Tone Adjustment of Underexposed Images Using Dynamic Range Remapping

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Abstract. We present a new method for automatically adjusting the tonal values of underexposed digital images. We make the most of the dynamic range of digital images, and adjust the tonal values through dynamic range remapping, with a specifically defined tone mapping operator. The operator comprises two concatenate terms. The first one is a global operator that adjusts the tonal values of underexposed image with a linear scale transformation as well as a nonuniform intensity reduction function. The second one is a local operator used for noise suppression and detail enhancement. With such operator, tone values of underexposed images are faithfully adjusted. Meanwhile, noises are suppressed without introducing noticeable artifacts into resulting images. Our method runs with high efficiency. Experimental results demonstrate its effectiveness.

Keywords: Image enhancement, Underexposed image, Tone adjustment.

1 Introduction

The rapid growth of digital camera (DC) market dramatically promotes the development of image enhancement techniques. For producing visually pleasing photographs, digital cameras require significant amount of image processing before or after the imaging procedure, e.g., white balance, defect correction and noise removal, to compensate or ameliorate the sensor output data. In this paper, we focus on the underexposed images, and present an automatic method for effectively adjusting the tonal values of such images.

Underexposed images may be frequently captured due to bad lighting conditions, wrong settings of shooting parameters, etc. Conventional methods for dealing with those images such as histogram equalization and gain/offset [1] are mainly global operators. They can only process few kinds of underexposed images with limited effect. A challenging case is to enhance images captured in the scene where bright and dark regions exist simultaneously. The single exposure time of modern DC will usually cause either underexposed foreground or

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overexposed background. Global operators generally cannot work well for such image. Recent method allows local control of tonal values in an image with a stroke-based interface [2], or capture noise free image with properly registered flash and no-flash image pairs [3] [4]. Although remarkable results are shown in these methods, they are generally unsuitable for real-time applications for energy optimization involved.

Recently, high dynamic range (HDR) image processing is becoming popular. HDR tone mapping techniques have been developed to compress the dynamic range of the data for displaying the image on prevalent monitors such as CRTs and LCDs. Global tone mapping techniques [5] usually cannot address contrast reduction as they use the same mapping function for all the pixels. Local methods [6] [7] perform in an spatially variant manner, but tend to introduce visual artifacts into the result. In general, most tone mapping operators are specifically designed for processing HDR images. For low dynamic range images we concern, they usually need different and sometimes cumbersome parameter setting for satisfactory effects.

As a consequence, an effective nonuniform tone adjustment algorithm for enhancing underexposed image is still desired. In this paper we present a new method for processing such image. In fact, the key issue is to compensate exposure in the underexposed regions and meanwhile keep those well exposed regions unaffected. This can be viewed as a dynamic remapping process. Our method is just built upon this point. It enhances the underexposed image with a specifically defined tone mapping operator. The operator consists of two terms, one for global intensity adjustment, and the other for local adjustment to suppress noise and to enhance detail as well. With a scale transformation and a nonuniform intensity scaling function, the global operator enhances intensity in dark regions, and meanwhile keeps the relatively bright regions almost unchanged. The local adjustment term simultaneously suppresses noise and enhances details when tone adjustment is performed. An adaptive bilateral filter is also developed here to avoid halos that can be induced by contrast enhancement during tone adjustment.

Existing methods generally need noise removal as post processing, since intensity adjustment may bring out originally unnoticeable noises. Our method however integrates noise suppression into the processing pipeline for the first time, enabling high processing speed. It achieves comparable tonal value adjustment performance relative to most existing techniques. Using our method, a visually pleasing photo can be easily produced without cumbersome parameters tuning and tedious user interaction. It can be used for applications in post image processing or be integrated into the camera imaging pipeline for enhancing camera raw data.

2 Related Work

Many approaches have been proposed to adjust the tonal values in images. They can be roughly classified as either traditional methods used for ordinary photographs or those specifically designed for high dynamic range images.

Traditional methods for enhancing underexposed images are mainly global operator. Histogram equalization compresses the dynamic range of intensity with sparse samples [1]. Nevertheless, it also expands contrast in highly populated intensity of the histogram, easily incurring bump artifacts in originally flat regions. Gain and offset linearly transforms the input intensity. But it could not manage widespread dynamic range images. Recent method proposed by Lischinski [2] allows local control of tonal values in an image based on an energy minimization framework, with stroke-based interface for designating interest regions. Although an approximate solution is provided to speed up energy optimization, this method is in general unsuitable for real-time applications, especially for preprocessing in imaging pipeline of camera. The work presented in [3] and [4] attempt to remove noise and improve the dynamic range of under-exposed images by incorporating features derived from properly registered flash and no-flash image pairs. The registration involved normally could not be directly achieved during capturing, especially for images captured by unexperienced users. As a result, it cannot be integrated into imaging pipeline as well. In contrast, our method can be easily ported into imaging pipeline of modern DCs for the high efficiency.

