Image Enhancement under Low Luminance with Strong Light Weakening

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Abstract**—In low luminance images (night scene), it suffers from various problems, e.g., low overall brightness, poor contrast and serious lack of information. However, in some scenario, strong light also appears in these images. In this case, the regions of high and low luminance both exist, which introduces a more complicated situation for image enhancement. In this paper, we present an enhancement method via dark channel prior to adaptively improve the contrast of given images, especially those containing strong light. To fully use of image dehazing, haze images are firstly obtained from original low luminance images, where the transmittance template is sequentially estimated by the dark channel prior. Later, we design a modified mapping transmittance function to optimize such template, where the factor of strong light is well taken into account. Moreover, to compensate the detail loss in strong light areas, an optimal model is further built to improve the aforementioned template. With a set of dehazing manipulations, enhanced images are finally achieved. Experimental results show that the proposed algorithm not only improves the brightness and contrast of traditional low luminance images, but also can deal with images with strong light, where the regions of strong light are efficiently suppressed.**

Keywords--dark channel; haze image; strong light; transmittance template

I. INTRODUCTION

In past decades, various methods are developed for image enhancement to deal with images in low luminance, especially in night scenaio, which are featured with poor contrast, low brightness and serious information loss [1]. Though low luminance images are very often assumpted to be achieved in low level of background light, in practice, strong light may also appears in these images. For example, images are taken including lamps lighting nearby. Unfortunately, different from the traditional low luminance images, there both exist high and low luminance in these images, which suffer from poor human vision. Therefore, in this paper, we more focus on this condition, and work for image enhancement under low luminance with strong light weakening.

In general, the methods for low luminance image enhancement can be included into three categories. 1) Some researches dedicate to dealing with these images in spatial domain, where the pixel-based and template-based operations are usually adopted. In the pixel-based operation, a variety of methods are presented via the gray-scale adjustment with histogram equalization in each color channels. However, due to the histogram equalization somewhat over-strengthens on the distribution of pixel values, details of images tend to be wiped. To address this issue, more algorithms are proposed to take the description of details into account, though this idea sometimes leads to the phenomena of 'discrete spots' [2]. As for the template-based operation, a multi scale Retinex with color restoration (MSRCR) algorithm is exploited recently, where the enhanced pixel is achieved with the weighted average of the surrounding pixels [3]. 2) Others handle the low luminance images in frequency domain. For example, a set of methods are proposed in the framework of wavelet transform. In these methods, images are decomposed through several subbands. Sequentially, a cuckoo search algorithm is used to optimize the wavelet coefficients in each subband [4]. However, to achieve an acceptable enhancement, these coefficients should be carefully set to fit each image, which may be loss of generality. 3) Moreover, the image enhancement problem can also be viewed as an image fusion problem to some extent, where several images at the same scenario are fused into one image. By this way, low luminance images become more visualized. For example, in [5], a Laplacian-pyramid-based fusion rule is proposed, where a set of low luminance images are merged in the maximum likelihood measure.

On the other hand, the physical model for low luminance images is also studied. It shows that there is a strong relationship between low luminance images and haze ones. Therefore, by the use of the haze image degradation model via dark channel prior (DCP), the light intensity of low luminance images can be extremely promoted [6]. For example, an improved dehaze model is presented to employ a Gaussian pyramid operation (GPO) to optimize transmittance template, and effectively enhances low luminance images [7]. Besides, a fast and effective low luminance video enhancement algorithm is recently exploited, where it further reduces noise in these videos by employing the Retinex theory with the DCP [8].

Motivated by the recent progress, we pay more attention to image enhancement with strong light weakening. In details, an improved algorithm is proposed based on image degradation model with the DCP. Meanwhile, an optimal transmittance template is designed by considering both strong light weakening and details protection for enhanced images. Experiment results show the output images can achieve better visual effects compared with traditional enhancement methods in different measures.

