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RESEARCH ARTICLE

Low lighting image enhancement using local maximum color value prior

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Abstract We study the problem of low lighting image enhancement. Previous enhancement methods for images under low lighting conditions usually fail to consider the factor of image degradation during image formation. As a result, the lost contrast could not be recovered after enhancement. This paper will adaptively recover the contrast and adjust the exposure for low lighting images. Our first contribution is the modeling of image degradation in low lighting conditions. Then, the local maximum color value prior is proposed, i.e. in most regions of well exposed images, the local maximum color value of a pixel will be very high. By combining the image degradation model and local maximum color value prior, we propose to recover the un-degraded images under low lighting conditions. Last, an adaptive exposure adjustment module is proposed to obtain the final result. We show that our approach enables better enhancement comparing with popular image editing tools and academic algorithms.

Keywords low lighting enhancement, image degradation model

1 Introduction

In low lighting conditions, the irradiance that a camera receives from scenes is attenuated along the line of sight. In addition, the incoming light is blended with the airlight. As a result, the images captured by cameras are degraded and the contrast is lost. The amount of degradation depends on the distances between scene points and the camera. In this paper, we study how to enhance degraded images in low lighting conditions.

Since mobile and surveillance cameras are increasingly widely deployed, and are expected to acquire high quality images in all lighting conditions, enhancing low lighting images is highly desired. First, it could improve the visibility of the images for human beings. Second, it could increase the performance of various vision algorithms in low lighting conditions such as image segmentation, object detection and recognition, and etc.

In low lighting image enhancement field, there are two main approaches, namely, infrared based systems and image processing based algorithms. Infrared systems include far and near infrared-based systems [1–5]. Although widely used, they are usually more expensive, harder to maintain, and have a relatively shorter life-span than conventional systems. On the other hand, image processing algorithms have made tremendous progress over the years, such as [6–7]. The algorithm in [6] uses contrast limited histogram equalization to enhance images. Bennett et al. [7] use non-linear curve adjustment to improve visual quality. However, they fail to consider the factor of image degradation during image formation. As a result, the lost contrast could not be recovered. Recently, we propose a novel algorithm [8, 9] by de-hazing inverted low-lighting videos. Zhang et al. [10] improve the work in [8, 9] by utilizing joint bilateral filter to suppress the noise. Although the methods could adjust the contrast, they lack physical explanation to guarantee that the contrast added to the result is equal to the amount of degraded contrast.

In this paper, first, we use the image degradation model in

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[11] to model the degradation of sight of scenes in low lighting images. Second, we propose local maximum color value (LMCV) prior, i.e., in most regions of well exposed images, the LMCV of a pixel will be very high. Third, by combining the image degradation model with LMCV prior, we propose to enhance images captured in low lighting conditions. Last, we adaptively adjust the exposure of the recovered results.

Compared with industrial image editing software tools including the shadow-highlight, auto-level, auto-contrast of Adobe Premiere and academic algorithms [6, 7], our user studies show that the proposed algorithm benefits most typical consumers——especially for their daily photos processing. The subjective comparisons also demonstrate our algorithm can obtain better contrast and details and can adaptively adjust the exposure for images under low lighting conditions and under-exposed regions of images under high dynamic range conditions. Since our algorithm is simple and robust, it can be chosen as a better alternate in photo editing tools and a built-in camera component.

To sum up, there are three contributions in this paper. 1) We propose to use the image degradation model to describe the degradation of sight of scenes in low lighting images. 2) We propose LMCV prior and combine it with the image degradation model to enhance degraded images in low lighting conditions. 3) We propose soft-exposure strategy to adaptively adjust exposure for under-exposed regions of recovered images.

The paper is organized as follows: in Section 2, related work is introduced. Section 3 describes the proposed method in detail. We provide the experiment results and comparisons with other algorithms in Section 4 and conclude the paper in Section 5.

