RESTORATION OF UNEVENLY ILLUMINATED IMAGES

Mading Li[1], *Xiaolin Wu*[2], *Jiaying Liu*[1]*, *Zongming Guo*[1]

[1]Peking University [2]McMaster University

ABSTRACT

In this paper, we tackle the problem of restoring unevenly illuminated images. Generally, there exist three kinds of exposure conditions in these images: under-, normal-, and over-exposures. Thus, a three-component generalized Gaussian mixture model (3GGMM) is used to fit the histogram of the illuminance image, and probabilistically characterize the three exposure states. Based on the 3GGMM, separate optimal tone mapping functions are designed to enhance under- and over-exposed regions by maximizing expected contrast of these regions. The output illumination can be obtained by fusing the restoration results in different exposure states. Experimental results validate the effectiveness of the proposed image restoration approach.

Index Terms— Unevenly illuminated image restoration, generalized Gaussian mixture model, tone mapping

1. INTRODUCTION

One of the most common types of image degradation for majority of camera users is poor intelligibility of details caused by the uneven illumination condition. The problem typically occurs when the illumination condition in the scene varies dramatically. In the large and growing body of image restoration literature, most works addressed the problems of super-resolution, denoising, and deblurring, with little attention given to image restoration for uneven illumination. Ironically, nowadays even inexpensive main stream consumer-grade cameras can take high resolution, noise free and sharp pictures, whereas they suffer from poor image quality in uneven illumination conditions that are often out of users' control. In this regard, restoring this kind of images is arguably more important and pressing than other extensively studied tasks.

An obvious attempt to rectify the uneven illumination problem is tone mapping or contrast enhancement, which operates on a single image of a fixed exposure setting. Histogram equalization (HE) and its variant contrast limited adaptive histogram equalization (CLAHE) [1] are the representatives. However, HE conducts a global adjustment and hence it cannot adapt to drastically different intensity distributions of regions under different illumination conditions. CLAHE uses artificial blocks instead of natural segments and generates artifacts. These artifacts can be alleviated by edge-aware tone mapping methods, such as edge-preserving decomposition [2], and local Laplacian filtering [3]. They can amplify high frequency features such as edges, but at the expense of unnatural overall tone reproduction. Low-light image enhancement methods [4, 5] can effectively enhance under-exposed regions in unevenly illuminated images. However, they may over-enhance over-exposed regions.

In this paper, we aim to restore unevenly illuminated images by correcting the problem at its root cause: uneven illumination. In a typical unevenly illuminated image there are three types of regions: under-exposed, normally exposed, and over-exposed. We first estimate the illuminance image of the input image and then fit the histogram of image L to a three-components generalized Gaussian mixture model (3GGMM); the three components correspond to under-, normal-, and over-exposed regions, respectively. For the under-exposure and over-exposure components of the 3GGMM, we perform a modified optimal contrast-tone mapping (OCTM) on each component to enhance the image in under- and over-exposed regions. Finally, the input image is restored by fusing the results of the under-, normal- and over-exposed regions.

The remainder of this paper is organized as follows. Section 2 presents the development of the illumination model for unevenly illuminated images, via homomorphic filtering and the 3GGMM fitting of the input histogram. Section 3 details the design of adaptive tone mapping function for each of the three components of the 3GGMM, corresponding to under-, normal- and over-exposures. In particular, we elaborate on how to impose a lower/upper bound on the average intensity of the restored under-exposed/over-exposed regions. Also, we discuss how to prevent possible halo artifacts by fusing the results of multiple tone mapping functions according to the proposed 3GGMM. Experimental results and performance evaluations on backlit and flash photographs are reported in Section 4. Section 5 concludes the paper.