II. RELATED WORKS

A. Image dehazing using dark channel prior

With the statistics of outdoor haze-free images, the concept of the DCP is introduced in [9]. It demonstrates that the pixel intensity (a.k.a. pixel value) of the non-sky patches in one color channel is relatively low. In other words, the minimum value of pixels in such a patch can be used to describe the dark channel as

$$J^{dark}(x,y)=\min_{c\in\{r,g,b\}}\left(\min_{(x_p,y_p)\in\Omega(x,y)} J^c\left(x_p,y_p\right)\right)\to 0, \qquad (1)$$

以(x,y)为中心，周围15×15区域的像素最小值点，该点的RGB三通道中最小通道的像素值　　趋于0？？
表示为(x,y)点的暗通道值

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where $J(x,y)$ denotes the pixel value at the location position (x,y) of the haze image $\boldsymbol{J}$, $(.)^c$ and $(.)^{dark}$ represent pixels through the color and dark channels respectively. Here, $c \in \{r,g,b\}$ is the color channel index, and $\Omega(x,y)$ is a block region of size 15×15 centered at the position indices (x,y).

Moreover, the classical image degradation model [10] is introduced as

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$$J^c(x,y) = I^c(x,y)t(x,y) + A(1-t(x,y)), \tag{2}$$

where $I(x,y)$ denotes the scene radiance (or dehazed image pixel) value, A is the global atmospheric light, $t(x,y)$ is the transmittance coefficient at (x,y) in the corresponding transmittance template $\boldsymbol{T}$.

Thus, the final dehazed image $\boldsymbol{I}$ can be synthesized with each channel pixels $I^c(x,y)$ by

$$I^c(x,y) = A + \frac{J^c(x,y) - A}{\max(t(x,y), t_0)}, \tag{3}$$

where $t_0 = 0.1$ is an experiential coefficient, $t(x,y)$ is estimated by the corresponding $J^{dark}(x,y)$ in (1) (see in section III).

B. Just noticeable difference

给定可见性阈值，一旦目标像素与其相邻像素之间的差异低于该阈值，像素的波动就无法被人类视觉感知，其中图像的细节无法被检测到。

Just noticeable difference (JND) is a measure to evaluate the smallest detectable difference between two signals [11]. With the definition of JND, a visibility threshold is inferred. Given the visibility threshold, once the difference between the target pixel and its adjacent pixels is below such threshold, the value fluctuation of pixels are unperceived, where details of the image cannot be detected by human vision.

As for the visibility threshold, it is varied and nonlinear changed in different background luminance. It shows that, in the low and high background luminance, human need more large range of gray level to distinguish details. However, in the case of the moderate luminance, the quantity of gray level is decrease. Therefore, the JND matrix $\boldsymbol{D}$ can be modeled as:

$$D(x,y) = \begin{cases} 21\left(1 - \sqrt{\dfrac{\bar{J}(x,y)}{127}}\right) + 4 & if\, \bar{J}(x,y) \le 127 \\ \dfrac{3}{128}\left(\bar{J}(x,y) - 128\right) + 4 & otherwise \end{cases}, \tag{4}$$

where $\bar{J}(x,y)$ is the estimated value for the local background luminance at (x,y) with

$$\bar{J}(x,y) = \frac{1}{32}\sum_{i=1}^{5}\sum_{j=1}^{5} J(x-3+i, y-3+j)B(i,j), \tag{5}$$

where $B(i,j)$ is the coefficient of weighted matrix $\boldsymbol{B}$ at (i,j). From (4), the JND not only represents the human visual curve, but also brings the criterion to distinguish variations in details.

III. PROPOSED ALGORITHM

To deal with the low luminance image $\boldsymbol{Y}$, the hazed image $\boldsymbol{J}$ is firstly achieved via the reverse operation as

$$J^c(x,y) = 255 - Y^c(x,y), \tag{6}$$

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where $Y(x,y)$ is the pixel value of $\boldsymbol{Y}$ at (x,y).

Sequentially, the transmittance template $\boldsymbol{T}$ can be estimated with the DCP as

$$t(x,y) = 1 - \omega \min_{c \in \{r,g,b\}}\left(\min_{(x_p,y_p)\in\Omega(x,y)}\left(\frac{J^c(x_p,y_p)}{A}\right)\right), \tag{7}$$

where ω is heuristically set to 0.9. Note that, here, the parameter ω is described as a haze operator to keep a small amount of haze for the distant objects, which makes the dehazed image more natural. Moreover, to achieve the value of A, we label the locations of the top 0.1% brightest pixels in the dark channel. And then A can be simply set as the mean of the corresponding pixels with highest value selected in the haze image.