2 Related work

2.1 Infrared systems

Infrared systems such as [1–5] have been widely used for low lighting conditions. Far infrared camera systems typically have 7 μm–12 μm wavelength range and near infrared camera systems typically have 0.8 μm–1.2 μm wavelength range. As said in [4], far infrared based systems use radiation emitted by objects' temperature for detection based on high spectrum range while near infrared based systems cover both visible and near infrared spectrums which as a result provide appearances of objects similar to visible spectrum. Far infrared based system have the advantage of high range; however, it is not very useful since negative features are usually dominating. In addition, near infrared based systems suffer some disadvantages such as unclear boundaries and road markings, not visible traffic signs since these signs adopt quickly to the surrounding environment; therefore, they are not "warm" enough for detection. Unfamiliar appearances of persons and animals due to differences in temperature are also a disadvantage when far infrared based cameras are used.

Comparing with image processing strategy, infrared systems are usually more expensive, harder to maintain, with a relatively shorter life-span than conventional systems. They also introduce extra, and often times considerable power consumption. In many consumer applications such as video capture and communications on smart phones, it is usually not feasible to deploy infrared systems due to such cost and power consumption issues.

2.2 Flash non–flash algorithms

Another strategy for capturing images in low lighting condition is flash/non-flash technique such as [12–14]. By taking two images i.e., one flash image and another non-flash image and fusing them into one image, they could avoid introducing noises with the help of flash image and recover the natural result with the non-flash image. However, this strategy needs to have access to the hardware of the camera, making it difficult to be applied to post-processing applications such as enhancement for shared images on social networks or images editing softwares. In addition, since each image needs a flash input, it might be difficult to be used for practical video enhancement such as video surveillance systems.

2.3 Low lighting enhancement algorithms

The algorithm in [6] utilized the temporal correlations of pixels and spatial-temporal smoothing to reduce the noise, followed by further enhancement through contrast limited histogram equalization. Bennett et al. [7] use bilateral filtering and tone mapping to improve visual quality. Recently, we propose a novel low complexity video enhancement algorithm [8, 9] based on the observation that if one inverts the pixel values of low lighting videos, the statistical characteristics of the resulted video are very similar to videos captured in hazy weather conditions. Therefore, image de-hazing algorithms could be applied to inverted low-lighting video for enhancement. Zhang et al. [10] improve the work in [8, 9] by utilizing joint bilateral filter to suppress the noise.

Although they are designed for enhancement under low lighting conditions, they are not good at recovering the contrast of the original un-degraded images. [6] [7] do not consider the factor of image degradation during image formation. As a result, the lost contrast could not be recovered. [8–10] could improve the contrast after enhancement, however, they lack physical explanation to guarantee that the contrast added to the result is equal to the amount of degraded contrast.

2.4 Image degradation model based enhancement algorithms

In haze removal fields, various methods such as [15–19] have been proposed based on image degradation model. Fattal et al. [15] estimate the albedo of the scene and the medium transmission under the assumption that the transmission and the surface shading are locally uncorrelated. This approach is physically sound and can produce impressive results. He et al. [16] propose the dark channel prior and devise an algorithm that is simple yet produces good enhancement results for images. Based on the dark channel prior, the transmission map and airlight value are calculated from dark channel map, followed by a matting method to refine the result. To reduce the computational complexity for haze removal, the algorithm in [17] uses a median filter to generate the median dark channel prior to estimate transmission map. The work of [18] proposes a novel algorithm based on a filtering approach and introduces a smoothing algorithm preserving edges and corners with obtuse angles. For video dehazing, [19] extracts the background image through the frame differential method, and estimates a universal transmission map of the background image through a process of multiscale retinex, parameter adjustment, bilateral filtering, and total variation denoising filtering.

Although these methods are based on the image degradation model [11] and could work well for image/video haze removal, they could not be directly used for low lighting enhancement because the assumptions for haze images are not correct for images in low lighting conditions.