2. ILLUMINATION MODELING

In order to estimate and model the illumination conditions in which the input image I is acquired, we adopt the image formation model $I = LR$, with L being the 2D illumination

*Corresponding author
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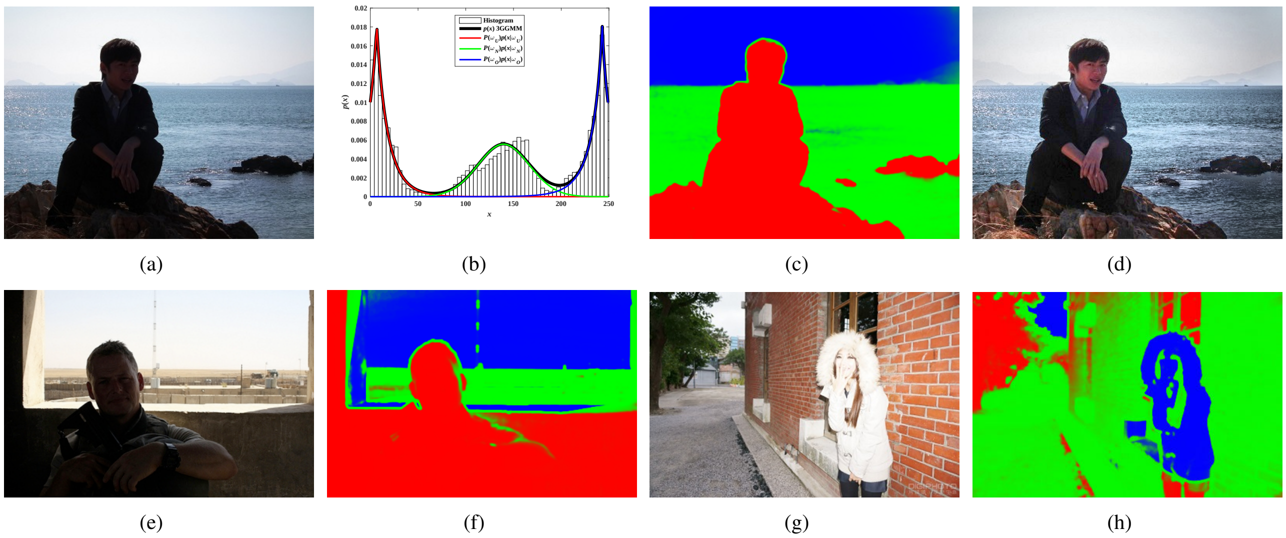


Fig. 1. (a) The input unevenly illuminated image I; (b) the histogram of the illuminance image L, and the fitting of a three-components generalized Gaussian mixture model (black curve) with each component represented in different colors (red, green, blue curves for under-, normal-, and over-exposed regions, respectively); (c) the 3GGMM fitting result encoded by color, with R, G, and B values of pixel (i, j) being the probabilities that the pixel (i, j) is in states ω_U, ω_N, and ω_O, respectively; (d) result generated by the proposed method. More test images (e)(g) and their corresponding 3GGMM fitting results (f)(h).

strength image and R the 2D surface reflectance image [6]. Given the illumination image, if the abnormally exposed regions can be identified, one can restore the input image by algorithmically adjusting the illumination levels in different regions; this is to compensate for the insufficient illumination in under-exposed regions and reduce the excess illumination in over-exposed regions. In our work, we perform the non-linear homomorphic filtering on I to extract an estimated illuminance image L, and use 3GGMM to model the illumination and separate the three different regions.

In the 3GGMM, each component $\mathbf{p}_j$, $j \in \{U, N, O\}$, is a generalized Gaussian distribution. A generalized Gaussian distribution is given by [7]

$$\aleph(x|\mu, \sigma, \lambda) = A(\lambda)\text{exp}\left(-B(\lambda)\left|\frac{x-\mu}{\sigma}\right|^{\lambda}\right), \quad (1)$$

where μ, σ, and λ are the mean, the standard deviation, and the shape parameter. $A(\lambda)$ and $B(\lambda)$ are defined as:

$$A(\lambda) = \left[\frac{\Gamma(3/\lambda)}{\Gamma(1/\lambda)}\right]^{\frac{1}{2}} \frac{\lambda}{2\sigma\Gamma(1/\lambda)}, B(\lambda) = \left[\frac{\Gamma(3/\lambda)}{\Gamma(1/\lambda)}\right]^{\frac{\lambda}{2}}. \quad (2)$$

As the dynamic range of digital images is a finite interval $[0, 255]$, the 3GGMM should be defined on finite support $[0, 255]$. For this reason, the bounded generalized Gaussian mixture model [8] is used to fit the histogram $\mathbf{h}$ of the illuminance image L. In 3GGMM, each component is defined as a bounded generalized Gaussian distribution $\Psi(x|\mu, \sigma, \lambda)$.