Thus, the dehazed image $\boldsymbol{I}$ can be obtained from (3). The enhanced low luminance image $\tilde{\boldsymbol{Y}}$ is finally achieved as

$$\tilde{Y}^c(x,y) = 255 - I^c(x,y), \tag{8}$$

where $\tilde{Y}(x,y)$ is the pixel value of $\tilde{\boldsymbol{Y}}$ at (x,y).

From (6) to (8), it shows that the enhancing performance of this method almost depends on the design of the transmittance template. Though such template is given by a classic approach in [9], recently more optimized templates are proposed. For example, the multiplier DCP (MDCP) is introduced to adaptively adjust the template and maintain the spatial continuity in [12]. However, to cope with low luminance images with strong light, the existing algorithms either suffer from black holes or tend to obscure the enhanced images in strong light areas. To this end, we adopt the JND to update the transmittance template, which aims to weaken the strong light. Meanwhile, a contextual regularized optimal method is utilized to pursuit a more refined template for the further improvement on low luminance images.

A. Weaken strong light with JND

Since the haze image $\boldsymbol{J}$ is directly transferred from the corresponding low luminance image $\boldsymbol{Y}$, the region luminance in $\boldsymbol{J}$ still is varied seriously, that is, both areas of high and poor luminance exist. Thus, we deal with various regions via different methods. By the use of the JND, we build a new transmittance template with a piecewise function, where in the different piecewise case either the suppression of strong light or the enhancement of the low luminance is considered

To achieve this piecewise function, the threshold T is firstly taken into account, where the values of the low and high luminance can be adaptive distinguished, as

$$T = \frac{\sum t(x,y) \le 0.2}{\sum t(x,y) \le 1}. \tag{9}$$

For notational simplicity, from here on, the position indices (x,y) are omitted, e.g., $t(x,y)$ will be expressed as t. Now, to update the transmittance template $\boldsymbol{T}$ into $\hat{\boldsymbol{T}}$, a template transfer function is used as

$$\hat{t} = \begin{cases} T - \log(T\rho - t\rho + 1)T/K_1 & t < T \\ T + \log(t\rho - T\rho + 1)(1-T)/K_2 & otherwise \end{cases}, \tag{10}$$

where $\hat{t}$ is the transmittance coefficient of $\hat{\boldsymbol{T}}$. K_1 and K_2 are two weighted coefficients. More details are given as

$$\begin{cases} K_1 = \log\left(T\rho + 1\right) \\ K_2 = \log\left(\rho - T\rho + 1\right) \\ \rho = \exp\left(D_{\max} / D\right) \end{cases}, \tag{11}$$

where $D_{\max}$ is the maximum value of $\boldsymbol{D}$. To illustrate the performance of the updated template $\hat{\boldsymbol{T}}$, an example of the template transfer function is given in Fig. 1, where the corresponding low luminance image (named as lamp) is also shown in Fig. 2. In Fig. 1, given t, in the case of $t \geq T$, it indicates the corresponding pixel at the position indices (x, y) belongs to the region with the strong light. Thus, the larger $\hat{t}$ is achieved to suppress such high luminance. On the other hand, to deal with the low luminance regions, the smaller $\hat{t}$ is used to replace the traditional transmittance coefficient t so as to improve their luminance.

The comparison of transmittance templates $\boldsymbol{T}$ and $\hat{\boldsymbol{T}}$ is given in Fig. 2. Moreover, we visualize the difference between the traditional template and updated one, where green regions denote the values of updated template are larger than traditional template and red ones represent those are smaller. In Fig. 2, it shows that in the strong light regions, more green components exist. In other words, a number of higher transmittance coefficients $\hat{t}$ are achieved with the updated template, which can be well suppressed in the following procedures. Meanwhile, the low luminance areas are almost labeled with red. With this operation, the lower transmittance coefficients $\hat{t}$ can be adopted. Moreover, it is worth mentioning that the threshold T is efficiently employed to separate the components of strong light from others.