3 Low lighting image enhancement using LMCV prior

We introduce LMCV prior based low lighting image enhancment algorithm in this section. First, we introduce the image degradation model [11] to describe the image formation in low lighting conditions. Second, we propose LMCV prior and prove it with statistics. Third, by combining image degradation model with LMCV prior, we propose a novel algorithm to enhance low lighting images. Since the enhancement might not be correct at boundary regions, we propose to correct the errors in the following subsection. Last, since the recovered images are not always well-exposed, an adaptive exposure adjustment module is proposed.

3.1 Image degradation model in low lighting conditions

We propose to use the image degradation model introduced by Koschmieder [11] to describe the formation of images in low lighting conditions. This model has been widely used in haze removal algorithms such as [15, 16], and according to the definition of the image degradation model in [11], it is also effective for low lighting images. The model is:

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

where $I(x)$ is the observed image, A is the global airlight (ambient light reflected into the line of sight by the atmosphere), $J(x)$ is the surface radiance vector at the intersection of the scene and the ray for pixel x, and $t(x)$ is the transmission function. As shown in Fig. 1, in this model, each degraded pixel is a mixture of the airlight and the surface radiance. The intensities of both are influenced by the medium transmission, determined by the scene depth and the scattering coefficient of the atmosphere. Although the degradation model is the same as the model used in haze removal methods such as [15, 16], the haze removal methods could not be directly used for low lighting image enhancement because the assumptions of haze removal methods are not correct in low lighting conditions.

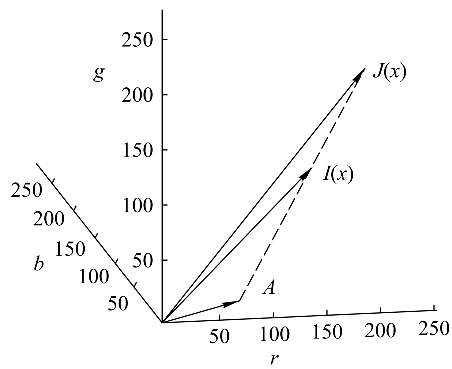

Fig. 1 Image degradation model in low lighting conditions

3.2 LMCV Prior

We propose LMCV prior for enhancing low lighting images. The LMCV is defined as:

$$J^{LMCV}(x) = \max_{c\in\{r,g,b\}} \max_{y\in\Omega(x)} J^c(y), \tag{2}$$

where J^c is a color channel of J and $\Omega(x)$ is a local patch centered at x. The LMCV prior is based on the following observation on well exposed outdoor images: in most of the regions, at least one color channel has very high intensity at some pixels. In other words, the maximum intensity in such a patch should have a very high value. The high intensities of the LMCV are mainly due to two factors: a) colorful objects or surfaces such as green grass/tree/plant, red flower, and blue water occupying high color intensity in any color channel will result in high LMCV; b) bright objects or surfaces such as lamps and car lights which are common in low lighting images. In addition, the lights will affect many neighboring objects via reflection and refraction.

Mathematic expression of LMCV prior is

$$J^{LMCV}(x) \rightarrow 225. \tag{3}$$

To verify the effectiveness of the LMCV prior, we collect a set of 20 000 images from image search engines including Google and Bing using the tag “well exposed images” and from ImageNet data-set. Some of the images and the corresponding LMCV maps are shown in Fig. 2. The intensity histogram over all LMCV maps are shown in Fig. 3. Before calculating the intensity histogram, all maps are resized to 100×100. According to Fig. 2 and 3, LMCV are very high for most pixels, meaning that only a small portion of well exposed maps deviate from our prior. Thus, we utilize this property with image degradation model to enhance low lighting images.