$$\Psi(x|\mu, \sigma, \lambda) = m\aleph(x|\mu, \sigma, \lambda)H(x), \quad (3)$$

where m is a constant normalizing the distribution and

$$H(x) = \begin{cases} 1, & \text{if } x \in [0, 255], \\ 0, & \text{otherwise.} \end{cases} \quad (4)$$

In the illuminance image L, pixels are classified into three different illumination states: under exposure, normal exposure, and over exposure, denoted by ω_U, ω_N and ω_O; each state corresponds to a component in the 3GGMM. The probability distribution $p(k)$ of grey level k is a linear combination of three generalized Gaussian models

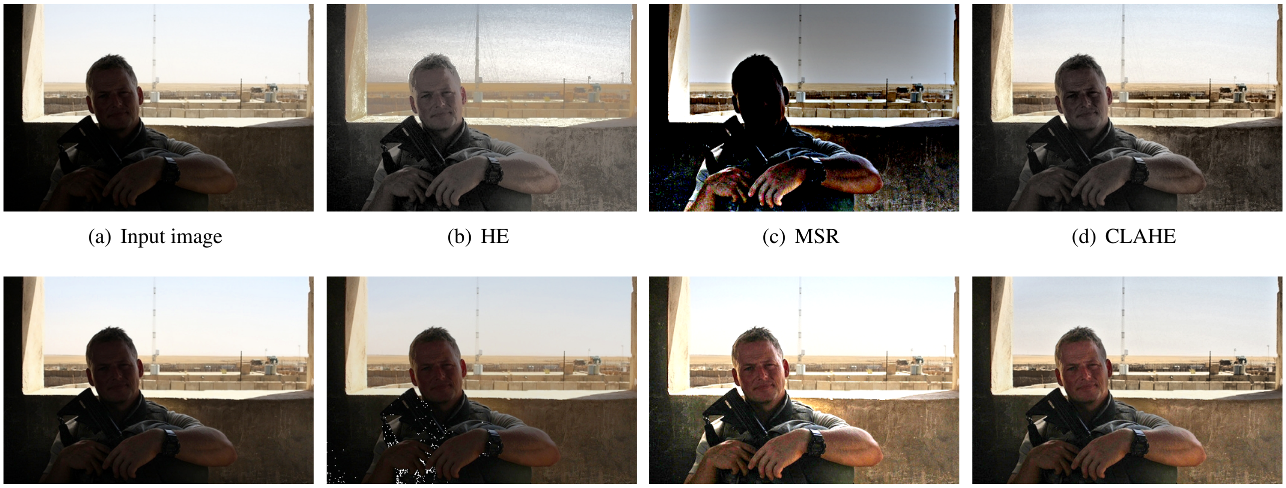
$$p(k) = \sum_j P(\omega_j)p(k|\omega_j), j \in \{U, N, O\}, \quad (5)$$

where $p(k|\omega_j) \sim \Psi(\mu_j, \sigma_j, \lambda_j)$ is the probability distribution function of the bounded generalized Gaussian component ω_j specified by the mean μ_j, the standard deviation σ_j, and the shape parameter λ_j. $P(\omega_j)$ is the prior probability of ω_j. The parameters of each generalized Gaussian component can be obtained by an EM-type iterative algorithm [8].

After obtaining the parameters of each generalized Gaussian component, the probability of grey level k being in state j can be calculated by

$$\phi_j(k) = P(\omega_j)p(k|\omega_j), j \in \{U, N, O\}. \quad (6)$$

A visualization of the proposed 3GGMM can be found in Fig. 1. The figure shows that the 3GGMM fits the input histogram very well; more importantly, in the image domain, the 3GGMM generates a remarkably good segmentation in terms of under, normal, and over exposures.



(a) Input image (b) HE (c) MSR (d) CLAHE

(e) SRIE (f) CHIR (g) LIME (h) Proposed

Fig. 2. Backlit image restoration by different methods.

3. ADAPTIVE TONE MAPPING

After its construction as discussed in the preceding section, the resulting 3GGMM is used to extract from the real data histogram $\mathbf{h}$ three component histograms $\mathbf{h}_U, \mathbf{h}_N, \mathbf{h}_O$ for the three exposure types, namely,

$$h_j(k) = \frac{\phi_j(k)}{p(k)} h(k), j \in \{U, N, O\}. \tag{7}$$

These classified histograms provide statistics for the designs of optimal tone mapping functions for under- and over-exposed regions.

