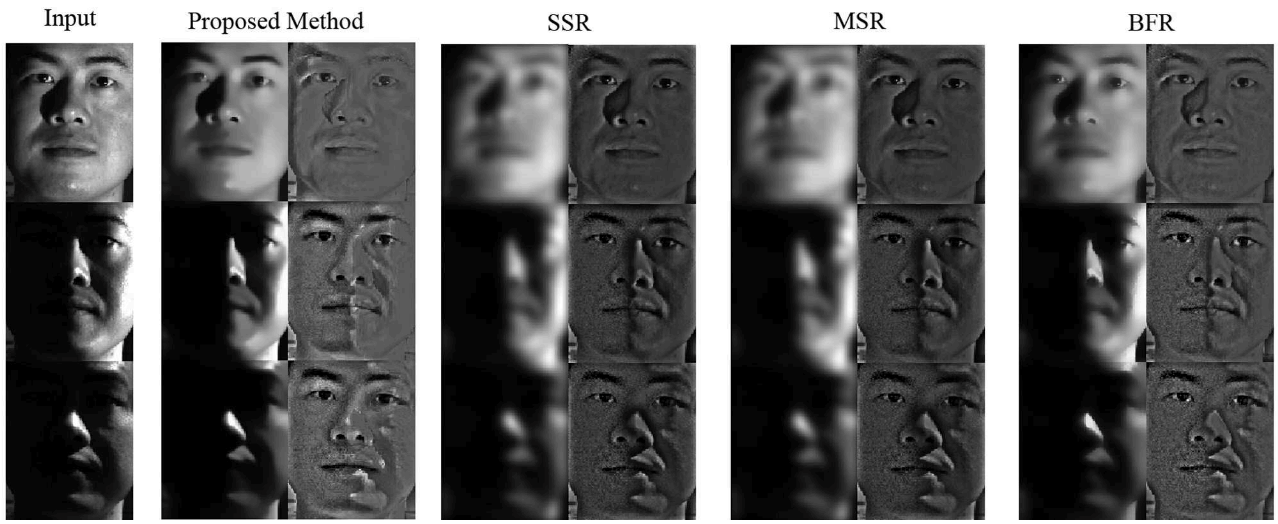

Figure 2. Illumination and reflectance separation results for Face Test 1. Rows represent the same face imaged under varying illumination conditions. In each case, the proposed method preserves strong shadows and other sharp illumination changes in the illumination images much better than any of the other three methods (SSR [9] , MSR [10], BFR [11]), consequently resulting in noticeably less illumination-related artifacts in the reflectance images.