Enhancing under-exposed images has great similarities with HDR image processing. Tumblin et al. first formalized the problem of mapping an HDR image for displaying on devices with limited dynamic range in [12]. They develope a global mapping function supported by results in psychophysics on brightness and contrast perception. Later, Larson et al. [11] proposed the histogram adjustment technique which allocates dynamic range space in proportion to the percentage of pixels with similar brightness, again taking contrast perception into account. Drago et al. developed an adaptive logarithmic mapping for displaying high contrast scenes in [10]. In gradient domain HDR compression, Fattal et al. [13] manipulated the gradient field of the luminance image by attenuating the magnitudes of large gradients. Raskar et al. also used gradient domain methods [14]. They fuse day and night images together by adding daytime context to nighttime footage. Reinhard et al. [5] introduced the dodge and burning technique used in photographic practice and gave an automatic tone mapping method. Bae et al. [15] used a two-scale non-linear decomposition of an image to modify the different layers based on their histograms and meanwhile introduced a technique that controls the spatial variation of detail.

Few methods deal with underexposed video. Bennett et al. [9] enhanced low dynamic videos by adaptively varying the exposure at each pixel in every frame. The virtual exposure they devised is a dynamic function of both the spatial and temporal neighboring information of the pixel. But the implementation is rather slow since it relies on multiple non-linear filtering steps. As mentioned in their paper, the processing of 640×480 video normally takes approximately one minute per frame. In addition, although their adjustment operator can be applied to underexposed images, we show in experimental results such global operator usually cannot work well for image with non-uniformly exposed regions.

3 Our Method

Our primary goal is to increase intensity of underexposed regions to make the details in those regions clearly visible, and meanwhile to enhance details in well exposed regions. This can be viewed as a nonuniform and local virtual exposure adjustment procedure that can not be achieved by modern camera settings. We simulate such procedure with a pixel-wise operator. For gray image, we adjust the intensity with the following formula,

$$I' = GMap(I) * I, \tag{1}$$

where I is the original intensity, and I' is the adjusted intensity. $GMap$, named as gain map, is a pixel-wise gain factor map that accounts for the virtual exposure time in a nonuniform manner. To increase the intensity value in underexposed regions, gain factor should be bigger than 1.0 which is similar to prolonging the exposure time. Otherwise, if gain factor is smaller than 1.0, the intensity value is reduced.

As intensity adjustment may amplify and bring out original unnoticable noises, we also integrate noise suppression into our algorithm. Hence, coupled with tone adjustment and contrast enhancement, gain map consists of two terms:

$$GMap(I) = f(I) * g(I). \tag{2}$$

Here f accounts for the global tonal value adjustment. g determines whether local contrast should be enhanced or noise should be suppressed. We evaluate it with a confidence level, quantified from the input intensity. The definitions of f and g are described in detail in the following subsections.

3.1 Global Tone Adjustment

To reveal details in dark regions, we first uniformly scale the intensity of input gray image with a constant s:

$$I_s(x, y) = s * I(x, y), \tag{3}$$

where I is the input intensity. s is a scale parameter that greatly influences the effect of adjustment. It is calculated as:

$$s = k * I_m + b. \tag{4}$$

Here, I_m is the mean value of input intensity calculated in log domain. k and b are two parameters learnt from our image library through least squares method. They are set as $-6.36E - 5$ and 0.143 separately in implementation.

Through the above linear transformation, details in dark regions are revealed. Whereas in bright regions the image may be overexposed. A nonlinear compression is thus required to further adjust the scaled intensity. We adopt here the following compression formula [5]:

$$I' = \frac{I_s}{1 + I_s^{\gamma}} * (I_w^{\gamma-1} + \frac{I_s}{I_w^2}). \tag{5}$$

The first term in the right side of Eq. 5 is the compression term. Higher intensity pixels will receive more compression and lower intensity pixels will be compressed less in contrast. γ controls the sensitivity of low intensity adjustment . For typical dark-lighting images, γ is set bigger than 1.0 for enabling significant enhancement of the dark area. I_w is the white point mapped to the brightest intensity. To ensure a suitable illuminance range after adjustment, an adaptive and robust setting of I_w is suggested as:

$$I_w = min(255 * s, Ratio(I_s, 80\%) * 1.25), \tag{6}$$

where $Ratio(I_s, 80\%)$ is an intensity threshold satisfying that the ratio of number of pixels whose intensity is less than it to the total pixel number equals 80%.