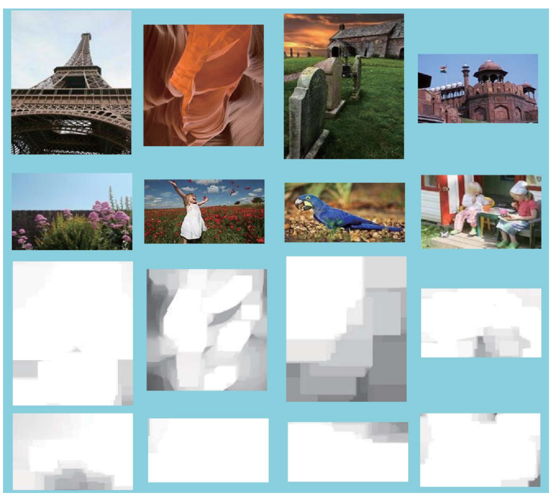

Fig. 2 Examples of well exposed maps and the corresponding LMCV maps

3.3 Degraded images recovery

According to the image degradation model i.e., Eq. (1), the transmission value $t(x)$ and airlight value A are required to be estimated to recover map J. By combining LMCV prior with the image degradation model, we propose a novel algorithm to estimate transmission value for low lighting images. Taking the max operation in the local patch and the three color channels in Eq. (1), we have:

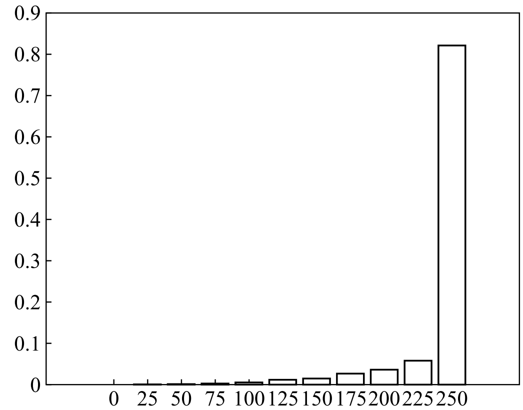

Fig. 3 Histogram of the intensity of the pixels in all of the LMCV maps (each bin stands for 25 intensity levels)

$$\max_{c\in\{r,g,b\}} \max_{y\in\Omega(x)} \mathrm{I}^c(\mathrm{y}) = t'(\mathrm{x}) \max_{c\in\{r,g,b\}} \max_{y\in\Omega(x)} \mathrm{J}^c(\mathrm{y}) + (1-\mathrm{t}'(\mathrm{x})) \max_{c\in\{r,g,b\}} \mathrm{A}^c, \tag{4}$$

where $t'(x)$ is the transmission value, A^c is a color channel of the airlight value, and J^c is a color channel of J. According to LMCV prior i.e. Eq. (3), we have:

$$\max_{c\in\{r,g,b\}} \max_{y\in\Omega(x)} \mathrm{I}^c(\mathrm{y}) = 255 \times \mathrm{t}'(\mathrm{x}) + (1-\mathrm{t}'(\mathrm{x})) \max_{c\in\{r,g,b\}} \mathrm{A}^c, \tag{5}$$

thus, with linear transformation, we could estimate the transmission value $t'(x)$ by

$$\mathrm{t}'(\mathrm{x}) = \frac{\max_{c\in\{r,g,b\}} \max_{y\in\Omega(x)} \mathrm{I}^c(\mathrm{y}) - \max_{c\in\{r,g,b\}} \mathrm{A}^c}{255 - \max_{c\in\{r,g,b\}} \mathrm{A}^c}, \tag{6}$$

i.e.,

$$\mathrm{t}'(\mathrm{x}) = \frac{I^{LMCV}(x) - A^{LMCV}}{255 - A^{LMCV}}. \tag{7}$$

In low lighting enhancement problem, because lots of pictures are taken in low lighting conditions without existence of strong light sources, such as the pictures taken at night, pixels of sky regions usually have low intensities in all color channels. Thus, the LMCV prior will fail at sky regions.

However, the color and intensity of the sky is usually very similar to the airlight value in a low lighting image and we have

$$I \rightarrow A, \tag{8}$$

at these regions. Thus, according to Eq. (5), we have

$$t'(x) \rightarrow 0, \tag{9}$$

in the sky regions. Since the sky tends to has zero transmission, the Eq. (5) gracefully handles both sky regions and non-sky regions. We do not need to separate the sky regions beforehand.

To calculate airlight value, we first pick the top 0.1 percent darkest pixels in LMCV map. These pixels are mostly in the sky regions. Among these pixels, the pixel with lowest intensity in the input image I is selected as the airlight value.