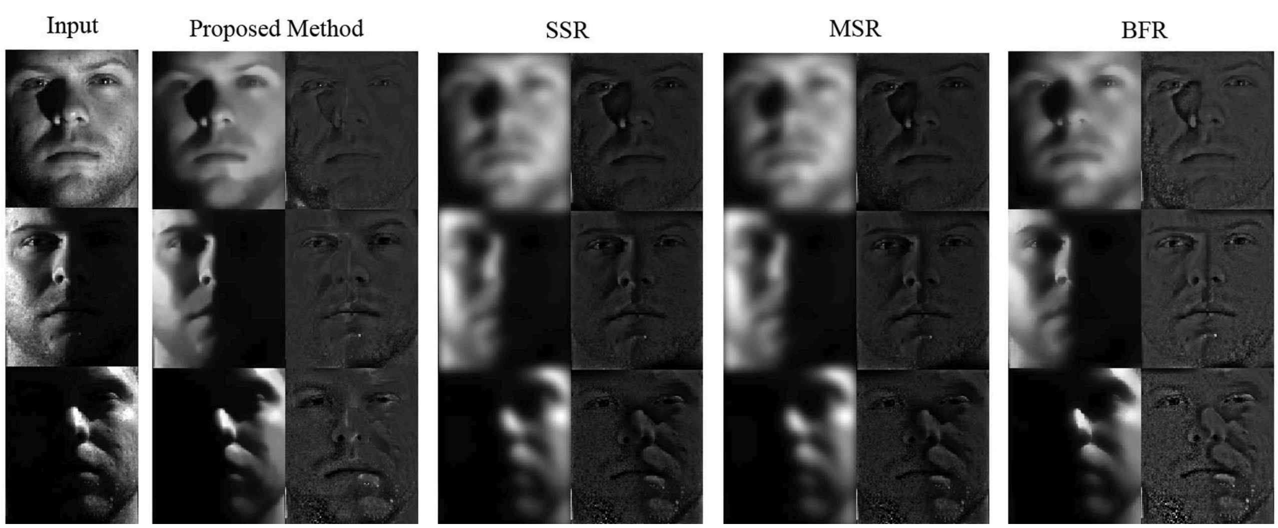

Figure 3. Illumination and reflectance separation results for Face Test 2. Rows represent the same face imaged under varying illumination conditions. In each case, the proposed method preserves strong shadows and other sharp illumination changes in the illumination images much better than any of the other three methods (SSR [9] , MSR [10], BFR [11]), consequently resulting in noticeably less illumination-related artifacts in the reflectance images.

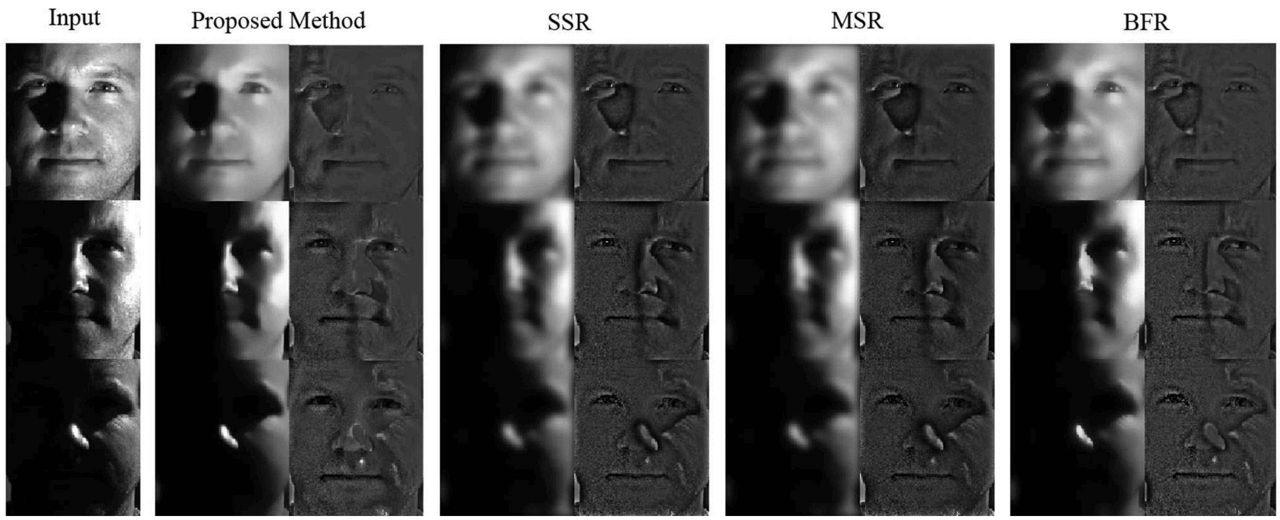

Figure 4. Illumination and reflectance separation results for Face Test 3. Rows represent the same face imaged under varying illumination conditions. In each case, the proposed method preserves strong shadows and other sharp illumination changes in the illumination images much better than any of the other three methods (SSR [9] , MSR [10], BFR [11]), consequently resulting in noticeably less illumination-related artifacts in the reflectance images.

