Image detail extraction via dark region approximation

Chaobo Min

College of Internet of Things Engineering, HoHai University, Changzhou 213000, China

E-mail: chaobomin@outlook.com

Abstract. In this paper, we propose a simple but effective approximation—dark region approximation (DRA) to extract details from gray-scale images. The DRA is based on an assumption: there is little illumination in the dark regions of visible images. The Retinex model using the DRA is developed to improve the performance of preserving details from the dark regions in gray-scale images during reflectance estimation. Then, Gaussian field criterion is introduced to construct the objective function which could be solved by quasi-Newton method, in order to estimate the reflectance via the DRA-based Retinex model. The reflectance is considered as the final result of image detail extraction. Experiments on a variety of gray-scale images demonstrate the power of the DRA and the superiority of our method.

1. Introduction

Extracting details from gray-scale images (i.e. single-channel images) is a critical step for many applications, such as image enhancement [1], image fusion [2] and image compression [3], etc. The accuracy of detail extraction directly determines the performances of these applications. When the captured gray-scale images suffer from low illumination and low contrast, detail extraction will become more difficult. Moreover, compared to real color images (i.e. multi-channel images), gray-scale images has poorer information, resulting in a tough challenge for detail extraction. Accordingly, we mainly focus on detail extraction from gray-scale images in this work.

In recent years, numerous methods of detail extraction have been developed owing to the fast-rising demand. Multi-scale decomposition [4] based on various transform models performs well on feature representation and detail extraction. The transform models, such as wavelet [5], pyramid [6], curvelet [7], non-subsampled contourlet transform (NSCT) [8], and Gaussian filters [9], are often used to depict the spatial distribution of the variety of image intensity. Retinex decomposition [10], considering the captured image as the product of reflectance and illumination layers, is applicable to detail extraction, because the reflectance can be recovered from the captured image by various Retinex-based models. Typically, bilateral filtering (BF) [11] and Gaussian filtering (GF) [12] are employed to estimate the illumination for Retinex decomposition.

In this work, dark region approximation (DRA) is proposed for extracting details from gray-scale images. First, the DRA-based Retinex model is developed to improve the performance of preserving details from the dark regions in gray-scale images during reflectance estimation. Then, on the basis of the DRA-based Retinex model, reflectance estimation is formulated as an unconstrained optimization problem by Gaussian field criterion and solved by the quasi-Newton method, in order to achieve image detail extraction. Qualitative comparisons between our method and three other approaches are conducted on a publicly available dataset. Experiment results show that our method is superior on detail preservation, and thus it is able to improve the performance of low-light image enhancement, image fusion and image haze removal, etc.
2. Proposed method

2.1. Dark region approximation

The Retinex model considers a captured image \( L \) as the multiplication of a reflectance layer \( R \) and an illumination layer \( T \):

\[
L = R \circ T
\]

where the operator \( \circ \) means element-wise multiplication. In logarithmic space, the Retinex model could be rewritten as:

\[
\hat{L} = \hat{R} + \hat{T}
\]

where \( \hat{L} = \log(L) \), \( \hat{R} = \log(R) \) and \( \hat{T} = \log(T) \). \( \hat{R} \) is considered as a map depicting the structural details of the captured objects. Thus, in the traditional Retinex-based methods of image enhancement, such as SSR and MSR, the reflectance is directly estimated by \( \hat{R} = \hat{L} - \hat{T} \) and \( \hat{T} \) is estimated from \( \hat{L} \) by Gaussian filtering. However, if the captured image is decomposed to bright and dark regions, we can find the problem of the Retinex model. The captured image consists of bright and dark regions so that \( \hat{R} = \hat{L} - \hat{T} \) becomes:

\[
\hat{R} = \hat{R}_L + \hat{R}_H = (\hat{L}_L - \hat{T}_L) + (\hat{L}_H - \hat{T}_H)
\]

where \( \hat{R}_L, \hat{L}_L \) and \( \hat{T}_L \) are the dark regions of \( \hat{R}, \hat{L} \) and \( \hat{T} \), respectively. \( \hat{R}_H, \hat{L}_H \) and \( \hat{T}_H \) are the bright regions of \( \hat{R}, \hat{L} \) and \( \hat{T} \), respectively. Due to good illumination, the differences between \( \hat{L}_H \) and \( \hat{T}_H \) are salient. In other words, the details \( \hat{R}_H \) in bright regions are easily preserved in \( \hat{R} \). But, because the intensity of \( \hat{L}_L \) is at low level, \( \hat{T}_L \) can only have low intensity. Therefore, compared to \( \hat{R}_H \), the differences between \( \hat{L}_L \) and \( \hat{T}_L \) are relatively insignificant. This means that it is easier to lose the details \( \hat{R}_L \) of dark regions in \( \hat{R} \). Figure 1 shows the illustration of reflectance estimation via the Retinex model. We can see that the details in the bright regions (the blue box) are more salient and distinguishable than the details in the dark regions (the red box). Accordingly, the directly estimated reflectance in the logarithmic domain typically loses the desired details.