3.4 Transmission value correction

Directly using LMCV to estimate transmission values i.e. Eq. (6) will fail at the boundaries of scenes. It is because between different scenes, the transmission values vary a lot due to different distances to cameras. However, when we calculate LMCV, the pixels that do not belong to current scene might be included into the window. As a result, at boundary regions, the estimation of transmission will be affected by neighboring scenes and get wrong results.

To correct the estimated transmission value, we propose to perform joint filtering for $t'(x)$ with $I(x)$ as the guidance image so that transmission values of pixels among the same scene will be smoothed so the errors at boundary regions could be corrected. The filter we use is guided filter [20]. The mathematic expression is:

$$t(x) = G(t'(x), I(x)). \tag{10}$$

The parameters are $r = 20$, $\varepsilon = 0.001$ for the guided filter G. Fig. 4 is an example to compare the transmission estimation results with and without transmission correction. While the estimation without correction has wrong results at boundary regions, the errors are corrected after filtering.

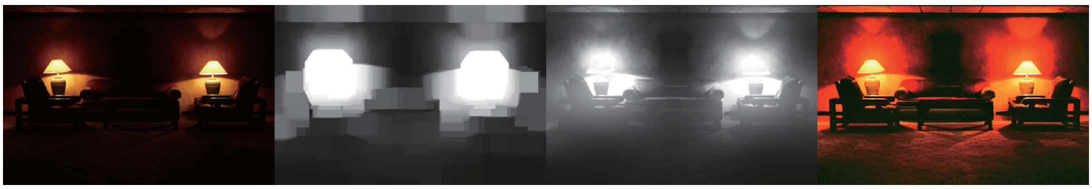

Fig. 4 Example of transmission value correction. (a) Input low lighting image; (b) estimated transmission map; (c) refined transmission map after transmission value correction; Final low lighting enhancement image

Once A and $t(x)$ are estimated, from the degradation model i.e., Eq. (1), we could get

$$J^c(x) = \frac{R^c(x) - A^c}{t(x)} + A^c. \tag{11}$$

In short, the surface radiance map J could be recovered using the estimated transmission value $t(x)$ and airlight value A.

3.5 Adaptive exposure adjustment

After recovery of degraded image, we propose an exposure adjustment module because the recovered map J are sometimes under-exposed due to lack of exposure time during the image formation.

Most existing exposure correction algorithms always need setting parameters for different inputs such as [7–9]. This makes it difficult to apply the algorithms in practical systems. We propose to soft-expose maps to different exposure levels so that for each scene there will always exist one well-exposed level. Then, we use exposure fusion method [21] to fuse images of different exposure levels. For each pixel, the fusion method will adaptively select the well-exposed level.

In doing so, we define dark pixels as those having a value less than 16 [22]. If the percentage of the dark pixels in the input image is higher than 20%, we will successively create a series of images $O_0, O_1, \cdots, O_n$ in the following manner until O_n's dark pixels occupy less than 20%.

$$O_i^c(x) = \begin{cases} J^c(x), & i = 0; \\ E_i \times O_{i-1}^c(x), & i > 0, \end{cases} \tag{12}$$

where $J^c(x)$ and ${O_i}^c(x)$ are the color channel c's values of the original recovered image and image of *ith* exposure level respectively, and E_i is a scaling factor (1.5 in our experiments). The color channels include r, g, and b. The resulted images of different exposure levels are then combined via image fusion to produce the exposure adjustment result. In our experiments, we use the fusion algorithm introduced by Mertens et al. [20] because all computations are carried out using regular eight bit images, without producing an intermediate high-dynamic-range image and then tone-mapping it for display, as is done in many other high dynamic range algorithms. When implementing this algorithm, the pyramid levels are set to $\left\lfloor \frac{log(h)}{log(2)} \right\rfloor$, where h is the height of the image.