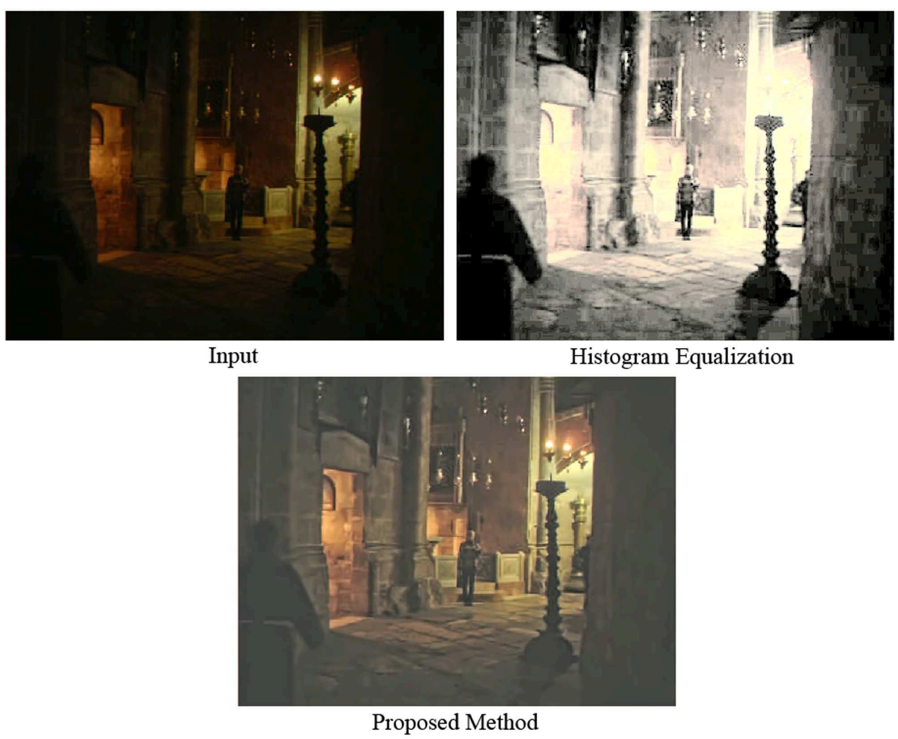

Figure 5. Color image enhancement results for Color Test 1 [11] for the proposed method and histogram equalization. While both methods noticeably improves image contrast, the proposed method does a significantly better job at preserving the original photographic tone of the image. Furthermore, the image produced by the proposed method does not exhibit the strong blocking artifacts visible in the image proposed by color image histogram equalization.