Next, we develop the modified OCTM algorithm for restoring under-exposed regions in an unevenly illuminated image. In the original OCTM algorithm [9], the goal is to increase the expected contrast maximally under a tone distortion constraint over the entire image. For the task of unevenly illuminated image restoration, we apply the OCTM algorithm not on the global histogram $\mathbf{h}$ but on the histogram $\mathbf{h}_U$ and $\mathbf{h}_O$ of the under-exposed and over-exposed regions. Moreover, in the linear program framework of OCTM, we add one more constraint that the average intensity μ_U/μ_O of the under-exposed/over-exposed regions should be increased/decreased to μ_U^*/μ_O^* such that μ_U^*/μ_O^* is sufficiently close to the average intensity μ_N of the normal-exposed regions. The role of this constraint is to artificially enforce proper strength of the illumination on excessively or inadequately illuminated objects. As in [9], we present the tone mapping function $\mathbf{T}_U$, which maps grey level k to $T_U(k)$, as a discrete step function

$$T_U(k) = \sum_{i=0}^{k} s_i, \;\; 0 \le k < K, \tag{8}$$

where the vector $\mathbf{s} = (s_0, s_1, \cdots, s_{K-1})$ uniquely determines $\mathbf{T}_U$ and vice versa. Then, the expected contrast achieved by $\mathbf{T}_U$ is

$$G(\mathbf{h}_U, \mathbf{T}_U) = \sum_{k=0}^{K-1} h_U(k) s_k. \tag{9}$$

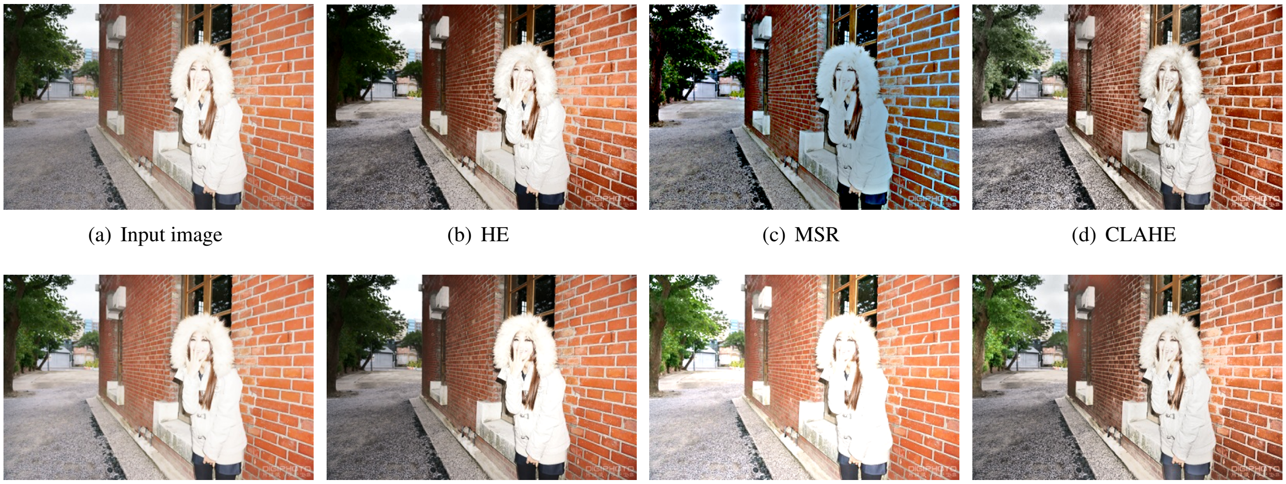
The objective of restoring under-exposed regions is to find the tone mapping function $\mathbf{T}_U$, or equivalently the vector $\mathbf{s}$, that maximizes the expected contrast gain $G(\mathbf{h}_U, \mathbf{T}_U)$ while satisfying a tone distortion bound d and a lower bound on the output average intensity $\mu_U^*(\mathbf{s})$, which can be formulated as the following constrained optimization problem

$$\begin{aligned} \arg\max_{\mathbf{s}} \; & \sum_{k=0}^{K-1} h_U(k) s_k, \\ s.t. \; & \sum_{k=0}^{K-1} s_k < K \\ & s_k \ge 1/d, \; 0 \le k < K \\ & \mu_U + (\mu_N - \mu_U)\xi \le \mu_U^*(\mathbf{s}) \le \mu_N, \; 0 < \xi \le 1. \end{aligned} \tag{10}$$