Figure. 5 is an example to compare the enhancement result with and without adaptive exposure adjustment. While the enhancement result without exposure adjustment is a little under-exposed, the map becomes well-exposed after exposure adjustment. More results are shown in the section of Experimental Results.

Fig. 5 Example of enhancement with and without adaptive exposure adjustment. a) Input image; b) Middle: recovered image without adaptive exposure adjustment; c) Recovered image with adaptive exposure adjustment

4 Experimental results

There are 500 images in our experiments. They are divided into two groups. Group A are images under low lighting conditions. Group B are images under high dynamic range conditions, where some regions are under-exposed while other regions are well-exposed. Group A and B have 280 and 220 images, respectively. We compare the proposed method with automatic tools in Adobe Premiere including shadow-highlight, auto-level, and auto-contrast. In addition, we also compare with academic algorithms including low lighting enhancement methods in [6, 7]. The experiments are conducted on a Windows PC (Intel Core 2 Duo T6500 at 2.0 GHz with 3 GB of RAM). The implementation language is Matlab. The computational time for 480p images is 1.6 seconds on average. The computational time for 720p images is 3.1 seconds on average.

4.1 Usability study

We conduct a user study to compare our algorithm with Premiere adjustment tools (shadow-highlight, auto-level, auto-contrast) and algorithms in [6, 7]. The user study results are shown in Fig. 6. There are 15 volunteers to perform the comparisons. For each comparison, the subject has three options: better, worse or no preference. The user study is performed in the same settings and the image order is randomized.

As shown in Fig. 6, on average, the subjects prefer our results to inputs (96.9% vs. 2.2%), results of shadow-highlight of Premiere (43.3% vs. 21.1%), results of auto-contrast of Premiere (95.3% vs. 1.6%), results of auto-level of Premiere (85.3% vs. 7.6%), results of enhancement in [6] (72.3% vs. 15.6%), and results of enhancement in [7] (75.3% vs. 12.6%).

Comparisons with auto-contrast and auto-level of Premiere demonstrate our method works much better in both Group A and B. It is because auto-contrast and auto-level tools of Premiere are not designed for low lighting conditions and the intensities of under-exposed pixels will not be enlarged to well-exposed levels. As a result, the scenes in under-exposed conditions are difficult for the observers to recognize. However, our method could properly adjust the contrast and exposure of scenes in under-exposed conditions and the enhanced result would help the observers easily recognize the scenes.

The shadow-highlight tool of Premiere could get good enhancement results and performs better than auto-level, auto-contrast, [6, 7] as shown in Fig. 6. It is because the algorithm could adjust the exposure adaptively and under-exposed scenes will become well-exposed after the adjustment. However, the exposure of the results are not always adjusted properly and the contrast and details are not enhanced as well as our algorithm because it does not consider image degradation. Accordingly, the user study result of our algorithm is better than it.

Comparisons with methods in [6, 7] also demonstrate our method works better in both Group A and B. Although the algorithms of [6, 7] are designed for low lighting conditions, they do not consider the factor of image degradation during image formation. As a result, the contrast and details of their enhancement results will be lost. The more the input images are enhanced, the more contrast and details of the results will be lost. On the contrary, since our algorithm takes image degradation into consideration, our result could preserve contrast well. In addition, the transmission correction module could help preserve details.