![Figure 1. Illustration of reflectance estimation via the Retinex model.](image)

According to the observation on the dark regions of the captured images, we propose the DRA: it is assumed that there is little illumination in the dark regions of the captured images, i.e. \( \hat{T}_L = 0 \). Thus, the model (3) becomes the DRA-based Retinex model as follow:

\[
\hat{R} = \hat{R}_L + \hat{R}_H = \hat{L}_L + (\hat{L}_H - \hat{T}_H)
\]
Retinex model enhances the details of dark regions in \( \mathbf{R} \) since \( \mathbf{L}_L > \mathbf{L}_U - \mathbf{T}_U \). Hence, the trade-off between the details of bright and dark regions in \( \mathbf{R} \) is balanced by the DRA-based Retinex model.

However, the model (4) cannot be directly used on reflectance recovery because it is difficult to distinguish from \( \mathbf{L}_L \) and \( \mathbf{L}_U \). In the next Section, we will discuss how to apply the DRA-based Retinex model on reflectance estimation.

2.2. Object function

As we all know, the reflectance is partly caused by the illumination on objects. Therefore, we consider the reflectance \( \mathbf{R} \) as a map function \( \psi \) that depends on the illumination layer \( \mathbf{T} \). Then, the model (2) becomes

\[
\hat{\mathbf{L}} = \psi(\mathbf{T}) + \hat{\mathbf{T}}
\]

(5)

On the basis of the model (5), Gaussian fields criterion is used to construct an objective function, in order to solve the map function \( \psi \). The Gaussian-fields-based objective function is given by

\[
\min_{\psi} E(\psi) = \min_{\psi} -\sum_{i=1}^M \exp \left\{ -\frac{(L_i - \sum_{j=1}^N \psi(T_i j))}{2\sigma^2} \right\}
\]

(6)

where \( L_i \) and \( T_i \) respectively denote the intensity values of the \( i \)-th pixel in \( \mathbf{L} \) and \( \mathbf{T} \), \( \sigma \) is a range parameter, \( M \) is the total number of pixels in \( \mathbf{L} \). The objective function enforces closeness between the map function \( \psi(\mathbf{T}) \) and \( \mathbf{L} - \hat{\mathbf{T}} \). The Gaussian fields criterion is a good distance measure because it is continuously differentiable and has superiority on computational convenience. Furthermore, the Gaussian fields criterion in the objective function (6) is an important basis to distinguish from dark and bright regions in a single-channel image. This will be discussed later in this section.

2.3. Reflectance model

In this work, the reflectance is considered as a transformation result from the illumination. We assume that there is a regular pattern of the transformation from illumination to reflectance in the captured image. Thus, the map function \( \psi \) (i.e. the reflectance model) can be formulated as

\[
\psi_n(\mathbf{T} i) = \sum_{i=1}^N \left( \sum_{k=0}^n \alpha_{nk} x_{i1}^{k} y_{i2}^{n-k} + \beta_n y_{i1}^{n} \right)
\]

(7)

where \( [x_{i1}, y_{i2}]^T \) is the coordinate vector of the \( i \)-th pixel in the captured image, \( \alpha_{nk} \) and \( \beta_n \) are the reflectance parameters, \( N \) is the order of the reflectance model. The first term in the model (7) indicates the space distribution of the reflectance, and the second term describes the regular pattern between the reflectance and the illumination on objects.

Essentially, the proposed model is the mixture of the various polynomials that depend on coordinate vector and intensity value. Its high non-linearity is useful for the representation of the complex pattern in the reflectance.

The matrix form of the model (7) is given by

\[
\psi_n(\mathbf{T} i) = \mathbf{c}_n^T \mathbf{p}_i = \begin{bmatrix} c_1^n \mid c_d^n \end{bmatrix} \begin{bmatrix} p_{c1}^n \mid p_{d1}^n \end{bmatrix}^T
\]

(8)

where \( \mathbf{c}_n = [\alpha_{10}, \alpha_{11}, \alpha_{20}, \alpha_{21}, \ldots, \alpha_{NN}] \) is the \( 1 \times N_p \) \( (N_p = N(N+3)/2) \) dimensional vector containing all parameters \( \alpha_{nk} \) of the first term in equation (7). \( \mathbf{c}_d = [\beta_1, \beta_2, \ldots, \beta_N] \) is the \( 1 \times N \) dimensional vector containing all parameters \( \beta_n \) of the second term in equation (7). Hence \( \mathbf{c}_n \) is the \( 1 \times (N_p + N) \) dimensional reflectance parameter vector. \( \mathbf{p}_i = [c_{c1}^n, c_{d1}^n] \) is the \( 1 \times N_p \) dimensional vector containing all \( x_{i1}^{k} y_{i2}^{n-k} \) and \( \mathbf{p}_i^N \) is the \( 1 \times N \) dimensional vector containing all \( y_{i1}^{n} \). As a result, \( \mathbf{c}_n \) is the \( (N_p + N) \times 1 \) dimension polynomial vector of the \( i \)-th pixel in \( \mathbf{T} \). \([ \cdot ]^T \) denotes matrix transposition.