Substituting Eq. 3 for I_s in Eq. 5 and dividing Eq. 5 with I, we derive the intensity adjustment function f:

$$f(I) = \frac{s * (I_w^{\gamma-1} + s * I_{abf}/I_w^2)}{1 + (s * I_{abf})^\gamma} \tag{7}$$

Here, I_{abf} is the resulting image by applying our adaptive bilateral filter to I. We use I_{abf} instead of I to avoid local contrast reduction. We describe it in subsection 2.3.

3.2 Local Adjustment

The global tone adjustment operator $f(I)$ is designed to increase the intensity of underexposed images. As tone adjustment may bring out original unnoticeable noises and details, we desire to suppress the potential noise and meanwhile enhance details during tone adjustment. According to a predetermined confidence level CL, we achieve this goal with the following local adjustment operator:

$$g(I) = (\frac{I + \delta}{I_{abf} + \delta})^{CL(I_{abf}) - CL(\eta)}. \tag{8}$$

η is a threshold we set to 30 by default. The confidence level CL is a metric for each pixel obtained from quantified intensity value that determines whether noise should be reduced or detail should be enhanced:

$$CL(I) = log(I + 1)/log(256) \tag{9}$$

For pixels with big CL, such as $I_{abf}(x, y) > \eta$, Eq. 8 serves the role of enhancing local details. Assume that a dark pixel (x, y) lies in relatively bright region. Its intensity produced with bilateral filter normally satisfies $I_{abf}(x, y) > I(x, y)$, hence $g(I)$ is smaller than 1. This will relatively decreases the resulting intensity, as a result increasing contrast at that pixel. This is similar to photographic "dodging". Similarly, a bright pixel in relatively dark region will be boosted more, and is thus "burned". In either case, the pixel's local contrast is increased. On the contrary, for pixels with smaller CL value satisfying $I_{abf}(x, y) < \eta$, Eq. 8 can be used to suppress noise. For a relatively bright pixel in a dark region, $g(I)$ will be smaller than 1.0, hence the intensity in this pixel is averaged with respect to its neighbors. Similar effect exists when the dark pixel lies in relative bright region.

3.3 Adaptive Bilateral Filter

As aforementioned, to avoid local contrast reduction, we need to compute a local averaged image I_{abf} in configuration of the gain map. Since simple filters easily incur halos around strong edges, due to increase of local contrast, we employ here an adaptive bilateral filter, and use it to produce I_{abf}.

Given a pixel p, the bilateral filter is defined as [8],

$$B(\sigma_h, \sigma_i) = \frac{\sum\limits_{q \in N_p} g_{\sigma_h}(\|q-p\|) g_{\sigma_i}(|I_q - I_p|) I_p}{\sum\limits_{p \in N_p} g_{\sigma_h}(\|q-p\|) g_{\sigma_i}(|I_q - I_p|)} \tag{10}$$

where N_p is the neighborhood of pixel p and $g_\sigma(x)$ is the Gaussian kernel. σ_h dominates the spatial neighborhood. σ_i controls the intensity influence. It penalizes the neighboring pixels with big intensity difference and is typically chosen based on the estimation of the SNR of input image.

It is difficult to select a constant σ_i to fulfill our requirement. If σ_i is too big, the filter tends to be simple box filter and halos still exist. On the contrary, if σ_i is set smaller, trivial effect is exerted. Note that halos always occur around the strong edges because of excessive contrast enhancement. If enhancement around strong edges is weaken, we can eliminate the halo phenomenon during detail enhancement. This is achieved by calculating σ_i as follows:

$$\sigma_i(p, q) = exp(-|log(I_p) - log(I_q)|) \tag{11}$$

Here σ_i is estimated based on the brightness difference between the central pixel p and its neighboring pixel q in N_p. For the pixel near strong edges, σ_i is smaller enough such that q makes minor contribution to the average on p. Local contrast at pixel p will not be excessively magnified. Consequently, halos artifact is effectively eliminated.

3.4 Extension to Color Images

To process color image, an alternative way is to first convert it into the color space that can best encode chromaticity and luminance with different channels such as YIQ or $YCbCr$, and then only apply the algorithm to luminance component. Nevertheless, through extensive experiments we find that the results thus obtained are easily prone to chroma loss or color derivation, due to the non-independent of the chromaticity and luminance for these color spaces. Our solution here is to simultaneously adjust three color components of the image in RGB space by multiplying them by a gain factor map $GMap$ obtained from the image brightness:

$$I'_{r,g,b} = GMap(B) * I_{r,g,b}. \tag{12}$$

Fig. 1 compares the results generated using different schemes.

(a) (b) (c)

Fig. 1. Comparison between the result (b) obtained by adjusting Y component in $YCbCr$ space and result (c) generated by processing R, G, and B components simultaneously. Obviously, (c) contains more chromatic information than (b).