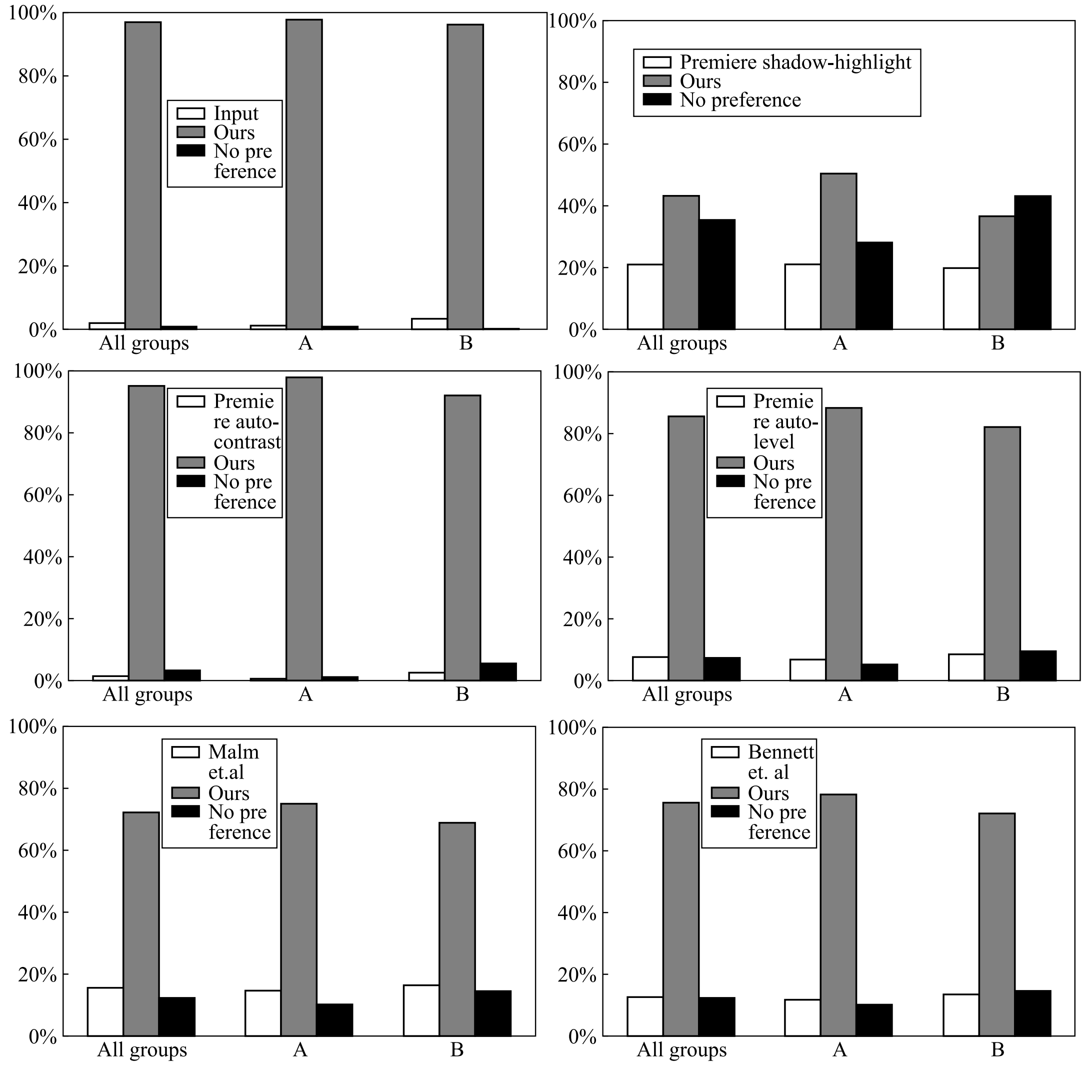

Fig. 6 Usability studies of results in two image groups. Each color bar shows the average percentage of favored image.

4.2 Results comparison

Besides the user study results, we demonstrate some enhancement results of different algorithms in this subsection for comparison.

First, we compare our algorithm with Premiere adjustment tools including shadow-highlight, auto-level and auto-contrast. The input image and enhancement results of different algorithms are shown in Fig. 7. As shown in the figure, auto-level and auto-contrast tools enhance little at the low lighting regions. Although the shadow-highlight tool manages to enhance the low lighting regions such as the sofa, the enhancement result is not bright enough. On the contrary, our result could enhance the under-exposed regions properly and make them easy to be recognized such as the sofa and the box on the wall. In addition, the contrast and details of our result are more obvious than Premiere tools due to our consideration of image degradation and transmission correction.