Substituting equation (8) into equation (6), the optimization function becomes

\[
\min_{\mathbf{c}_n} E(\mathbf{c}_n) = \min_{\mathbf{c}_n} -\sum_{i=1}^M \exp \left\{ -\frac{(L_i - \sum_{j=1}^N \mathbf{c}_n p_{jn}^N)^2}{2\sigma^2} \right\}
\]

(9)
2.4. Optimization  
It is obvious that the optimization function (9) is always continuously differentiable with respect to the reflectance parameter $C^N$. Thanks to the reflectance model which is defined in polynomial form, it is easy to write the corresponding derivative of equation (9) as follows:

$$\frac{\partial E(C^N)}{\partial C^N} = \frac{1}{\sigma^2} \sum_{i=1}^{M} p_i^N (C^N p_i^N + \hat{T}_i - \hat{L}_i) \exp \left\{ - \frac{(L_i - C^N p_i^N - \eta)^2}{2\sigma^2} \right\}$$  (10)  

On the basis of the derivative (10), gradient-based numerical optimization approaches such as quasi-Newton method [13] can be employed to solve the optimal parameter $C^N$. But before that, there is still a difficult problem in reflectance estimation: how to obtain the illumination layer $T$. Estimating the illumination and reflectance layers from the captured image simultaneously is an ill-posed problem, which cannot be solved by using the objective function (9) and the derivative (10). Thus, the illumination layer must be determined before reflectance estimation.

2.5. Calculating the illumination layer  
From the objective function (9) we can see that reflectance estimation is considered as a fitting problem in this work. The capture image $\hat{L}$ and the illumination $\hat{T}$ are the known data points. The reflectance model (7) is a fitting function and the objective function is a fitting criterion. Accordingly, the purpose of the objective function is to make the reflectance model approximate $\hat{L} - \hat{T}$. Since the reflectance model consists of polynomials, it can describe the regular pattern of the reflectance ($\hat{R} = \hat{L} - \hat{T}$). In the traditional Retinex-based methods such as the single-scale Retinex [14] and multi-scale Retinex [15], the illumination layer is typically obtained from the captured image by using Gaussian filter. If the Gaussian-based illumination layer obtained by $\hat{T}_g = \log (T_g)$ is used to the optimization of the objective function, the estimated reflectance may have the same disadvantage as the directly estimated reflectance (it has been discussed in Section 2.1).

The penalty curve of the Gaussian criterion (e.g. $1 - \exp \left\{ -x^2/(2\sigma^2) \right\}$) is shown in Figure 2. We can see that the Gaussian criterion has high tolerance for large $x$. In other words, the Gaussian criterion has little response to the large value of $x$. With this property, coarse blur is developed for obtaining the illumination, in order to reflectance estimation via the DRA-based Retinex model (4).

![Figure 2. The penalty curve of the Gaussian criterion](image)

Actually, the coarse blur is very simple: the Gaussian-based illumination layer $\hat{T}_g$ is further degraded by setting the pixel values whose $x$ and $y$ coordinates are both odd or even numbers to 0 (as shown in Figure 3). Here, $\hat{T}_g$ denotes the coarse-blur-based illumination layer and $\hat{T}_i$ denotes the pixel value in $\hat{T}_g$. In the optimization of the objective function (9), by using the pixels with $\hat{T}_i \neq 0$, the reflectance model is fitted to the differences between $\hat{L}$ and $\hat{T}_i$. According to the Retinex model, in the case of $\hat{T}_i \neq 0$, the reflectance model prefers to represent the regular pattern of the reflectance in bright regions. Meanwhile, the term $[\hat{L}_i - (\psi (\hat{T}_i) + \hat{T}_i) ]^2$ of the pixels with $\hat{T}_i = 0$ in the objective function becomes $[\hat{L}_i - \psi (\hat{T}_i)]^2$. As can be seen in Figure 2, the objective function has little response to the large value of $[\hat{L}_i - \psi (\hat{T}_i)]^2$. Therefore, by relaxing the range parameter $\sigma$ to a proper value, we can make the reflectance fit to the low intensities of the capture image. In other words, in the case
of $\hat{T}_C^c = 0$, the reflectance model incline to depict the regular pattern of the intensity distribution of the dark regions.