4 Experimental Results and Analysis

We have implemented our approach with Visual C++. Some typical underexposed images were tested. The results are shown in Figs. 1, 2, 3, 4, and 5. Fig. 2 compares our approach with traditional methods. Gain/offset exerts trial effect (Fig. 2 (b)) for the widespread range of input image. The result of histogram equalization loses details in some regions (Fig. 2 (c)). We also realize the operator used in [9]. The results produced by this operator with different parameter settings are Fig. 2. (d) and Fig. 2. (e). In comparison, our approach achieves more satisfactory effect (Fig. 2 (f)).

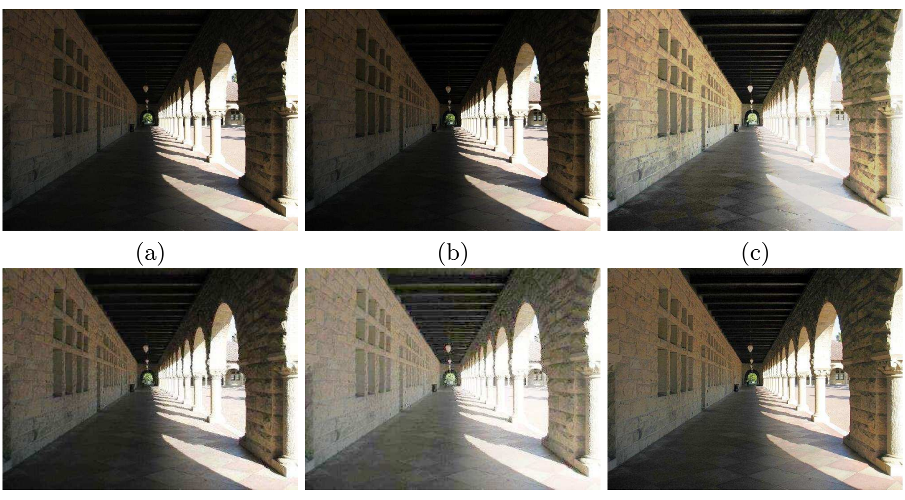

Fig. 2. Comparison of our approach with previous methods. (a) Input image; (b) Result of gain and offset; (c) Result of histogram equalization; (d) Result of the operator used in [9] with parameter $\psi = 4$; (e) Result of the same operator to (d) with $\psi = 32$; (f) Our result.

(a) (b) (c) (d)

Fig. 3. Tone adjustment results (b) and (d) for a lantern image (a) and a water fall image (c) separately. (Resolution of (a): 481×630; execution time: 0.06s; resolution of (c): 864×1152, execution time: 0.18s.).

Fig. 4. Left: original under-exposed image; Right: result of our method by setting CL threshold to 0

With our approach, original unnoticeable details in underexposed images are faithfully revealed as shown in Figs. 3 and 4. Our approach also works well for the image with dark foreground and bright background (Fig. 5).

Performance was measured in a PC equipped with P4 2.4 GHZ CPU and 512MB memory. Computation time varies roughly linearly with image resolution, thanks to our pixel-wise processing. For instance, normally, it takes less than 0.15 second for processing a 1024×768 resolution image (Fig. 5). Computation time is mainly dominated by the computation of gain map. Actually, $GMap(x, y)$ is a function of $I(x, y)$ and $I_{abf}(x, y)$, ranging from 0 to 255. Therefore, we can establish a 256×256 slots cache table for rapid computation of $GMap(x, y)$ from the values of $I(x, y)$ and $I_{abf}(x, y)$. Furthermore, in practice, Eq. 10 can be

(a) (b)

Fig. 5. Tone adjustment result (b) for an image (a) with dark foreground and bright background. (Resolution: 1024×768; Time: 0.14s.).

simplified by removing the spatial weight. Since the intensity weight $g_{\sigma_i}(I_q - I_p)$ relies only on the intensity of I_q and I_p, another 256×256 cache table could be used here for acceleration. All the results were obtained by using a 5×5 neighborhood.

5 Conclusions and Future Work

We have presented an approach for effectively adjusting the tonal values of underexposed images. Our approach globally increases intensity in underexposed regions, and meanwhile locally enhances details and suppresses noises. Our approach runs with fast speed for most low dynamic range images with ordinary sizes. This makes it feasible to be integrated into the digital camera imaging pipeline to improve the sensor output image data.

Although initial experiments have shown encouraging results, our approach is not robust enough to handle all cases. Our approach cannot distinguish black objects from those underexposed regions. To tackle this issue, we intend to integrate image analysis into our tone adjustment pipeline, and process image with divided-and-ruled scheme in future.

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