B. Image enhancement with contextual regularization

Though the transmittance template $\hat{\boldsymbol{T}}$ can be used to weaken strong light, unfortunately, more details are lost in the strong light areas. To protect these details, we further refine the template as $\tilde{\boldsymbol{T}}$, where an optimal problem is founded with a contextual regularization by

$$\tilde{\boldsymbol{T}} = \arg\min_{\boldsymbol{T}} \left(\frac{\lambda}{2} \left\| \boldsymbol{T} - \hat{\boldsymbol{T}} \right\|_F^2 + \sum_{k \in S} \left\| \boldsymbol{W}_k \circ (\boldsymbol{C}_k \otimes \boldsymbol{T}) \right\|_1 \right), \tag{12}$$

where k belongs to an index set S, $\boldsymbol{C}_k$ is a high-order differential operator selected from several given Kirsch and Laplacian operators for preserving image edges and corners, symbols $\circ$ and $\otimes$ respectively denote the element-wise multiplication and convolution operators, W_k is the corresponding weighted function of $\boldsymbol{C}_k$ (see more details in [13]).

In order to solve the problem (12), the classical Bregman method is adopted, where it turns the complex problem into a number of simple sub-problems with an iterative procedure. In brief, given other parameters are fixed, only one variable is optimized in each iteration. Thus, in the framework of the Bregman method, problem (12) can be turned into

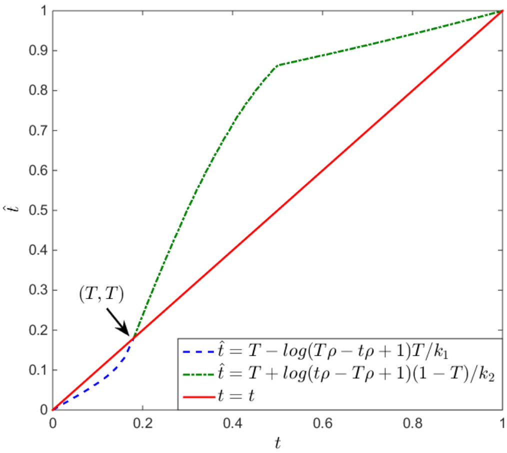

Fig . 1. Example of the template transfer function.

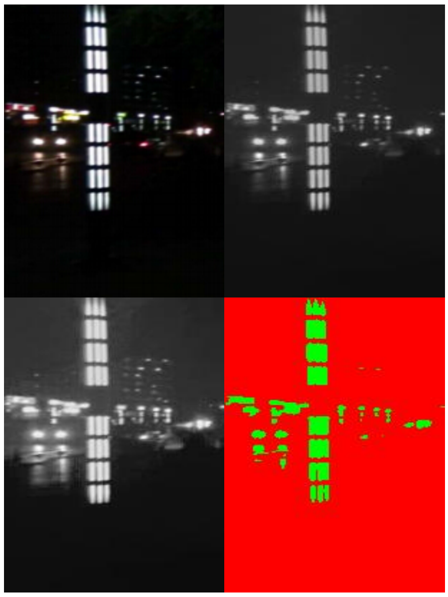

Fig . 2. Comparison of transmittance templates. Top-left: low luminance image "Lamp", top-right: transmittance template $\boldsymbol{T}$, bottom-left: updated transmittance template $\hat{\boldsymbol{T}}$, and bottom-right: comparison between $\boldsymbol{T}$ and $\hat{\boldsymbol{T}}$.

$$\begin{aligned} \left\langle \tilde{\boldsymbol{T}}, \tilde{\boldsymbol{U}}_k \right\rangle = \arg\min_{\boldsymbol{T}, \boldsymbol{U}_k} \frac{\lambda}{2} \left\| \boldsymbol{T} - \hat{\boldsymbol{T}} \right\|_F^2 \\ + \sum_{k \in S} \left(\left\| \boldsymbol{W}_k \circ \boldsymbol{U}_k \right\|_1 + \frac{\beta}{2} \left\| \boldsymbol{U}_k - \boldsymbol{C}_k \otimes \boldsymbol{T} \right\|_F^2 \right) \end{aligned}, \tag{13}$$

where $\boldsymbol{U}_k$ is introduced as a variable, β is a weighted coefficient. Obviously, as $\beta \to \infty$, the solution of (13) converge to that of (12). Given $\boldsymbol{T}$, (13) can be rewritten as

$$\tilde{\boldsymbol{U}}_k = \arg\min_{\boldsymbol{U}_k} \left\| \boldsymbol{W}_k \circ \boldsymbol{U}_k \right\|_1 + \frac{\beta}{2} \left\| \boldsymbol{U}_k - \boldsymbol{C}_k \otimes \boldsymbol{T} \right\|_F^2. \tag{14}$$