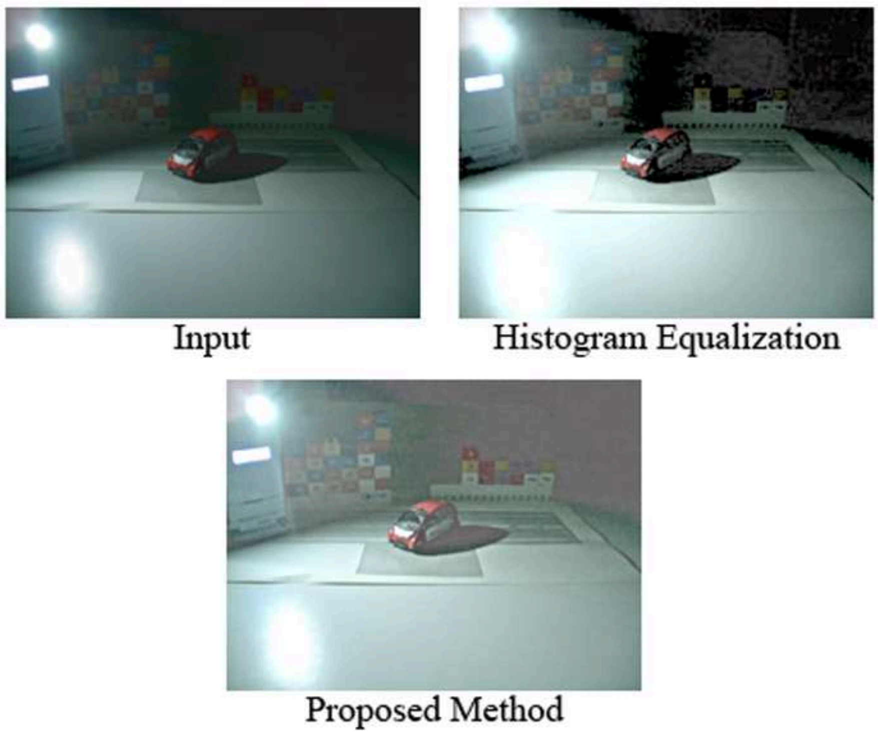

Figure 6. Color image enhancement results for Color Test 2 [1] for the proposed method and histogram equalization. While both methods noticeably improves image contrast, the proposed method does a significantly better job at preserving the original photographic tone of the image. Furthermore, the image produced by the proposed method exhibit noticeably less noise in dark regions when compared to that produced by color image histogram equalization.

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References

[1] A. Yamasaki, H. Takauji, S. Kaneko, T. Kanade, and H. Ohki, "Denighting: Enhancement of Nighttime Images for a Surveillance Camera", *Proc. ICPR*, 2008.

[2] X. He, S. Yan, Y. Hu, P. Niyogi, and H. Zhang, " Face Recognition Using Laplacianfaces", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 27, no. 3, pp. 328-340, 2005.

[3] E. Land and J. McCann, "Lightness and Retinex Theory", *J. Optical Soc. of America A*, vol. 61, pp. 1-11, 1971.

[4] D. Marini and A. Rizzi, "A Computational Approach to Color Adaptation Effects", *Image and Vision Computing*, vol. 18, no. 13, pp. 1005-1014, 2000.

[5] T. Cooper and F. Baqai, "Analysis and Extensions of the Frankle-McCann Retinex Algorithm", *J. Electronic Imaging*, vol. 13, no. 1, pp. 85-92, 2004.

[6] E. Provenzi, M. Fierro, A. Rizzi, L. De Carli, D. Gadia, and D. Marini, "Random Spray Retinex: A New Retinex Implementation to Investigate the Local Properties of the Model", *IEEE Trans. Image Processing*, vol. 16, no. 1, pp. 162-171, 2007.

[7] E. Provenzi, C. Gatta, M. Fierro, and A. Rizzi, "A Spatially Variant White-Patch and Gray-World Method for Color Image Enhancement Driven by Local Contrast", *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 30, no. 10, pp. 1757-1770, 2008.

[8] E. Land, "An alternative technique for the compution of the designator in the Retinex theory of color vision", *Proc. Nat. Acad. Sci.*, vol. 83, pp. 3078-3080, 1986.

[9] D. Jobson, Z. Rahman, and G. Woodell, "Properties and performance of a center/surround Retinex", *IEEE Trans. Image Processing*, vol. 6, no. 3, pp. 451-462, 1997.

[10] D. Jobson, Z. Rahman, and G. Woodell, "A Multiscale Retinex for Bridging the Gap between Color Images and the Human Observation of Scenes", *IEEE Trans. Image Processing*, vol. 6, no. 7, pp. 965-976, 1997.

[11] M. Elad, "Retinex by Two Bilateral Filters", *Proc. The 5th International Conference on Scale-space and PDE in Computer Vision*, 2005.

[12] K. Pearson, "Mathematical contributions to the theory of evolution, XIX: Second supplement to a memoir on skew variation," *Philosophical Transactions of the Royal Society of London. Series A, Containing Papers of a Mathematical or Physical Character*, vol. 216, pp. 429-457, 1916.

[13] A. Georghiades, P. Belhumeur, and D. Kriegman, "From Few to Many: Illumination Cone Models for Face Recognition under Variable Lighting and Pose", *IEEE Trans. Pattern Anal. Mach. Intelligence*, vol. 23, no. 6, pp. 643-660, 2001.