Second, we compare our algorithm with academic algorithms including [6. 7]. As shown in Fig. 8, results of [6, 7] will lose contrast and details because they do not consider the degradation during image formation. In addition, the exposure are not always enhanced properly because there are some parameters that must be tuned manually. For example, results of [6] are a little over-exposed. Contrast and color information of results of [7] are not preserved well. On the contrary, our algorithm could adjust the exposure properly and preserve contrast well.

Third, we compare with histogram equalization. The results are shown in Fig. 9. As shown, the results of histogram equalization look a little un-natural because it could not keep the texture structure well during enhancement. On the contrary, our results look natural and the under-exposed regions are enhanced. It is because out algorithm is able to recover the lost contrast and the exposure is adjusted adaptively.

(a)

(b)

(c)

Fig. 7 Comparisons of proposed algorithm and automatic adjustment tools of industrial software Adobe Premiere. Top: input and result of auto-level of Premiere. Middle: results of auto-contrast and shadow-highlight of Premiere. Bottom: result of proposed algorithm.

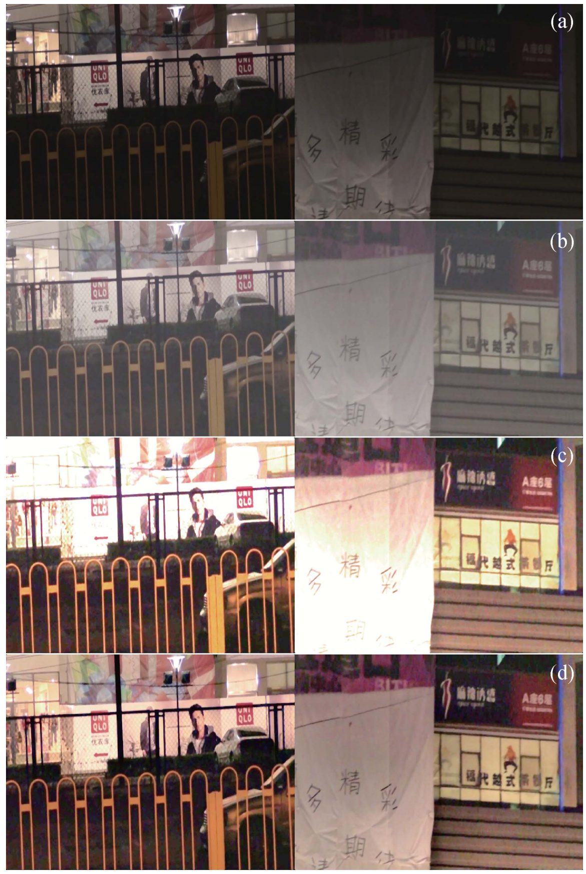

Fig. 8 Comparisons of proposed algorithm and academic algorithms. From Top to Bottom: input frames, results of Benett et al. [?]'s algorithm, results of Malm et al. [?]'s algorithm, results of the proposed algorithm.

(a) (b) (c)

Fig. 9 Comparison of proposed algorithm and histogram equalization. Left: input images. Middle: results of histogram equalization. Right: our results.

The lack of considering the noise issue is the limitation of the proposed method in this paper. Accordingly, noise might become noticeable after we lighten the under-exposed areas. We show some results in Fig. 10. The input images are captured by iPhone 4. As shown in the enhancement results, there are some noises in the under-exposed regions that are enlarged during our enhancement. The issue may be addressed by suppressing the excessive noise amplification or applying denoising for these regions in the pre-processing step. Possible denoising methods include NLM [23], BM3D [24] and those in [6, 7, 10]. We will further explore this issue in the future work.

(a) (b)

Fig. 10 More results of proposed algorithm with mobile phone images as inputs. Left: input image. Right: enhancement result.

5 Conclusions

We have presented an adaptive method for low lighting image enhancement. The heart of this method is the image degradation model, the LMCV prior, and the adaptive exposure adjustment. Like most image enhancement problems, there are no ground-truth data to evaluate our result. However, the user studies and subjective comparisons with different image editing tools and academic algorithms demonstrate we are able to obtain appropriate contrast and exposure and produce natural-looking results.

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