Thus the closed-form solution of (14) can be given as

$$\tilde{\boldsymbol{U}}_k = \max\left(\left| \boldsymbol{C}_k \otimes \boldsymbol{T} \right| - \frac{\boldsymbol{W}_k}{\beta}, 0 \right) \circ sign\left(\boldsymbol{C}_k \otimes \boldsymbol{T} \right), \tag{15}$$

where $sign(.)$ represents a sign function. Sequentially, to solve $\boldsymbol{T}$, fix all $\boldsymbol{U}_k$, (13) is rewritten as

$$\tilde{\boldsymbol{T}} = \arg\min_{\boldsymbol{T}} \frac{\lambda}{2}\left\|\boldsymbol{T}-\hat{\boldsymbol{T}}\right\|_F^2 + \sum_{k\in S}\frac{\beta}{2}\left\|\boldsymbol{U}_k - \boldsymbol{C}_k \otimes \boldsymbol{T}\right\|_F^2. \quad (16)$$

Since (16) can be viewed as a quadratic and convex optimization problem, we achieve its solution with the FFT approach as

$$\tilde{\boldsymbol{T}} = F^{-1}\left(\frac{\frac{\lambda}{\beta}F(\hat{\boldsymbol{T}}) + \sum_{k\in S}\bar{F}(\boldsymbol{C}_k)\circ F(\boldsymbol{U}_k)}{\frac{\lambda}{\beta} + \sum_{k\in S}\bar{F}(\boldsymbol{C}_k)\circ F(\boldsymbol{C}_k)}\right), \quad (17)$$

where symbols F and F^{-1} are Fourier transform and inverse Fourier transform, respectively, and $\bar{F}$ denotes the complex conjugate of F.

IV. EXPERIMENT RESULTS.

We test our method compared with some existing low luminance image enhancement methods, i.e., the MDCP and GPO methods. Here, some parameters are set as follows. In (13), the parameter λ is set to 0.5, while β ranges from 2 to 2^{20} with its value increasing by a scaling factor 4 in each iteration. Moreover, to evaluate the proposed method, we utilize some measures to evaluate the effect of image enhancement just as [14].

A. Entropy

Image entropy is a measure to estimate the average information in the image, which is defined as

$$H = -\frac{1}{3}\sum_{c\in\{r,g,b\}}\sum_{i=0}^{255} p^c(i)\log_2 p^c(i), \quad (18)$$

where $p(i)$ is the distribution probability of pixel values. Note that, though the concept of entropy is obtained from information theory, in enhanced luminance images, the higher entropy usually means the contrast of images is improved. Thus, the high quality of images is achieved.

B. Average gradient

Average gradient presents the smallest change of the image contrast and texture details, defined as

$$G = \frac{1}{3(M-1)(N-1)}\sum_{c\in\{r,g,b\}}\sum_{i=1}^{M-1}\sum_{j=i}^{N-1}\sqrt{\left(\Delta I_x^{c\,2} + \Delta I_y^{c\,2}\right)/2}, \quad (19)$$

where ΔI_x and ΔI_y represent the first-order differences in the direction of horizontal and vertical respectively, the size of input images is $M \times N$.

C. Clarity

Clarity refers to the clear degree in the aspect of detail and boundary. It can be described as

$$\begin{cases} L = 1 - \dfrac{1}{3MN}\displaystyle\sum_{c\in\{r,g,b\}}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\min\left[q(x,y), 1-q(x,y)\right] \\ q(x,y) = \sin\left[\dfrac{\pi}{2}\times\left(1 - f(x,y)/f_{\max}\right)\right] \end{cases}, \quad (20)$$

Fig. 3. Comparison of enhancement performances. Top-left: low luminance image "Street", top-right: MDCP method, bottom-left: GPO method, and bottom-right: our method.