With the objective function (9), we can firstly decompose a single-channel image into dark and bright regions by soft thresholding. Then, the reflectance layers of dark and bright regions could be modelled by $\hat{R}_L = \hat{L}_L$ and $\hat{R}_H = \hat{L}_H - \hat{T}_H$ respectively. Finally, the reflectance model is used to compromise the regular patterns of the reflectance in dark and bright regions. Thus, the optimal reflectance model, estimated by the objective function with the coarse-blur-based illumination layer, is able to describe the regular pattern of the reflectance via the DRA-based Retinex model $\hat{R} = \hat{L}_L + (\hat{L}_H - \hat{T}_H)$.

When the optimal reflectance model is determined, a DRA-based reflectance layer $R^c$ could be obtained by

$$R^c = \exp\{\psi^c_N(\hat{L})\} \quad (11)$$

where $\psi^c_N$ represents the optimal reflectance model with order $N$. Figure 3 shows an example of reflectance estimation based on DRA. Compared to the directly estimated reflectance in Figure 1, the DRA-based reflectance saliently enhances the details in the bright regions while illuminating the details in the dark regions. Our method is outlined in Algorithm 1.

**Figure 3.** Reflectance estimation based on the DRA. $T^c$ denotes the coarse-blur-based illumination layer obtained from $T^0$. The red box indicates a dark region and the blue box indicates a bright region.

**Algorithm 1.** Detail extraction based on the DRA

**Input:** The captured image $L$, the range parameter $\sigma$, the order $N$ of the reflectance model

1. $\hat{L} = \log(L)$;
2. Generate the coarse-blur-based illumination $\hat{T}_C^c$ from $L$;
3. Estimate the optimal reflectance model $\psi^c_N$ via the quasi-Newton method with equation (9) and (10);
4. Calculate the DRA-based reflectance $R^c$ via equation (11) based on $\psi^c_N$;

**Output:** Final result $R^c$

3. Experiments

3.1. Dataset and parameter setting

The tested images are from the TNO dataset. These images have low contrast, insufficient brightness and narrow dynamic range. These increase challenge for detail extraction. To evaluate the performance of our method, we compare it with three other approaches of detail extraction, namely, BF [11], GF [12] and patch-based contrast quality index (PCQI) [16]. All these competitors are implemented based on Matlab codes, and their parameters are set by referring to their original papers. All the experiments are conducted on a computer running Windows 10 OS (64 bits) with Intel Core i7-9700K CPU @3.60GHz and 16GB RAM.

Our method needs two input parameter: the range parameter $\sigma$ and the order $N$ of the reflectance model. Parameter $\sigma$ determines how wide the response range of the Gaussian fields criterion in the
objective function (9). Parameter $N$ controls the nonlinearity of the reflectance model. In this work, the optimal setting is $\sigma = 0.6$ and $N = 4$, which is determined through multiple experiments. What’s more, since we scale the gray range of the input image into $[0,1]$, the optimal value of parameter $\sigma$ and $N$ in general will be similar on various samples.

3.2. Qualitative comparison

Figure 4 shows the qualitative comparisons of BF, GF, PCQI and our proposed method on four gray-scale images. It is apparent that BF, GF and PCQI could to some extent extract the detail information from gray-scale images. By using BF, GF and PCQI, the textures in bright regions are easily preserved but with the loss of the details in dark regions. Compared to the competitors, the results of our method have more textural details and better contrast. Moreover, the contrast in the dark regions is increased significantly. The details with low visibility in the captured images are preserved and enhanced by our method, such as the windows in Figure 4(a) and (c), the shrubs and trees in Figure 4(b), the man in the shadow of Figure 4(d). These demonstrate that the DRA-based reflectance has superiority on detail preservation and the proposed DRA is helpful for extracting the detail information from the dark regions of images.
**Figure 4.** Qualitative comparisons of BF, GF, PCQI and our proposed method. The arrows highlight the regions where there are significant differences between our method and the others.

### 4. Conclusion

In this work, reflectance estimation based on the DRA is proposed to detail extraction of gray-scale images. First, the DRA is introduced to improve the performance of the Retinex model, especially on detail preservation in the dark regions of gray-scale images. Then, with the Gaussian field criterion, the DRA-based reflectance of images is estimated by the quasi-Newton method and considered as the final result of detail extraction. The experiments reveal the superiority of our method on detail preservation.

Our experiments show that reflectance estimation based on the DRA could extract rich textures and details, especially from the dark regions of the captured images. But, due to unnatural intensity distribution, the DRA-based reflectance cannot be used as the desired results of image enhancement directly. Accordingly, in future, we mainly focus on how to apply the DRA-based reflectance on image enhancement, image fusion and image restoration, etc.

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