The last constraint is the lower bound on the average output intensity, which is an increment of $(\mu_N - \mu_U)\xi$ above the original mean μ_U for the under-exposed regions. This can increase the dynamic range of under-exposed regions without suffering from the underflow problem. Also, note that $\mu_U^*(\mathbf{s})$ is a linear function in $\mathbf{s}$, because

$$\mu_U^*(\mathbf{s}) = \sum_{k=0}^{K-1} h_U(k) T_U(k) = \sum_{k=0}^{K-1} h_U(k) \sum_{i=0}^{k} s_i = \sum_{k=0}^{K-1} s_k \sum_{i=k}^{K-1} h_U(i). \tag{11}$$

Therefore, the problem of Eq. (10) is one of linear program with K variables, and it can be solved fairly efficiently as $K = 256$ in most cases.



(a) Input image (b) HE (c) MSR (d) CLAHE

(e) SRIE (f) CHIR (g) LIME (h) Proposed

Fig. 3. Flash photography restoration by different methods.

A symmetric approach can be used to restore over-exposed regions. The tone mapping function $\mathbf{T}_O$ in state ω_O can be computed with the constraint $\mu_N \leq \mu_O^*(\mathbf{s}) \leq \mu_O - (\mu_O - \mu_N)\xi$, $0 < \xi \leq 1$. For normally exposed regions, nothing needs to be done, *i.e.*, $\mathbf{T}_N$ is the identity tone mapping function, $T_N(k) = k, 0 \leq k < K$.

Finally, with tone mapping functions $\mathbf{T}_j$, $j \in \{U, N, O\}$, the output k^* for each input grey level k is given by fusing the OCTM results of the under-, normal- and over-exposed regions

$$k^* = \sum_j \phi_j(k) T_j(k). \tag{12}$$

An intuitive way to generate the final result is to replace the original Y channel of the input image by the output illuminance image. However, this measurement generates color degradation and we use the method suggested in [10] to produce our final result.

4. EXPERIMENTAL RESULTS

We conducted extensive experiments with the proposed image restoration method on two kinds of typical images: backlit and flash photography. State-of-the-art methods HE, CLAHE [1], the multi-scale retinex algorithm (MSR) [11], the simultaneous reflectance and illumination estimation (SRIE) [12], the low-light image enhancement via illumination map estimation (LIME) [4], the cultural heritage image restoration (CHIR) [13] are compared to evaluate the effectiveness of the proposed method. Test images contain various scenes are found in the Internet. More experiments can be found in our website .

Fig. 2 and Fig. 3 present results of backlit image/flash photography restoration, respectively. As can be observed, in backlit image restoration, all methods except ours and LIME fail to sufficiently enhance the backlit surfaces, leading to less legibility of the object illuminated from behind than the proposed method. Since LIME is designed specifically for low-light images, it can effectively enhance the under-exposed regions. However, other regions, especially over-exposed regions, are over-enhanced by LIME.

As for flash photograph restoration, all the methods except HE are able to compensate for insufficient lighting on background regions to some extent. However, not all of them are effective on repairing over-exposed regions. In fact, instead of decreasing the excessive illumination strength in over-exposed regions, SRIE, CHIR, and LIME move in the opposite direction by increasing the intensity levels in these regions. MSR and CLAHE generate unnatural appearances of the restored image, of which the proposed method is immune.

5. CONCLUSION

An unevenly illuminated image restoration method of illumination modeling and adaptive tone mapping is proposed. An illuminance image is extracted by homomorphic filtering and a 3GGMM is applied to fit the histogram of the illuminance image. The resulting 3GGMM provides statistics for the designs of optimal tone mapping functions for under- and over-exposed regions. By imposing a lower/upper bound on the output illumination of under-exposed/over-exposed regions in the OCTM framework, the corresponding tone mapping function increases/decreases the illumination strength on the under-exposed/over-exposed surfaces to compensate for abnormally weak/strong illuminations at the image acquisition stage. Experiments and comparison studies indicate that the proposed image restoration method performs satisfactorily and competitively.

http://www.icst.pku.edu.cn/struct/Projects/UnevenIllumination.html

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