Fig. 4. Comparison of enhancement performances. Top-left: low luminance image "Car", top-right: MDCP method, bottom-left: GPO method, and bottom-right: our method.

where $f_{\max}$ is the maximum pixel value of the image.

The performance of image enhancement is shown in Fig. 3, where the low luminance image without strong light is test. In general, these enhanced images with the MDCP, GPO and our methods are all acceptable. However, it shows that, the luminance of the whole image is relatively improved in our method, where more details are enhanced compared with the MDCP and GPO. In our method, since the contrast of the enhanced image is promoted, the higher clarity of the image is also achieved. It benefits from the updated transmittance template, where it adaptively identifies the relative low and high luminance regions.

We also test images with strong light as shown in Fig. 4 and 5. In these images, the MDCP performs the worst, where no attribute of strong light is considered. The performance of the GPO is better. However, this method tends to generate the obscure area on the edge of the strong light region. It is mainly

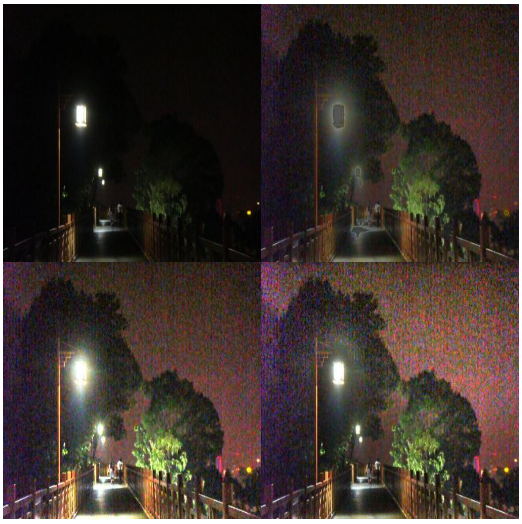

Fig. 5. Comparison of enhancement performances. Top-left: low luminance image "Park", top-right: MDCP method, bottom-left: GPO method, and bottom-right: our method.

TABLE I
RESULTS OF DIFFERENT ENHANCEMENT METHOD

		clarity	entropy	gradient
	MDCP	16.10	6.149	10.74
Street	GPO	16.09	6.056	14.24
	Our	**32.69**	**6.539**	**21.79**
	MDCP	6.77	6.520	4.364
Car	GPO	11.76	**7.189**	7.814
	Our	**12.31**	7.159	**8.029**
	MDCP	10.40	6.399	6.281
Park	GPO	16.09	6.917	9.977
	Our	**30.19**	**7.527**	**18.08**

because the median filter is used in the procedure of the transmittance template optimization. With the median template of larger size used, more obscure area is produced. As for our method, such phenomena is effectively avoided, due to no median filtering is adopted. Moreover, with the updated transmittance template, the luminance of strong light is suppressed. Meanwhile, the details are further preserved due to the optimal model via the contextual regularization.

The statistical results of three methods are shown as Table 1, where the aforementioned measures, i.e., clarity, entropy and gradient, are used. It shows that, our method still performs best, especially in clarity and gradient. In the measure of image entropy, our method achieves higher scores on *Street* and *Park*. It means the contrast of the corresponding enhanced images is obtained. However, for the GPO, it seems the highest score is got on *Car*. As seen in Fig.4, this score is produced by the false-enhancement, where the edge region of strong light is over strengthened with an amount of obscurity. As for the clarity and gradient, our method benefits from both updated transmittance template and the contextual regularized optimal model.

V. CONCLUSIONS

We propose an enhancement method via dark channel prior to adaptively improve the luminance of given images, especially those containing strong light. The method utilizes the transmittance template which is obtained via the dark channel prior. Sequentially, an updated template is got by a modified mapping function, where the factor of strong light is considered. Later, an optimized problem is used to achieve the refined transmittance template. With these procedures, the final enhanced images are rebuilt with such refined template by a set of dehazing operations. Experimental results show that the proposed algorithm not only improves the brightness and contrast of traditional low luminance images, but also can deal with images with strong light, where the regions of strong light are efficiently suppressed

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